A black and white photograph of a person standing in a shower, with water splashing around them. The person is shirtless and appears to be looking down. The water is captured in motion, creating a dynamic and textured background.

FLEXIBILITY IN LAND AND WATER USE FOR COPING WITH RAINFALL VARIABILITY

CHRISTIAN SIDERIUS

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FLEXIBILITY IN LAND AND WATER USE FOR COPING WITH RAINFALL VARIABILITY

CHRISTIAN SIDERIUS

Thesis

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1

INTRODUCTION



1.1 BACKGROUND

How to produce enough food in an environmentally sustainable way will be one of the major challenges in the coming decades (Godfray et al., 2010). An unprecedented combination of socio-economic changes will test the resilience of local to global food production systems. By 2050, a growing world population of more than 9 billion people will need more food (FAO, 2009a; Molden, 2007). Those 9 billion people will have diets that are different from today; major changes in social preferences in combination with an increase in affluence will translate into the consumption of more grain, meat and dairy products, which require more water to produce (Fresco, 2009; Godfray et al., 2010). On top of this, biomass production for bio-fuels will compete for the same resources (Fraiture et al., 2008; Hellegers et al., 2008). Not only will more people consume more, the changing food pattern and transformation to more urban societies will lead to a different, less flexible demand for safe food (Gale and Huang, 2007). Combined, these changes will increase the pressure on land and water resources needed to produce food (Foley et al., 2011; Godfray et al., 2010; Tilman et al., 2011).

Over the same period, climate change will increasingly affect our weather. By mid-century, annual average river runoff and water availability are projected to decrease by 10-30% over dry regions at mid-latitudes and in the dry tropics, according to the Intergovernmental Panel on Climate Change (IPCC) (Parry et al., 2007). Not only will the average climate change, but so will its variability. Increased variability in total rainfall is expected to lead to both more droughts and floods (Field, 2012). In addition, changes in strength and direction of atmospheric circulation patterns will lead to fluctuations in monsoon onset (Goswami et al., 2010; Kajikawa et al., 2012; Ren and Hu, 2014), and the variation in the active-break cycle of the monsoon which governs intra-seasonal droughts (Joseph and Sabin, 2008; Singh et al., 2014), affecting crop production in the (semi) arid and subtropics. Especially in areas currently already water stressed, this increase in inter- and intra-annual rainfall variability forms a great challenge to food production.

How can the world cope with increased rainfall variability in a future climate? Food production has always been affected by rainfall variability and extremes; famines have struck South Asia as recent as 50 years ago, and East Africa only 10 years ago. In response, large increases in food production have been realized in the past decades, mainly through the 'green revolution' in agriculture, the introduction of high yielding crops which boosted yield per hectare. Rainfall variability has been buffered by the increasing use of irrigation water. Irrigated areas currently provide 40% of our food from only 17% of the agricultural lands

(Molden, 2007). Large reservoirs have been built to temporarily store water and supply the irrigated areas, with the massive Aswan dam in southern Egypt being able to store more than twice the amount of yearly runoff from the Nile River. Since the 1970s, groundwater has been tapped on a massive scale (Shah, 2010; Siebert et al., 2010), by now supporting food production on more than half of the irrigated lands in the vast irrigation systems of the Indo-Gangetic plains.

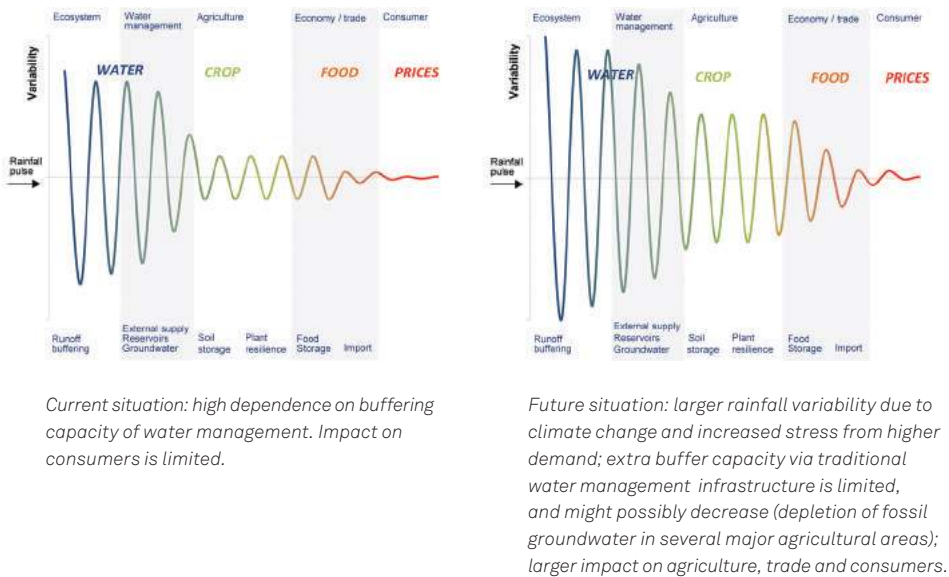


Figure 1 Conceptual framing of current and future propagation of inter-annual rainfall variability through the agro-ecosystem and the food supply chain.

Few possibilities to further develop the supply side of water resources are left, however. In many regions in the world all existing water resources are already fully allocated or even overused (Biemans, 2012). Expanding irrigation systems or building more reservoirs will not increase water availability under these conditions. There are limits to groundwater use as well, with groundwater levels in many areas falling (Richey et al., 2015; Rodell et al., 2009; Tiwari et al., 2009). Some gains can be made in reducing water losses, by increasing water use efficiency. But in many basins these gains are limited at the larger scale as these 'losses' were originally reused further downstream (Perry et al., 2009). While the world narrows in upon its planetary boundaries (Rockström et al., 2009b; Steffen et al., 2015) current approaches to deal with rainfall variability seem not to be viable anymore; the dominant paradigm of a guaranteed and optimum water supply to optimize returns from land has reached its limits (English et al., 2002). In water stressed areas, rainfall

variability propagates through the agro-ecosystem system, affecting the water and food sector, as is illustrated in Figure 1; the propagation of variability is likely to move further towards the consumer in the coming decades. In those regions where water resources are fully developed and allocated, an increase in rainfall variability cannot be buffered by water management measures alone anymore and food production will be increasingly affected. More adaptive, flexible approaches are required.

1.2 COPING WITH RAINFALL VARIABILITY; FLEXIBILITY IN LAND AND WATER USE

Flexibility generally refers to the capacity of a system to react in a situation of uncertainty, postponing decisions until more information comes in (Sethi and Sethi, 1990). In economic, management and manufacturing literature the concept of flexibility is well recognized and elaborated on as a specific strategy of companies to adapt to changing circumstances (Golden and Powell, 2000; Jones and Ostroy, 1984; Sethi and Sethi, 1990; Slack, 1987; Volberda, 1996). In this thesis, the concept is applied to agriculture, with a focus on rainfall variability and resulting water availability as the main uncertainties, and land and water as the production factors that can be varied. Flexibility here refers to the ability of farmers and local water managers to seasonally anticipate variations in water availability by changing the cropping type or overall land use practices resulting in a dynamic system of land and water use modifications.

Flexibility can be seen as the temporal counterpart of diversification (Holmelin and Aase, 2013; Pandey et al., 2007). By diversification, risks due to uncertainty are spread by using a portfolio of land use and water management options (Aerts et al., 2008; Stirling, 2007). By being flexible, on the other hand, decisions are postponed and options are kept open until more information becomes available. While diversification is linked to portfolio theory, flexibility relates more to real options theory (Amram and Kulatilaka, 1998). Farmers maintain flexibility with regard to input decisions until uncertainties about weather realizations are reduced, for instance by shifting the time when crops are planted (Burke and Lobell, 2010). In this way, preference is given each year to certain options in the portfolio, based on information on rainfall and expectations about water availability. While in each individual year land use and water management responses at a farm or in a region might be rather uniform, over longer time periods the portfolio stays diverse.

Together with diversification, flexibility forms an evolutionary potential to adapt to changing circumstances (Rammel and van den Bergh, 2003). But whereas diversification has been given ample attention as an approach to adapt to climate change in agriculture and water

management (Aerts et al., 2008; Howden et al., 2007; Smit and Skinner, 2002; Stirling, 2007; Werners, 2010), flexibility, with its focus on temporal and intentional, pro-active aspects of adaptation, has received less attention. In studies focusing on changes in land use there has been an overemphasis on the impact of permanent land-cover conversions, which are more easy to measure and describe due to their discrete nature, than the more seasonal land-use modifications (Lambin et al., 2003). In hydro-meteorological model studies, mostly long term average values are presented with models calibrated and validated at this level. Similarly, current water accounting methods, like the water footprint (Hoekstra and Hung, 2002; Hoekstra and Mekonnen, 2012), generally use only single, average values for water, land and/or production. The discussion of use and applicability of these methods focuses largely on the impact of different spatial scales (e.g. Molden and Sakthivadivel (1999)). Few impact studies (van Oel et al. (2010) being an interesting exception) take land use and water allocation decisions as a response to temporal rainfall variability into consideration.

Flexibility in land and water use is, at the same time, nothing new to agriculture and several individual aspects of it have been described in literature, with information derived mostly from local case studies. Changing crops or leaving land fallow has been identified as a local coping strategy of farmers in response to both short-term droughts and long-term declining water availability in irrigated areas (Molle et al., 2010; van Oel et al., 2010; Venot et al., 2010a). Similarly, flexible cropping patterns in rainfed agriculture supported by advanced information on soil moisture or the onset of the rainy season, were shown to give higher yields (Sadras and Roget, 2004; Weisensel et al., 1991). With the advance of communication technology and improved forecasting skill, the use of climate and weather forecasts - essential for a more flexible land and water use allocation - has been receiving more attention (Hansen et al., 2006; Meinke and Stone, 2005; Meza et al., 2008).

How and to what extent farmers, consumers and society as a whole can deal with an increasing effect of rainfall variability on food production is still a major question. This study will explore flexibility as a coping strategy across scales, analysing the impact of being flexible in land and water use at the local level, the extent to which it is applied at the regional level and its impact on food production at the basin level. It addresses flexibility under current climate conditions but does not explore the impact of future climate change explicitly. Still, learning on how to cope better with rainfall variability now is regarded vital for adapting to future change (Glantz, 1992; Kabat et al., 2002).

1.3 OBJECTIVES AND RESEARCH QUESTIONS

This study's two main objectives are to further enhance our understanding of flexible strategies for coping with rainfall variability in two important food producing regions, South Asia and eastern Africa, and to explore the future of food production under these variable conditions. To reach these objectives, four research questions are formulated:

1. *Can conjunctive use of water from rain, tank and groundwater reserves buffer rainfall variability and thereby improve water productivity and overall food production of traditional irrigated agriculture in South Asia?*

Here I focus on flexibility in land and water use at the very local scale, in a single village, and assess the sustainability of improved conjunctive use of rainfall, tank water and groundwater in a tank irrigation system.

2. *How can we observe and measure flexibility in land use in the Ganges basin in response to rainfall variability?*

Via the use of remote sensing techniques I aim to understand where crop production is affected by rainfall variability at the regional scale in one of the largest basins in South Asia, one that relies heavily on irrigation. A sub-question is, whether yearly anomalies in vegetation are merely a biophysical response of the crop to varying rainfall or whether a coping strategy, i.e. flexibility, in the form of changing cropped area is involved. Can such a flexibility be detected using remote sensing?

3. *What factors influence flexibility in land use and how can we determine the value of this type of flexibility as a coping strategy?*

Current impact assessments using hydrological and land surface models largely ignore seasonal flexibility by adjustments in cropped area as a strategy for coping with rainfall variability. By introducing seasonal cropped area as an endogenous variable in a hydro-economic model, I aim to better simulate current variability in production. A relevant topic to explore with such an improved model is the value of flexibility for farmers, in terms of gross margin. The Indian part of the Ganges basin forms the case study site.

4. *Will reallocation of water in the Nile be sufficient to achieve water and food security in the Nile basin given the basin's high rainfall variability?*

To date, most analyses of the Nile basin focused on the interaction between irrigation and hydropower. By including not only irrigated agriculture, but also rainfed agriculture in a hydro-economic model of the Nile basin I aim to widen the solution space. An additional question is whether rainfall variability affects this solution space.

1.4 METHODOLOGY

OBSERVATIONS COMBINED WITH HYDRO-ECONOMIC MODELLING

To answer the research questions a classic approach of empirical studies combined with exploration by modelling is followed: two retrospective studies determine the extent of current rainfall variability and flexibility in land use. For the Ganges and Nile basin, I further developed an existing hydro-economic model called 'WaterWise' (www.waterwijs.nl; van Walsum et al. (2008) to explore the concept of flexibility.

No new hydrological basin models for Nile and Ganges are constructed. For the Ganges basin applications, use is made of an existing coupled hydrology-vegetation model with managed land use, LPJmL (Gerten et al., 2004; Rost et al., 2008). A version adapted for the South Asia region is described in Chapter 4. For the Nile basin well-known FAO approaches for calculating evaporation and runoff are being combined (Figure 2, Annex II). The basic hydrology, i.e. a description of the balance between precipitation, evaporation and infiltration of water and how this leads to localized drainage and runoff and ultimate river discharge, is taken from these models. The difference in approach between the two basins has mainly a practical reason; a sufficiently calibrated and validated LPJmL application for the Nile basin was not available at the time of the start of the Nile study.

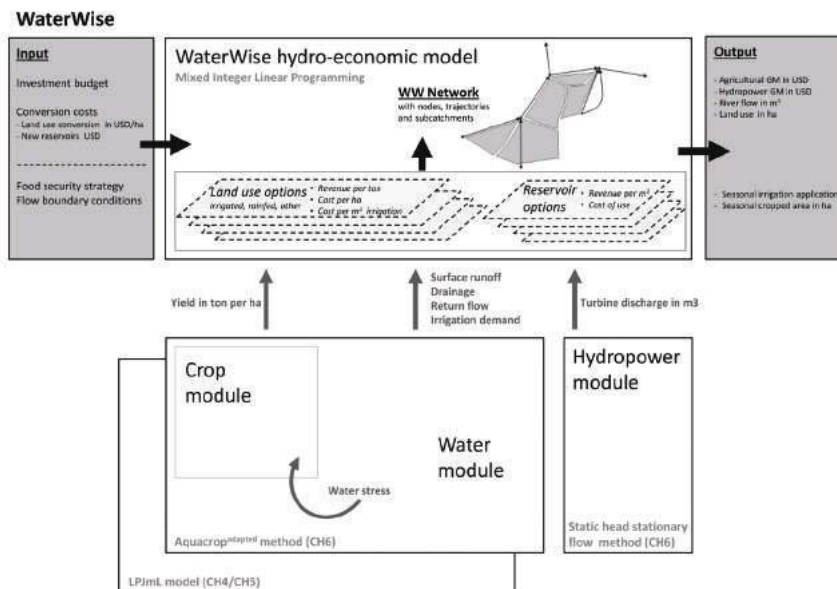


Figure 2 Model set-up of the WaterWise model, with the different water and crop modules as used in this study.

WATERWISE: A HYDRO-ECONOMIC MODEL TO EVALUATE FLEXIBLE LAND AND WATER USE

Hydro-economic models are used to determine how water should be allocated across time, space, and uses to produce the greatest overall economic net benefit (Harou et al., 2009; Jeuland et al., 2014). Often, cooperation in planning and operation of water-related infrastructure is assessed (Jeuland et al., 2014; Rogers et al., 2002; Sadoff and Grey, 2002; Whittington et al., 2005) and gains in economic efficiency translate into the value of such cooperation or, inversely, the cost of non-cooperation. In hydro-economics models economic behaviour is usually included through a profit maximization objective function, where fixed and variable production costs are subtracted from yield benefits (Cai, 2003, Brouwer, 2009). Land and water availability form resource constraints.

WaterWise (WW) is a hydro-economic model designed to study the interactions between water and the economy (van Walsum et al., 2008). WW is an example of an holistic model that incorporates elements of the modular approach; in terms of the typologies by Brouwer and Hofkes (2008) and Jeuland et al. (2014) it is a hybrid, basin-wide, optimization model. Land use is an endogenous variable in the WW model which allows for optimization of seasonal variability in land use. Unlike other hydro-economic models (Cai, 2008; Cai et al., 2003; Yang et al., 2013), WW does not contain a crop-water production function. In WW, the nonlinearities between water and crop production are dealt with in the off-line water-crop modules. Crop productivity and water fluxes from the offline water-crop modules are then attached to continuous decision variables in WW that represent the area fraction for which a land and water management option is actually applied. By decreasing cropped area, production decreases, but also water demand is reduced and cultivation costs are avoided.

WW was further developed in this thesis to include seasonal land use and water allocation decisions and applied to the two main river basins in eastern Africa and South Asia, the Nile and Ganges basin. These applications resemble existing models like the Nile Economic Optimization Model, NEOM (Whittington et al., 2005), the Ganges Economic Optimization Model, GEOM (Wu et al., 2013) and the Indus River Basin Model, IBRM (Yang et al., 2013). Just like these models, WW describes the whole basin, including all the existing irrigation schemes and hydropower reservoirs, and most of the proposed hydropower plans. However, NEOM, GEOM and most other hydro-economic models primarily address the water allocation side, whereas water input into the system is fixed, based on prior calculations. WW adds to this concept the dynamics of the supply side of water, by modelling the land use within the whole catchment as an endogenous variable.

The distinctive functionality of WW to vary the area of various pre-processed options, rather than to optimize along a crop-water production curve, is not only a useful feature to combine the essential detail of complex non-linear hydrology-vegetation processes with the agility of linear programming. It actually represents the core idea behind this research; by seasonally varying the area cropped and/or irrigated, part of the rainfall variability is buffered. Yield on the remaining areas is less affected (Figure 3). While this shift does not necessarily reduce variability in overall production, it does matter for a farmer's income; leaving land fallow means saving inputs in the form of labour, capital and water, which in the case of yield reduction or complete crop loss would be at least partially lost. The model is, thus, based on the economic assumption that farmers act rationally concerning the seasonal allocation of their land resources, to which all other inputs are linked, rather than that they optimize one of the inputs, water, throughout the season.

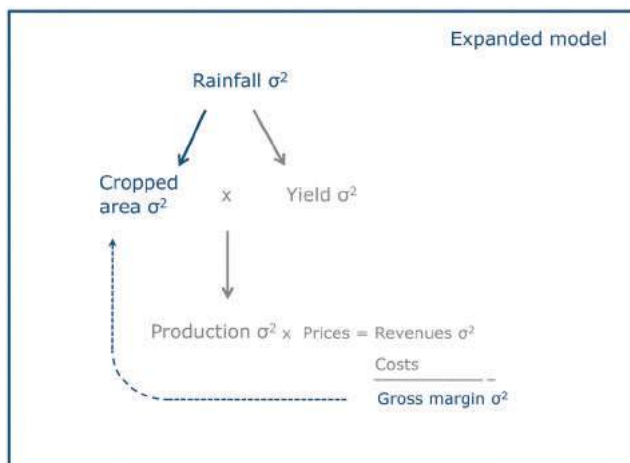


Figure 3 Conceptual model, with rainfall variability (σ^2) influencing cropped area (in ha) and yield (as in ton/ha).

Prices of produce and costs of production are assumed constant in the model. The effect on cropped area will be largest in regions where farmers have information (and –partial- control) over seasonally available water resources, e.g. in soil or surface reservoirs, or where farmers have information about expected rainfall, i.e. where there is sufficient lead time and skill in seasonal weather forecasting.

Two regions: South Asia and eastern Africa

This study aims to learn from two regions already facing increased water stress; the Ganges basin in South Asia and the Nile basin in East Africa. Water will be a major constraint for agriculture in coming decades and particularly in Asia and Africa this will require major institutional change (Rijsberman, 2006). South Asia, home to ~25% of the world population, is currently food secure but economic inequality still leads to widespread undernourishment

(Rasul, 2015). It is also identified as one of the future water stress hotspots (Biemans, 2012; Kummu et al., 2014; Wada et al., 2011) with serious concerns over the sustainability of current groundwater use (Richey et al., 2015). In East Africa, where almost a third of the population is undernourished (FAO et al., 2012), conflicts rise over the distribution of its main surface water source; the water in the Nile River.

In both regions' the major rivers, respectively Ganges and Nile, supply irrigation water during times of rainfall shortage. Rainfall varies within the Ganges basin due to the monsoon circulation patterns and large orographic differences, with high amounts of rainfall along the Himalayas and rainfall scarcity in the southwest. Inter-annual variability in rainfall is high throughout the basin. In the Nile there is a large gradient from south to north in rainfall, with almost year round rainfall in the Great Lakes region, decreasing to a more seasonal pattern going north to scanty rainfall of less than 100mm per year in the Sahara and towards the Mediterranean coast. Inter-annual precipitation variability tends to increase as mean annual precipitation decreases (Conway and Hulme, 1993).

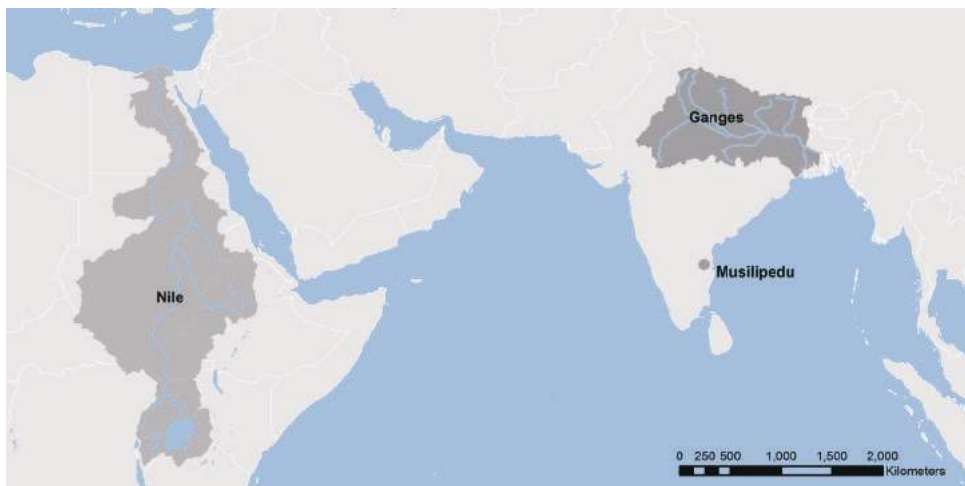


Figure 4 Case study areas.

The impact of inter-annual rainfall variability on the agro-ecosystem differs between both basins. South Asia does not experience the same type of multi-year drought East Africa and the Nile basin are renowned for (Joseph, 2014, Conway and Hulme 1993). In South Asia a strong decadal seasonality is observed, but at an annual time scale dry years are generally alternated by wet years due to ocean-atmosphere feedbacks, the so-called tropospheric biennial oscillation (Meehl, 1997). Multi-year storage of water has therefore also been less of a necessity. Once outside the Himalayas, the flat topography

also prohibits storage by large dams. In the Nile basin, multi-year storage to support Egypt's agriculture is provided mainly by the Aswan dam while several others major dams are just completed or under construction, most notably the Grand Renaissance dam in Ethiopia. The impact of these dams on downstream flows is the topic of much debate. While the waters of the Nile flow are almost fully allocated and utilized by irrigated agriculture in downstream Sudan and most of all Egypt, water allocation conflicts in the Ganges basin are more of a seasonal nature, during low flows which occur mainly during summer, just before the onset of the monsoon.

Both basins experience a strong seasonality in rainfall; the South-West monsoon over the Indian subcontinent brings rain primarily from June till September. This divides the cropping calendar in two distinguished seasons; the *Kharif* season during the monsoon, with rice being the main crop, and the *Rabi* season in the dry winter months after the monsoon, with irrigated wheat being the most important crop in the Indo-Gangetic plain. The East African monsoon is connected to the South Asian monsoon, but its rainfall characteristics are different; winds have a more continental origin and bring relatively low rainfall amounts during the monsoon. More rain falls in two distinct intermediate seasons, one from March till May and the other one from October till December. Parts of the Nile basin are also impacted by western winds loaded with moisture from the Congo, enabling a year-round cropping pattern.

1.5 THESIS OUTLINE

Broadly two axes define the structure of this thesis (Figure 5). The x-axis shows an increasing level of scale, going from a detailed study in a single village in southern India to the scale of the Ganges and Nile River basins, two of the largest river basins in the world. An increased level of abstraction can also be observed in this x-axis, going from empirical observations to the use of remote sensing and finally hydro-economic model assessments. Experience and empirical evidence from the local to regional scale thereby feed into the analysis at the basin scale. The y-axis describes a temporal dimension; from studying seasonal fluctuations in land and water use under current conditions I move on to the more permanent impact of land use changes and different water allocations in the future.

Together the five main chapters address the main hypothesis. In Chapter 2, the relationship between rainfall variability and seasonal land and water use adjustments, a form of flexibility, is identified in a tank irrigation system, at the very local level. The importance of local storage of water in village reservoirs (tanks) and shallow aquifers to buffer rainfall variability is highlighted. In Chapter 3 the occurrence of flexibility in response to rainfall variability is explored at the basin scale using remote sensing for the whole Ganges basin.

Chapter 4 paves the way for the hydro-economic assessment of seasonal land and water use decisions at the basin scale. A coupled hydrology-vegetation model, LPJmL, is improved with double crop rotation and monsoon-dependent planting dates in order to get more accurate estimates for water demand and crop production for South Asia. In Chapter 5, I then introduce cropped area as an endogenous, seasonal, decision variable in a hydro-economic optimization model (WW), coupled to LPJmL, and analyse to what extent its performance in the estimation of inter-annual variability in crop production improved. Local storage reservoirs, as studied in Chapter 2, form an important addition to the model. With WW the value of flexibility in cropped area in the Ganges basin is determined. Finally, in Chapter 6, the same hydro-economic model is applied to the Nile basin and the future of food and water security is explored along three future cooperation scenarios. Rather than assessing the inter-annual fluctuations in land use, as in Chapter 5, the model is now used to analyse more permanent alternative land uses and water allocations in a basin where most surface water is already allocated.

In the Synthesis (Chapter 7) the results of the previous chapters are combined, the research questions are answered, and the results are discussed and placed in a wider context.

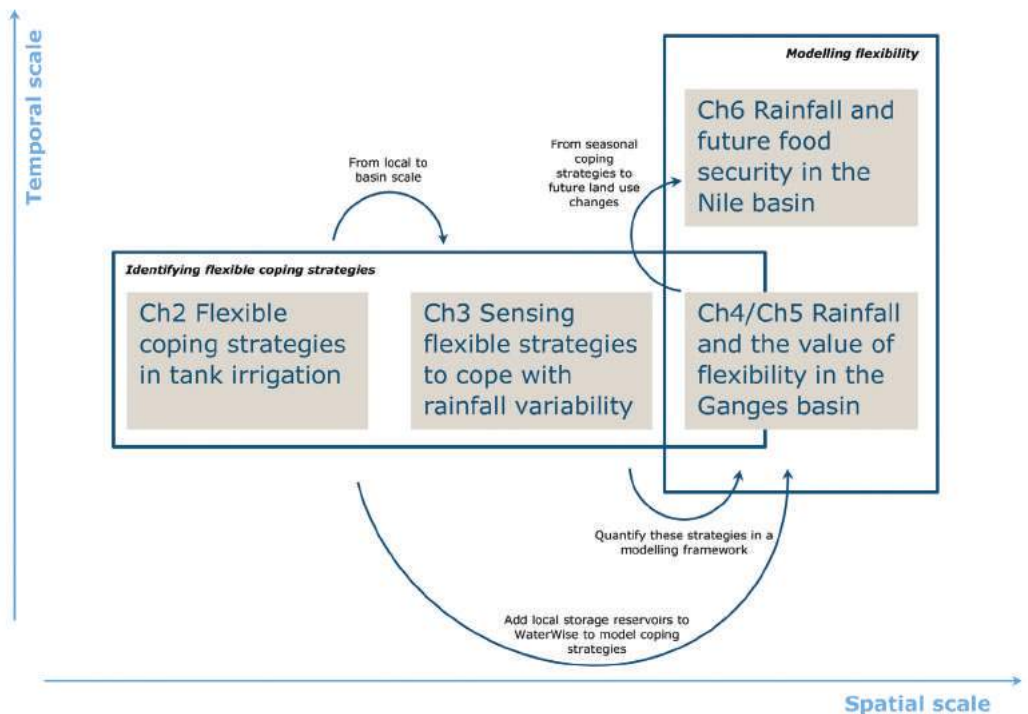


Figure 5 Thesis outline.

This chapter is based on:

Siderius, C., Boonstra J., Munaswamy V., Ramana C., Kabat P., van Ierland E., Hellegers P. (2015). Climate-smart tank irrigation: a multi-year analysis of improved conjunctive water use under high rainfall variability. *Agricultural Water Management*, 148: 52-62.

2

CLIMATE SMART TANK IRRIGATION: A MULTI-YEAR ANALYSIS OF IMPROVED CONJUNCTIVE WATER USE UNDER HIGH RAINFALL VARIABILITY



Although water harvesting is receiving renewed attention as a strategy to cope with increasing seasonal and inter-annual rainfall variability, many centuries-old local water-harvesting reservoirs (tanks) in India are rapidly deteriorating. Easy access to groundwater is seen as one of the major threats to their maintenance and functioning. Potentially, however, conjunctive use of water from rain, tanks and groundwater reserves, supported by proper monitoring, could improve the resilience and productivity of traditional tank irrigation systems. To date, few quantitative multi-annual analyses of such climate-smart systems have been published. To redress this, we assess the sustainability of a rehabilitated tank irrigation system, by monitoring all inputs and outputs over a period of six years (12 cropping seasons). Our results show that during the period considered, improved conjunctive use resulted in a more stable cropping intensity, increased economic water productivity and higher net agricultural income. Groundwater tables were not negatively affected. We argue that improved conjunctive use can considerably reduce the vulnerability of tank irrigation to rainfall variability and thus is a valuable strategy in light of future climate change.

2.1 INTRODUCTION

India faces severe seasonal and regional water shortages in the coming decades. Demand from agriculture, by far the biggest water user, is increasing, to support the growing and increasingly affluent population (National Academy of Agricultural Sciences, 2009). At the same time, availability of water is under pressure due to climate change and overexploitation of groundwater resources (Biemans, 2012; Rodell et al., 2009; Tiwari et al., 2009). Although average total rainfall over the Indian subcontinent is likely to remain unchanged, the variability in rainfall is expected to increase (Kumar et al., 2013; Mathison et al., 2013). In a monsoonal climate that is already erratic and highly seasonal in nature, this increased variability due to climate change will further impact water availability.

In order to cover periods of shortages, farmers in India have for thousands of years been constructing so-called tanks¹ to harvest and store rainfall and surface runoff (Gunnell et al., 2007; Von Oppen and Subba Rao, 1987). Serving more than 20% of cropped area in southern states, tank irrigation is still one of the major strategies for coping with rainfall variability. In tank irrigation systems, water is harvested during the monsoon and used during the subsequent dry season. It is a flexible system, in which the volume of water stored in the tank at the end of the monsoon determines what and how much area farmers crop. Although this does not guarantee a stable year-to-year production and income, farmers prevent loss of investments by making timely adjustments to the cropping plan and allocation of resources. Besides their primary purpose as a source of water for irrigation, tanks also have important secondary purposes, such as the provision of drinking water, flood mitigation and water for livestock and fish production (Meinzen-Dick and van der Hoek, 2001; Palanisami and Easter, 1983).

Despite their advantages, many tank irrigation systems have fallen into disrepair during the past 50 years (Kajisa et al., 2007; Palanisami and Meinzen-Dick, 2001; Sakurai and Palanisami, 2001): throughout India, the cropped area supported by tank irrigation has declined from 19% in the 1950s to 4% at present. The main causes of this decline have been (i). centralization of water management, whereby the state took over the responsibility of communal tanks, which led to an institutional breakdown with severe implications for maintenance schemes and the collection of water charges (Palanisami and Easter, 1983; Von Oppen and Subba Rao, 1987); (ii). siltation and encroachment of farming onto the tank bed, both symptoms of institutional breakdown and a higher population pressure (Dasog et al., 2012; Easter and Palanisami, 1985; Gunnell and Krishnamurthy, 2003; Palanisami and Meinzen-Dick, 2001), and; (iii) access to cheap and easily available canal water and groundwater (Dasog et al., 2012; Kajisa et al., 2007; Sakurai and Palanisami, 2001).

¹ artificial lakes, generally with earthen embankment dams, for harvesting and storing surface runoff after heavy rainfall.

While tank irrigation declined, irrigation with groundwater rose sharply in India: it now accounts for almost 60% of the irrigated area. Farmers with access to groundwater have less incentive to contribute to the communal maintenance of the tank once it has deteriorated (Sakurai and Palanisami, 2001). They prefer the rapid return on investments in boreholes rather than contributing to the rehabilitation of the tank system. The resulting free-riding undermines the runoff harvesting, storage and distribution capacity of the tank system. Groundwater also offers opportunities to enhance the performance of the tank system, however, by providing additional storage capacity to buffer seasonal and inter-annual shortages in rainfall and tank water (Ranganathan and Palanisami, 2004). Conjunctive use – maximizing the yield of water resources by the coordinated management of supplies of surface water and groundwater – is a well described concept in large-scale surface water supply systems (Bredehoeft and Young, 1983; Burt, 1964; Tsur, 1990), but empirical evidence on its benefit for tank irrigation and rehabilitation is limited. Early evaluation of tank rehabilitation programmes focussed largely on the merits of participatory execution (ADB, 2006; Gunnell and Krishnamurthy, 2003;). It mainly described how well programmes were executed and their internal efficiency, rather than their efficacy in terms of achieving the desired effect. Recently, Dasog et al. (2012) and Reddy and Behera (2009) followed a more quantitative approach, comparing yields and improvements to livelihoods before and after rehabilitation, but without paying specific attention to changes in water use. To our knowledge, no longitudinal empirical studies have been reported in which conjunctive use of water from rain, tanks and groundwater reserves has been monitored over several years, thus taking into account the high inter-annual variability in rainfall.

Our aim is to assess the sustainability of improved conjunctive use of rainfall, tank water and groundwater in a tank irrigation system. We base our assessment on primary data collected over a period of 6 years, comprising 12 cropping seasons. During this period, all water inputs and yield outputs of a single tank irrigation command area were measured at farm and tank level in an extensive monitoring campaign as part of a tank rehabilitation project. The performance of the tank system was assessed using three indicators; Cropping Intensity, Net Agricultural Income and Economic Water Productivity. Whether groundwater resources were used sustainably was assessed by groundwater level observations. The methods section explains the monitoring approach and three indicators used and gives a short background description of the study site and the rehabilitation measures implemented during the monitored period. In the results section we present the annual performance of the tank irrigation and the impact on groundwater levels. The paper concludes with a discussion on the observed changes and the wider relevance of our findings.

2.2 METHODOLOGY

2.2.1 STUDY AREA

Our case study area is a tank irrigation site near the village of Musilipedu, approximately 45 kilometres east of the town of Tirupati, in the Yerpedu Mandal² of Chittoor District, in the state of Andhra Pradesh, India (79°42'E and 13°36'N). The region is mostly influenced by the North-East monsoons (October–December) and, to a much lesser extent, by the South-West monsoons (June–September). Average annual rainfall at Tirupati is 988 mm (1975–2006 period) with a high inter-annual variability not only in quantity (238 mm Standard Deviation), but also in the number of low and high-intensity rainfall events.

The Musilipedu tank is a non-system tank, fed solely by rainfall in its catchment area, with no connections to other tanks, upstream or downstream. The area upstream of the tank, i.e. the tank's catchment area, is approximately 740 ha. When full, the tank covers 54 ha; the irrigated area is 188 ha (Figure 1). The tank has two compartments, separated by a low bund. When both compartments are full, excess water can flow over two surplus weirs into the Swarnamukhi River. Irrigation water from the tank can be diverted into the tank command area through a culvert, closed by a gate. It is then diverted by gravity from the main channels into a tertiary system consisting of field channels dug by the farmers.

The distribution of the tank water is managed by the Water User Association (WUA). Only farmers who own land can become members. The WUA farmers number 223, with an average land holding of 0.6 ha. In the *Kharif* cropping season (1 June–15 October) only a portion of the command area is cultivated, mainly with groundnuts and rice, and the limited rainfall during the South-West monsoon is supplemented by groundwater irrigation. During this season the tank remains empty. The area cropped in the *Rabi* cropping season (15 October–15 March) largely depends on how much water has accumulated in the tank during the North-East monsoon (September–November) at the start of the season. The main crop cultivated is paddy rice. Supplemental irrigation from groundwater is applied, especially at the end of the growing season and in the tail ends of the irrigation canals. From April to June the entire command area is left fallow, except for a small area cropped with sugarcane.

In common with the trend throughout India, groundwater use in the Musilipedu tank irrigation site has steadily increased in recent decades. Groundwater is abstracted from a shallow aquifer which is replenished during the monsoon, after which groundwater levels rise to near the soil surface. Although the initial investment required is substantial, bore-

² a *mandal* is an administrative division in India, above which is the district and below which are the villages.

holes are cheap to exploit (fuel and electricity are subsidized), reliable (under the farmer's own control) and efficient (water is available when and where needed). In Andhra Pradesh, electricity is provided for free to farmers, though only for several hours a day, with power cuts occurring regularly. 54% of the 223 farmers had access both to groundwater and tank water, 42% relied on tank water alone and 8% used only groundwater. The average farm size of farmers with access to both groundwater and tank water was, at approximately 1 ha, more than twice that of farmers with only tank water.

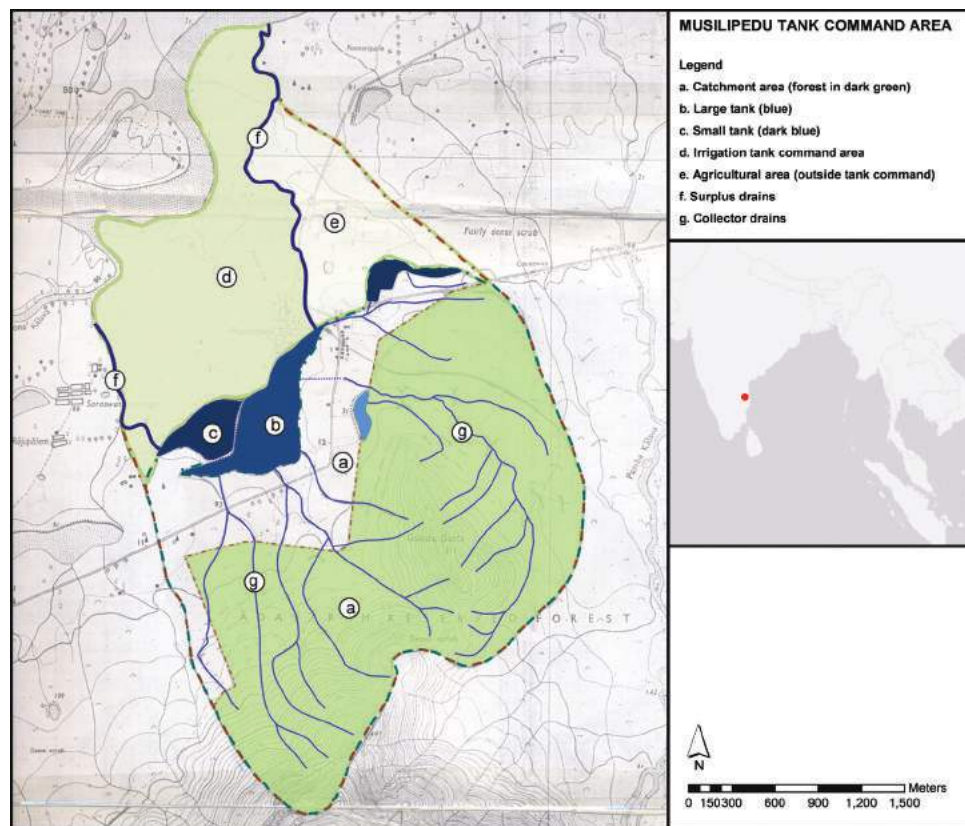


Figure 1 Location of the Musilipedu tank, with catchment boundaries (general direction of slope and flow of water is from south to north).

During the monitoring period the Musilipedu tank was rehabilitated using standard funds from the District Collector with further support from the FAO³. The rehabilitation entailed both institutional improvements, such as enhancing the empowerment of the WUA, and technical and agronomical improvements. To augment runoff into the tank through the four supply channels, farmers constructed revetments from boulders. Sediment in the tank

³ FAO, with the Dutch Government, funded the APWAM project, an 8-year project on improving water productivity in irrigated agriculture in Andhra Pradesh.

was removed with earth-moving equipment and a programme of chemical treatment each summer was instigated, to control noxious aquatic weeds. In the tank command area, the defective sluice was replaced by a new one by the Irrigation Department. A new gate was installed to regulate and control the total outflow of tank water into the tank command area. The two main irrigation channels were equipped with lock gates to measure and control the distribution of tank water to the fields. The main irrigation channels, with a total length of 1350 m including five division boxes, were gradually lined by the farmers, using cement and bricks. Costs for these measures are given in Table 1. The chronological order of the various interventions was mainly determined by the farmers.

On farmers' fields, several agronomic interventions were tested. Alternative rice crop water management packages were introduced, such as System of Rice Intensification (SRI) and Alternative Wetting and Drying (AWD). Different crops for green manuring, which increases soil fertility and crop yields, were demonstrated. Another groundnut variety better suited to local conditions was introduced to the farmers. Also, an improved tillage implement was designed. None of the agronomic measures was actively promoted or supported by financial incentives. Farmers had total freedom to adopt or ignore the measures demonstrated.

Table 1 Costs of technical interventions during the Musilipedu tank rehabilitation

Measure	Number of items	Cost per item (INR)	Total costs (INR)	Total costs (USD)
Sluice gates	2	60000	120000	2727
Lock gates	2	29000	58000	1318
Renovation sluice			270,000	6136
Division boxes	5	40000	200,000	4545
Lining irrigation channels	1350	1050	1,417,500	32216
Construction RBC flumes	3	5722	17,166	390
Weed removal tank bed			70,000	1591
Total			2,152,666	48924

* length in meters

2.2.2 METHOD

To evaluate conjunctive use in a tank irrigation site we developed an approach to monitor performance in terms of land and water use, based on low-cost and low-maintenance monitoring techniques. Using such techniques, farmers and WUA members could themselves do the monitoring, requiring only limited guidance from external agricultural extension workers or irrigation experts. The performance monitoring was primarily based on a crop-specific water budgeting method: for each cropping season, the actual volume of water supplied was compared with crop water requirements (Figure 2). Based on this comparison, land and water use strategies could be adapted in the subsequent cropping

season. The cycle was repeated for several consecutive years, which improved farmers' insight into their resource use and generated an overall insight into the effectiveness of the various improvements in the tank irrigation system. This integration of performance monitoring of land and water use to support conjunctive use, combined with a range of technical innovations in a participatory setting, we call 'improved conjunctive use'.

Actual water supplied was monitored from three sources: effective rainfall, tank water and groundwater. Effective rain within the command area, i.e. the amount of rain actually benefitting crop growth, i.e. not contributing to runoff or seepage, was calculated from total monthly rainfall as (Dastane, 1978):

if $P \leq 16.7$ mm/month	$P_{ef} = 0$
if $P > 16.7$ and < 75 mm/month	$P_{ef} = P * 0.6 - 10$
if $P > 75$ mm/month	$P_{ef} = P * 0.8 - 25$

With P as rainfall and P_{ef} as effective rainfall. Effective rainfall was furthermore assumed not to exceed the total monthly evapotranspirative demand of the major crops, rice, groundnut and sugarcane. Actual volume of tank water supplied was calculated using a standard tank conveyance efficiency of 70% in the initial three years and an estimated 80% efficiency after rehabilitation, correcting for losses between the tank outlet measurement location and farmer fields. Groundwater irrigation efficiency was set at 90%, as minimal losses are expected over short distances within the tank command area.

Crop water requirements for each of the major crops were based on the crop factor (Kc) method that uses the Modified Penman–Monteith equation (Allen et al., 1998) to estimate potential evapotranspiration. The meteorological data input were daily sunshine hours, humidity, wind speed and minimum and maximum temperature from the Tirupati weather station 40km away. Based on the comparison between actual supply and potential requirements, strategies to modify water allocations were formulated and discussed with the WUA members. If agreed upon, these strategies were then implemented by the WUA members voluntarily in the subsequent cropping season, and the above cycle was repeated.

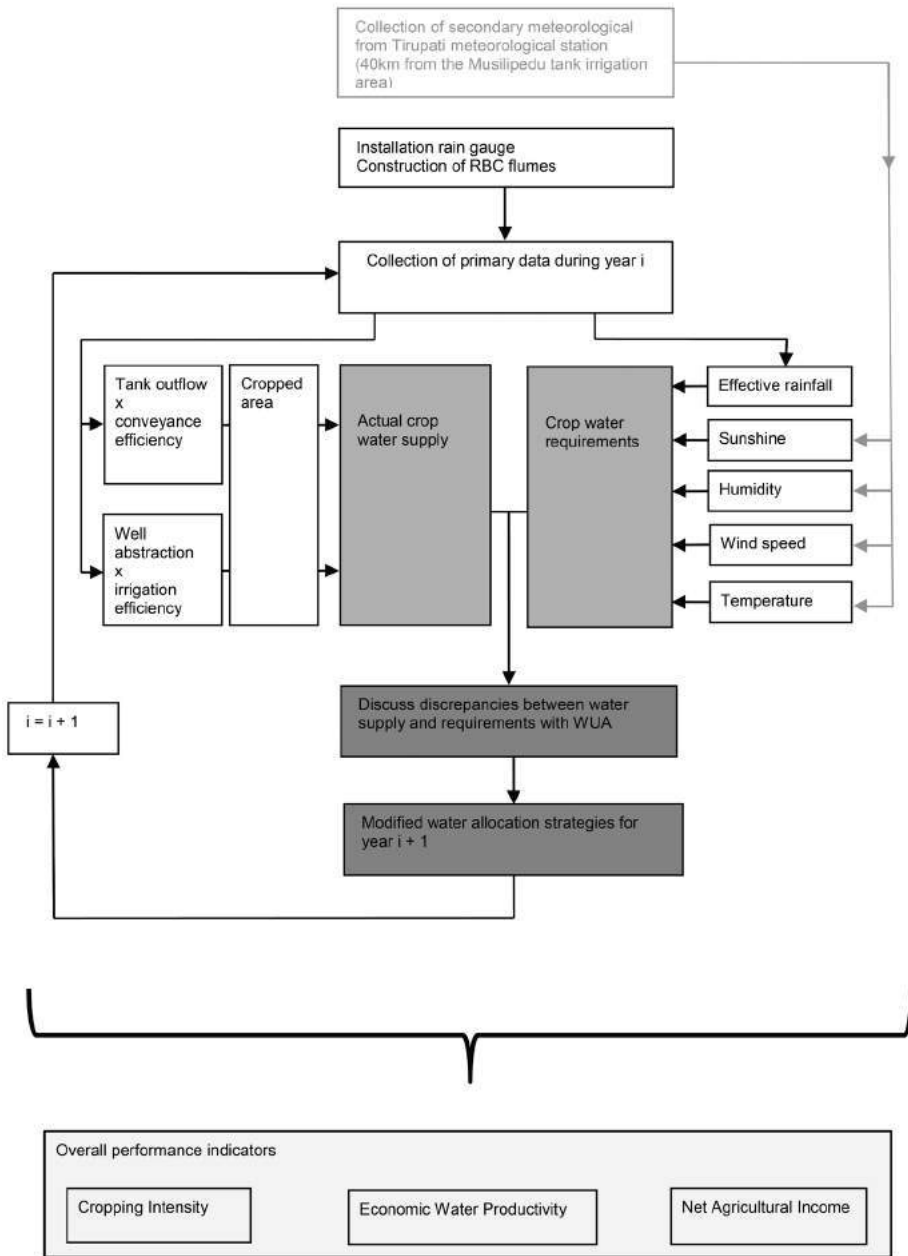


Figure 2 Flow diagram of the performance monitoring approach, with a cycle repeated after each year i .

To evaluate the impact of improved conjunctive use we used three indicators: two are related to the basic production factors land (Cropping Intensity) and water (Economic Water Productivity), whereas the third is related to the main output for a farmer (Net Agricultural Income). The production factor of labour was not monitored, because it was assumed it would be constant during the monitoring period, as sufficient labour was available. However, unsolicited comments from farmers on the rising cost of labour showed that changes can be significant over several years, suggesting that in future analyses, labour should indeed be taken into account more explicitly. In areas of high rainfall variability, analysing these indicators for six years rather than conducting an impact assessment by comparing two years (before and after rehabilitation) provides a better comparison. The three initial years broadly represent the initial situation, during which rehabilitation measures were gradually being implemented, while the last 3 years represent the “after” situation, with improved land and water management. Both periods contained years of drought and years of abundant rainfall.

Annual Total Cropped Area was calculated for the two cropping seasons of *Kharif* and *Rabi* individually for the major crops rice, groundnut, sugarcane and for sunflower. The cropped area of sugarcane, which has a growing period of 11 to 12 months, was added to the seasonal cropped area of both *Kharif* and *Rabi*. The Cropping Intensity (CI) was derived for each season by dividing seasonal cropped area by the total command area. To calculate overall annual Net Agricultural Income (I_{net}), cropped area was multiplied by yield and market prices per crop, after which crop-specific total costs of cultivation were subtracted. This was done annually, and for each farmer, and for the tank command area as a whole. Annual Economic Water Productivity (WP_{econ}) at tank command level was calculated as:

$$WP_{econ} = \frac{\text{Net Agricultural Income}}{\text{Water Available}} \text{ in INR or USD/m}^3$$

Water available was calculated at tank command level by totalling supplied tank water and groundwater, before subtracting any conveyance losses, and effective rainfall. Effective rainfall was included, as we considered it a resource that can be managed or used effectively in combination with targeted tank and groundwater applications. The inclusion of effective rainfall also prevents annual fluctuations in productivity that result from variations in effective rainfall from showing up in the indicator. By focussing on the tank command level, WP_{econ} is able to show productivity gains as a result both of crop water management practices at field level and improved distribution and timing of delivery within the command area, i.e. the quality of irrigation management. Improvements at both

field and command area scale are often interlinked (van Halsema and Vincent, 2012). We avoid the term Water Use Efficiency, as the numerous, often value-laden, interpretations complicate its use (Perry, 2007; van Halsema and Vincent, 2012).

2.2.3 DATA COLLECTION

The monitoring period covered six consecutive years of the tank rehabilitation, starting with the *Kharif* season of 2004. Primary data on water use, crop production and market prices were collected at intervals ranging from days to years. To derive water use, rainfall was measured daily using a rain gauge installed in the tank command area. Tank out-flow into the command area was derived from daily gauge readings of three installed RBC flumes, from November 2006 onwards. Before 2006, stage-discharge relations were used. Groundwater use was based on daily interviews with farmers on their pumping hours. For each borehole, pumped volume was calculated multiplying pumping hours with each pump's design capacity based on factory specifications; the accuracy of this method was checked by periodically inserting a commercial water meter in the discharge pipe. Groundwater levels were monitored weekly at 14 observation wells inside and outside the tank command area.

During each cropping season, the various types of crops grown were identified and their areal extent recorded per land holding. The dates on which crops were sown, planted or transplanted were recorded, and so were the harvest dates. At the end of each cropping season, crop cuttings experiments were made to determine the crop yield of certain preselected land holdings; one third of all land holdings were sampled each time. In addition, each farmer was interviewed to ascertain production in terms of kilograms of produce sold on the local market.

In 2005, a one-off socio-economic survey focussing on costs of production was conducted. Farmers in the command area were interviewed, to collect data on the operational costs (seed, fertilizers, chemicals, machine maintenance), labour costs and fixed costs (taxes, rental values of owned land), and from these the total production costs for each crop were estimated. In addition, prices in local and regional markets were collected, in order to calculate the farmer's income from each crop.

2.3 RESULTS

2.3.1 IMPACT ON CROPPING INTENSITY

Figure 3 shows the variation in total cropped area and the availability of rainfall, tank water and groundwater. Traditionally, the area cropped in *Kharif* depends on the onset of the South-West monsoon. If rains are insufficient or too late, planting is cancelled. In 2004/05 this led to a sharp decrease in area cropped with groundnut. During *Rabi*, the extent of cropped area depends mainly on the availability of tank water. If the tank is not full, the cropped area is reduced, as happened to the area cropped with rice in 2004/05 and 2006/07. Water supplied to the fields thus follows the fluctuations in the amount of water required during most seasons (Table 2). During years of relatively abundant rainfall, water supplied is 10% to 30% higher than water required, while during years of shortage it is approximately 10% to 30% less. When cropping strategies of all 223 individual farmers for the dry year of 2006/07 were compared with their strategies for 2007/08 and 2008/09, it was found that farmers who had access only to tank water reduced their cropped area most: over these three years, the average variation in cropped area during *Rabi* was more than 60% (Relative Standard Deviation). In contrast, for those farmers with access to groundwater water, the average variation in cropped area over these three years was only 25% and half maintained a stable cropping pattern during *Rabi*.

Over the course of the monitoring period, *CI* stabilized to over 60% during *Kharif* and almost 100% in *Rabi*. In particular, the area planted with rice, a crop with a high water demand, increased in both the *Kharif* and *Rabi* cropping seasons. This high *CI* was maintained during dry year of 2009/10, the last year of monitoring, when the amount of effective rainfall and tank water was as low as during the first year of the study: the dry year of 2004/05 (Table 2). A better conjunctive use of rain, tank and groundwater proved sufficient to buffer the rainfall shortage. Variations in cropped area are not only a resultant of water availability: sugarcane growing was actively promoted in the beginning of the study period by local sugar factories, and the area cropped reached up to 17% of the command area. However, a sharp increase in labour costs caused farmers to lose interest in growing sugarcane, with the result that the area under this crop shrank.

Table 2 Cropped area, Water Available, Water Supplied - after subtracting conveyance losses - and Water Required based on potential evaporation per crop for *Kharif* (K) and *Rabi* (R) season. Tank water could not be attributed to individual crops as it was measured at the tank outlet only. It is primarily used during the *Rabi* season. (* based on estimates of pumping hours. Source: village secretary)

	Crop	Area (ha)	Tank water (1000 m ³)	Effective rain (1000 m ³)	Groundwater (1000 m ³)	Water Available (1000 m ³)	Water Supplied (1000 m ³)	Water Required (1000 m ³)
2004/05	Rice K	8		10	55*			49
	Groundnut K	20		25	75*			94
	Rice R	113		61	220			843
	Groundnut R	38		7	16			170
	Sugarcane	3		16	65			33
	Total	182	670	120	431	1221	976	1187
2005/06	Rice K	10		22	86			54
	Groundnut K	72		161	129			317
	Rice R	145		306	31			1266
	Groundnut R	10		2	34			41
	Sugarcane	33		152	286			393
	Total	269	1033	643	565	2241	1875	2071
2006/07	Rice K	19		21	199			108
	Groundnut K	75		57	271			352
	Rice R	82		67	603			671
	Groundnut R	28		0	102			124
	Sugarcane	7		NA	NA			NA
	Sugarcane	32		123	493			362
	Total	242	446	269	1667	2382	2081	1617
2007/08	Rice K	15		31	120			98
	Groundnut K	81		238	89			379
	Rice R	147		211	0			1028
	Groundnut R	16		6	0			71
	Sugarcane	8		NA	NA			NA
	Sugarcane	16		96	165			178
	Total	282	1294	582	372	2250	1954	1754
2008/09	Rice K	37		27	317			235
	Groundnut K	71		51	247			333
	Rice R	152		163	383			901
	Groundnut R	14		0	24			69
	Sugarcane	9		29	79			101
	Total	283	784	269	1051	2103	1842	1638
2009/10	Rice K	34		46	301			207
	Groundnut K	79		104	143			363
	Rice R	167		22	383			1247
	Groundnut R	6		3	17			27
	Sugarcane	3		12	31			37
	Total	289	515	187	873	1576	1385	1883

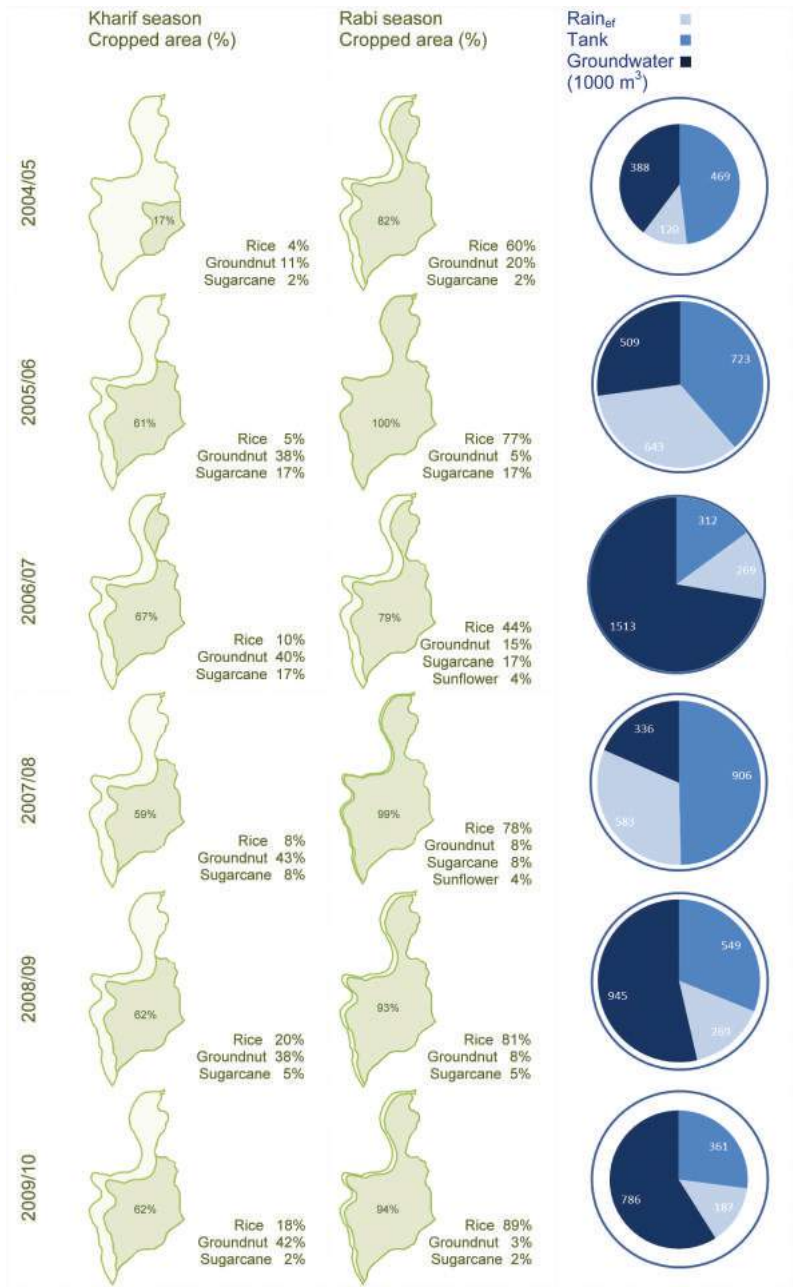


Figure 3 Cropped area per cropping season per year as a percentage of the total command area, and per crop. Crop water supplied from different sources per year (blue circle represents the maximum supplied amount of water, in the agricultural year 2005/06). Tank water and groundwater are net figures (1000 m³) after subtracting conveyance losses.

2.3.2 IMPACT YIELD, INCOME AND WATER PRODUCTIVITY

In addition to a more stable *CI*, an increase in productivity in terms of yield per hectare was observed. Table 3 shows yields of the main crops in the Musilipedu tank command area. The rice yield in the *Kharif* season rose gradually during the 6 years, whereas groundnut yields in both *Rabi* and *Kharif* seasons improved most in the last three years, after all rehabilitation measures had been implemented. Rice yields in the *Rabi* season also increased, but dropped again in the dry year of 2009/2010. For sugarcane, no trends were observed. Sunflower was only grown for 2 seasons and the yields were 1.5 and 1.4 t/ha. The yields of all the crops in both seasons are considerably higher than regional or national yields.

Table 3 Average crop yields (tons/ha) in the tank command area for each year and the Andhra Pradesh and all-India averages (tons/ha) for the 6-year period (Gol, 2012; Gol, 2013)

Agricultural years	Rice Kharif	Groundnut Kharif	Rice Rabi	Groundnut Rabi	Sugarcane
2004/05	4.4	2.0	5.3	2.5	97
2005/06	4.7	2.0	6.0	1.9	117
2006/07	4.4	2.0	6.0	2.4	91
2007/08	4.8	2.6	6.4	2.4	100
2008/09	5.1	2.6	6.6	2.7	76
2009/10	5.4	2.6	5.7	3.3	99
Andhra Pradesh average **	2.8	1.0	3.7	1.8	80*
all India average **	2.0	0.7	3.1	1.9	70*

* average of the 2010/11 and 2011/12 cropping seasons

** includes crop yields of all rainfed and irrigated systems, not only tank irrigation

The increase in *CI* and yields did not lead to a higher water use (Table 4). Improved conjunctive use of rainfall, tank water and groundwater led to a considerable increase in WP_{econ} , especially during dry years. An important effect of the yearly performance monitoring was a gradual adjustment of the water needed for paddy rice: from the national advised 1200 mm to approximately 800 mm per year, an amount sufficient under local climatic circumstances. As a result, the WP_{econ} increased by almost 40%, from US\$ 0.050/m³ for the first three years of monitoring to US\$ 0.069/m³ for the last three years (at 2005 exchange rates).

Table 4 Performance indicators for the Musilipedu tank command area. Water Available is calculated as effective rainfall plus water supplied from tank and groundwater reserves, before subtracting any conveyance losses. I_{net} is the total for the whole tank command area. WP_{econ} was calculated as an average for the tank command area.

Crop season	Water Available 10^3 m^3	Net Income (I_{net}) 10^6 Indian Rupee (INR)	Economic Water Productivity (WP_{econ}) INR/ m^3 (USD cents/ m^3)
2004/05	1221	2.82	2.31 (5.2)
2005/06	2241	5.71	2.55 (5.8)
2006/07	1903	4.37	2.30 (4.1)
2007/08	2251	6.11	2.72 (6.2)
2008/09	2268	5.98	2.64 (6.5)
2009/10	1576	5.52	3.51 (8.0)

As a result of higher yields and a more stable CI , overall I_{net} increased (Table 4). When average I_{net} per farm, expressed in USD per hectare, is plotted as a function of water availability, a clear difference is apparent between the initial three years and the last three years (Figure 4A). An indication of the increased buffer capacity of the tank system is the continued high I_{net} in the very dry season of 2009/10. The increase in average farm income seems to be the result of an increase in both maximum and minimum I_{net} (Figure 4B), though the spread between farmers' I_{net} remains large in later years too. Farmers with access only to tank water remain more likely to leave land fallow during the *Kharif* season, and to have a lower I_{net} .

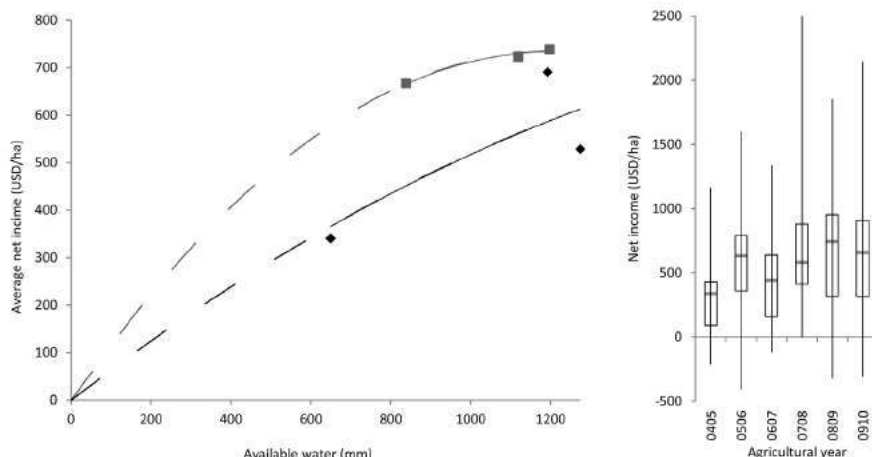


Figure 4 Average net agricultural income (I_{net}) as a function of water availability for the initial three years and last three years (A) and spread in individual farm I_{net} for the individual agricultural years, expressed in USD/ha (B).

2.3.3 SUSTAINABILITY OF CONJUNCTIVE USE OF TANK WATER AND GROUNDWATER

Conjunctive use of rainfall, tank water and groundwater requires land for seasonal storage of water and a groundwater aquifer for inter-annual storage. Groundwater depletion and encroachment of farming on the tank and upstream catchment area are two risks for a sustainable tank irrigation system.

Over the whole monitoring period, the current use of groundwater did not result in continuing groundwater depletion (Figure 5). The system is recharged every year by high-intensity rainfall events in the command area and by infiltration from the tank, which usually fills in October. During the *Kharif* and *Rabi* seasons, the system is depleted by natural lateral groundwater outflow towards the river and groundwater pumping. However, sustainable use of groundwater is not guaranteed. The performance monitoring revealed that farmers owning bore wells were over-irrigating their crops in the initial period, especially in the third year (2006/07, Table 5). The installation of automatic power switches resulted in pumps running whenever the power supply was on. This led to a noticeable reduced recovery of groundwater levels during the 2006/07 *Rabi* season (Figure 5). In reaction, specific pumping schedules were introduced, based on site-specific crop water requirements calculated using the available meteorological data. One of the elderly farmers was selected to act as a special pump operator, to ensure that the principles of these schedules were complied with. The partial groundwater recovery in 2006/07 was compensated in the subsequent two years, which indicates that the average annual groundwater recharge is just sufficient to cover incidental high pumping rates.

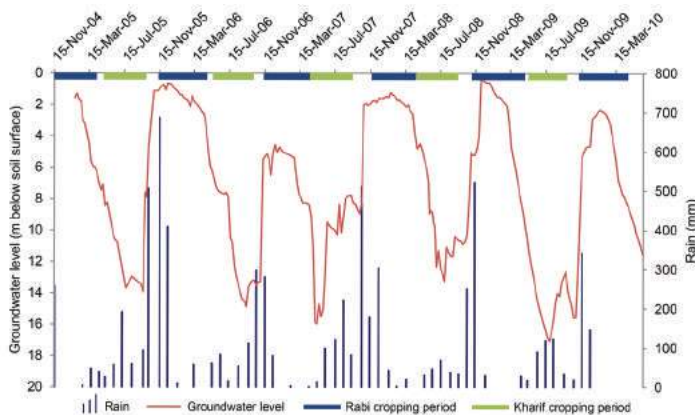


Figure 5 Composite groundwater level of the Musilipedu tank command area, based on the average of four observation bore wells in the tank command area. Duration of the Rabi and Kharif cropping periods is based on annual farmer interviews.

Although groundwater availability reduces the relevance of the tank for farmers owning pumps, switching to a system that is fed only by rainfall and groundwater is unlikely to be sustainable in the Musilipedu area. Conjunctive use of tank and groundwater to supplement rainfall allows farmers to cope with the erratic behaviour of the north-eastern monsoon: low- to medium-intensity rainfall events contribute mostly to effective rainfall, medium-intensity rainfall events lead to most groundwater replenishment, and only the high-intensity events fill the tank. Table 5 shows how rainfall during the north-eastern monsoon was distributed over different intensity categories during the six years of the monitoring programme. During the study period it was observed that significant tank fillings took place for rainfall events with intensities higher than 60 mm/day. From this dataset it can be seen that such rainfall events occurred in 3 of the 6 years. In years with high-intensity rainfall, these events contributed to more than 40% to total rainfall (Table 5) and the tank provided up to 40% to total water used (Figure 3). In years with fewer high-intensity events the tank fills only partly and the absolute contribution of tank water to irrigation is less. But in these years, effective rainfall is also less, which means that the contribution from the tank remains relatively important. Gradual encroachment of farming onto the tank bed or a deliberate conversion of the tank and part of the catchment area to cropland would result in an important source of water being lost. Such a loss of water cannot be compensated from the shallow groundwater aquifer, except by tapping deeper groundwater aquifers. Moreover, tank water and groundwater are highly connected and encroachment of farming on the tank area will also reduce groundwater replenishment, leading to a reduction in both tank and groundwater resources.

Table 5 North-east monsoon rainfall (Oct-Nov-Dec) for the Musilipedu tank site in mm per intensity category (with the number of events in brackets) and as total of all categories, and total annual rainfall

	0-20 mm/day	21-40 mm/day	41-60 mm/day	61-80 mm/day	81-100 mm/day	>100 mm/day	Total Oct- Dec	Total annual rainfall
year	mm (# of events)	mm (# of events)	mm (# of events)	mm (# of events)	mm (# of events)	mm (# of events)	mm	mm
2004	184 (15)	125 (4)	45 (1)	130 (2)	-	-	485	864
2005	162 (21)	333 (12)	157 (3)	131 (2)	86 (1)	733 (5)	1601	2120
2006	114 (20)	217 (7)	116 (2)	124 (2)	87 (1)	-	658	1049
2007	68 (12)	182 (6)	162 (3)	140 (2)	-	441 (3)	993	1534
2008	127 (12)	305 (10)	-	-	100 (1)	270 (2)	802	1083
2009	53 (6)	176 (6)	155 (3)	124 (2)	-	-	509	920

2.4 DISCUSSION & CONCLUSION

Traditionally, tank irrigation is a dynamic form of irrigation in India, in areas where high variability in rainfall leads to considerable inter-annual fluctuations in cropping intensity, income and water productivity. In our multi-annual analysis we have shown that improved conjunctive use of rainfall, tank water and groundwater can reduce these fluctuations and lead to higher and more stable Cropping Intensity, Economic Water Productivity and Net Agricultural Income. These increases appear sustainable, with groundwater being able to recover annually.

Whether improved conjunctive use can be successfully scaled out to other tank sites will depend on the local availability and distribution of land and water resources. A threat to most tank irrigation sites is the smallness of landholdings, with 'marginal' and 'small' landholding classes being dominant, and farmers having limited opportunities for expansion. There is therefore a continued risk of encroachment of farming on the tank and upstream catchment areas, and of overuse of groundwater in order to further increase cropping intensity. However, with yields almost double regional and all-India yields, improved conjunctive tank irrigation in our case study site appears to be economically viable. And further improvements in water productivity, using more advanced soil moisture monitoring and rainfall forecasting, seem feasible, which would preserve more groundwater for use in the *Kharif* period when at present 40% of the area is still left fallow. Linking these improvements to a better understanding of the resource base, as was done in the performance monitoring method presented here, can help limit the risk of overexploitation.

When upscaling these results, higher water productivity at tank command level will, in general, not linearly lead to higher water productivity at the larger basin scale. There is an on-going debate in the literature on the merits of efficiency improvements in basins where losses and return flows are fully used again by downstream users (Perry, 2007; Seckler et al., 2003; van der Kooij et al., 2013; van Halsema and Vincent, 2012). Often, higher water productivity leads to an increase in cropping intensity or cropped area, as in our case study, and to these losses being limited. However, whether this impacts downstream users will depend on the period in which losses occur and the location of the tank within a tank system or the river basin. In our case study site, an improved capture and storage of runoff mainly reduced losses during the monsoon, when water is abundant anyway. Outside the monsoon, return flows and conveyance losses contribute to the local groundwater system. As the area is close to the river mouth, any reduction in losses has little impact downstream.

Finally, whether tank irrigation is able to adapt to a future climate in which rainfall variability is expected to increase over India (Kumar et al., 2013) cannot be answered merely by an empirical study. But our results do show that improved conjunctive use in small-scale tank systems is able to buffer the kind of inter- and intra-annual variability in rainfall expected in future. More generally, decentralized systems with a potential for self-organization are considered to be very adaptable to change and to be less affected by sudden change or failure in parts of the system. Improved conjunctive tank irrigation, in which farmers have control over their land and water resources and pro-actively adapt to each season, shows clear characteristics of such a system. The lessons go beyond small-scale systems: decentralized storage and smart conjunctive use of water resources could also be considered in the case of large-scale canal irrigation, where the combination of higher rainfall variability, groundwater depletion, over-allocation of irrigation water and increasing competing claims from industrial and domestic uses jeopardizes the stable supply of water.

Improved tank rehabilitation, as presented in this study, requires little additional investment compared to traditional tank rehabilitation with its exclusive focus on technical interventions. One prerequisite is the availability of a local organization that can disseminate the required knowledge on crop-specific irrigation water requirements and water supply monitoring to WUAs. In the present study, the regional office of a State university fulfilled this role. Throughout India there is an extensive network of agricultural extension services under the Indian Council of Agricultural Research, which could do likewise. Strengthening their capacity to help WUAs should be promoted as part of a climate-smart agriculture. The benefits – a more stable income for farmers and a more stable food production to support a growing population – are likely to exceed the costs.

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3

SENSITIVITY OF THE AGRO-ECOSYSTEM IN THE GANGES BASIN TO INTER- ANNUAL RAINFALL VARIABILITY AND ASSOCIATED CHANGES IN LAND USE



The rate of growth in agricultural production has been decreasing in several regions of the world in recent years. The availability of water, which is one of the main inputs, is becoming limiting and more variable. In this article, we study the sensitivity of the agro-ecosystem to rainfall variability in order to identify vulnerable areas. We applied a longitudinal assessment of remote sensing time-series data, using the correlation between inter-annual rainfall anomalies and anomalies in Normalized Difference Vegetation Index (NDVI), a proxy for crop production. With a novel approach, we then identified whether the sensitivity results from a variation in crop growth or from a deliberate adjustment in the cropping pattern, reflecting a coping strategy. In our case study area, the Ganges basin, 25% of the basin area showed a significant correlation ($p < 0.10$) between rainfall and NDVI anomalies during the summer monsoon-dominated cropping season, both positive and negative. During the consecutive dry season, 18% of the basin area showed a significant correlation, mostly positive. This variation in sensitivity shows the added value of spatially explicit information from remote sensing over lumped crop statistics. Primarily in the drier western part of the basin, a coping strategy of increasing fallow land in years with below-average rainfall was detected. Distinguishing a coping strategy from a crop yield reduction is important from both an economic and a hydrologic perspective.

3.1 INTRODUCTION

A growing world population and changing diets will cause an increase in the demand for food in the coming decades (FAO, 2009a; Molden, 2007). At the same time the availability of one of the main inputs for food production, water, is becoming limiting and more variable (Biemans, 2012). By the mid-21st century, annual average freshwater availability is projected to decrease by 10-30% over some dry regions at mid-latitudes and in the dry tropics, several of which are water-stressed regions (Parry et al., 2007). In addition to changes in average rainfall, the inter-annual and inter-seasonal variability is expected to change with rainfall becoming more erratic (Parry et al., 2007).

Limited water availability has already affected the rate of growth in agricultural production (Funk and Brown, 2009; Molden, 2007). For large parts of the dry tropics, especially on the Indian sub-continent, the rate of yield growth has slowed since the mid-1990s (Milesi et al., 2010). This was mainly attributed to limitations in the expansion of irrigated areas and the unsustainable use of irrigation water. In the near future, higher water demand due to higher temperatures and increasing competing claims by other sectors are expected to further impact the agro-ecosystem. As a result, sensitivity to rainfall variability is likely to increase and coping strategies will have to adapt accordingly.

Coping strategies aim to either buffer variations in supply, by storage or the additional use of groundwater or canal water, or to adjust demand. Demand side coping strategies involve either structural measures such as crop diversification, or, more flexible measures, such as seasonal adjustment of the cropped area. Farmers in Uttarakhand, northern India, shift to less water-intensive crops in years with poor rainfall (Kelkar et al., 2008). In rainfed areas in Karnataka, southern India, the choice of crops in a specific year depends upon the timing of the sowing rains (Gadgil and Rao, 2000). In the command area of irrigation schemes along the Krishna river in Andhra Pradesh, southern India, farmers leave land fallow in below-average monsoon years or plant part of their fields with rainfed crops (Venot et al., 2010b). Outside India, in Queensland, Australia, a forecast 'likely to be drier than normal' leads to maximising no-till area (Meinke and Stone, 2005). In the north-east of Brazil farmers adapt cropped and irrigated area based on rainfall expectation and the quantity of stored water resources in reservoirs (van Oel et al., 2010). As a result of these strategies, land and water use in water-stressed catchments can be highly dynamic, changing from year to year and from season to season.

A detailed insight into these dynamics and the sensitivity of the agro-ecosystem to inter-annual rainfall variability and related coping strategies in land and water use

is often lacking, especially at the regional or catchment scale. Existing regional and global scale data, like land cover maps, describe only average, fixed land use patterns. Analyses that do describe inter-annual variability in land use, cropping patterns or crop production mostly use data aggregated at the scale of countries or states (e.g. Krishna Kumar et al. (2004) and Revadekar and Preethi (2012)). More detailed local scale statistics on cropping patterns and water allocation strategies are difficult to upscale and interpret. If available, they are often not complete for the whole area or time period of interest, or are outdated. Likewise, vulnerability studies based on socio-economic research techniques like interviews provide in-depth information on sensitivity, vulnerability and coping strategies at the local level, but do not cover larger areas (e.g., Molle et al., 2010; Venot et al., 2010a). As a result, feedbacks from coping strategies in response to changes in water availability, like a seasonal reduction of area under cropping, are hardly considered in most present-day water resources management assessments. This hampers our understanding of the present and future impact of hydro-climatic and socio-economic changes on the agro-ecosystem.

A way to overcome the gap between location-specific coping strategies at the very local level and the need for water resources and agro-ecosystem analysis at the catchment scale is the use of remote sensing. In this paper we apply a longitudinal approach, using remote sensing time-series on the Normalized Difference Vegetation Index (NDVI), an often-used proxy for net primary production, to provide information on the spatial and on the temporal, i.e. inter-annual, variation in crop production. The inter-annual variation in agricultural production and the influence of varying cropping patterns has to our knowledge not been fully studied. Some studies have used NDVI time-series to assess inter-annual relationships between rainfall and vegetation, but they either did not focus specifically on agriculture (e.g. Fang et al. (2001); Knapp and Smith (2001)), touched upon it only at a more aggregated state- or country-wide level (e.g. Milesi et al. (2010)), or studied the relation between climate and crop phenology at higher resolution, but did not go so far as to distinguish underlying management responses (e.g. Brown et al. (2010); Vrieling et al. (2011)). Biggs et al. (2010) and Gumma et al. (2011) did map agricultural responses to a water supply shock in 2002/03 in southern India with remote sensing, but focussed solely on this single drought event.

To identify those areas sensitive to inter-annual rainfall variability, we correlated NDVI anomalies to rainfall anomalies for the period 1982-2006 after correction for autonomous trends in crop yields over the years. For the most sensitive areas. We then distinguished whether correlation between rainfall variability and variability in NDVI is merely

a biophysical response of the crop to varying rainfall or whether a coping strategy in the form of changing cropped area was involved. We used the Ganges basin as our case study site. Census data at district level on cropped areas and production were used to verify the correlations found in the remote sensing data. The longitudinal approach gives not only the sensitivity to rainfall variability but can also be used to gain more insight into the coping strategies of farmers and thereby the dynamics as a result of anthropogenic responses to variability in rainfall.

3.2 STUDY AREA

The rice-wheat cropping system in the Ganges basin (Figure 1) provides the staple food for a large proportion of the rapidly expanding Indian population. Its productivity and overall production have been increasing in the previous decades, attributed to technological changes brought about by the Green Revolution, the expansion of irrigated areas and a surge in the use of groundwater. This increase has been levelling off since the early-1990s (Milesi et al., 2010), especially in drier areas, even though recent years saw record-breaking agricultural production for India as a whole (Gol, 2013). Rainfall varies within the Ganges basin due to the monsoon circulation patterns and large orographic differences, with high rainfall along the southern part of the Himalayan arc and low rainfall in the south-west. Inter-annual variability in rainfall is high throughout the basin (see Table 1).

Table 1 Land use (based on the South Asia Land Use and Irrigated Area Map), rainfall (APHRODITE) and NDVI-rainfall anomaly statistics for each model region

		Chambal	West plain	East plain	South	West Bengal	Himalaya
Total area (km ²)		267264	189728	152384	156001	46980	177953
Land use	irrigated	65%	97%	97%	57%	91%	0%
	rainfed	15%	1%	0%	2%	0%	0%
	shrubs & forest	20%	2%	3%	41%	9%	100%
Rain	mean (mm)	653	659	972	912	1018	1109
	relative standard deviation (%)	27%	28%	24%	21%	21%	20%
Correlation							
(p<0.1)	<i>Kharif</i> (% of area)	27%	19%	46%	24%	36%	15%
	<i>Rabi</i> (% of area)	35%	18%	12%	8%	5%	12%

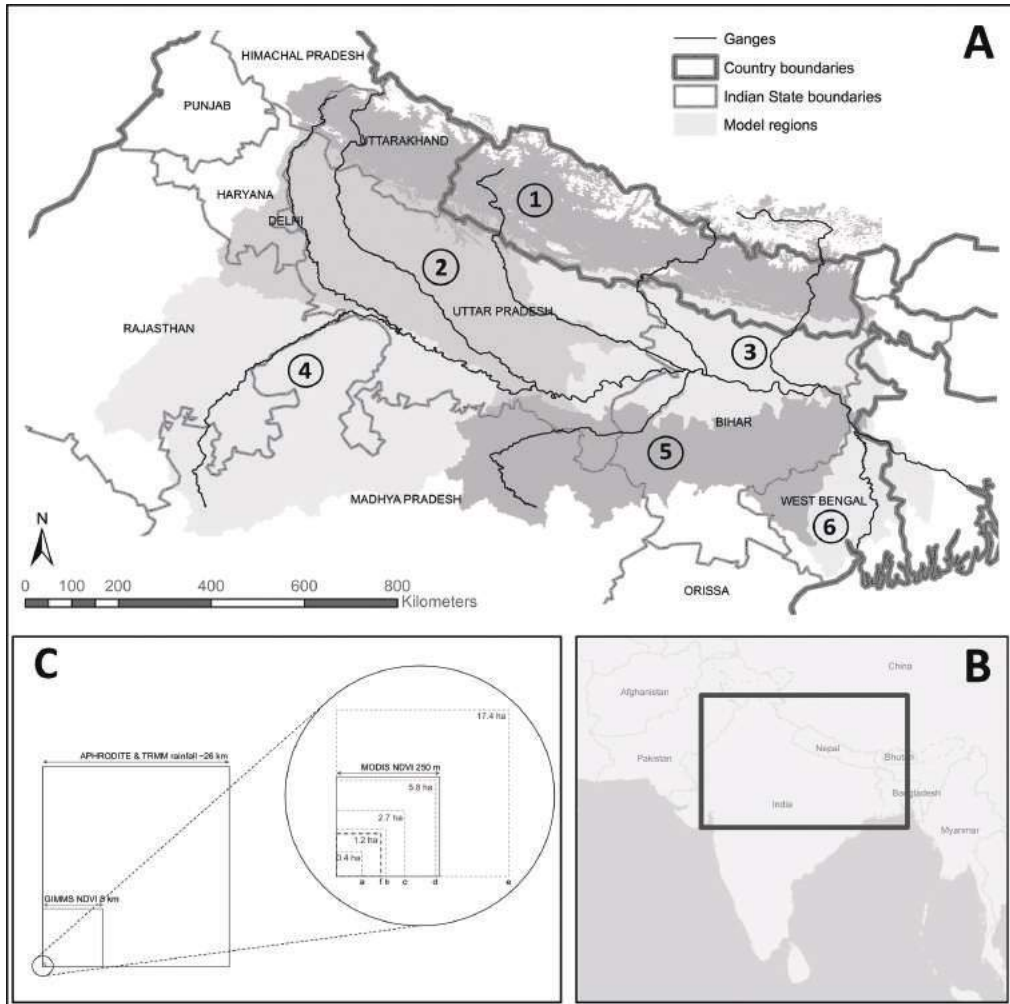


Figure 1 Ganges basin delineation. With (A) regions. 1 Himalayas; 2. West plain; 3. East plain; 4. Chambal; 5. South and 6. West Bengal region (rocks, snow and ice in Himalayas excluded); (B) location of the basin and; (C) spatial resolution of the used gridded rainfall and NDVI datasets and average size of different land holding classes in India: a. marginal (<1 ha, 22% of total area); b. small (1-2ha, 22 %); c. semi-medium (2-4 ha, 24%); d. medium (4-10 ha, 21%); e. large (>10 ha, 11 %), and; f. average of all size classes (as per Agriculture Census 2010-2011, Government of India, 2013).

The productivity of the rice-wheat cropping system heavily depends on the Indian summer monsoon occurring from June to September. In large parts of the basin this monsoon rainfall supports a double crop rotation, with a *Kharif* crop during the monsoon and a *Rabi* crop in the following dry season. During the *Kharif* season, crop development relies heavily on rainfall. *Rabi* season crop cultivation on the other hand, occurring after the end of the

monsoon, relies on over-year water storage in glaciers and deeper groundwater reservoirs or seasonal water storage in snow, soil and small reservoirs (e.g., village tanks). For those farmers having only access to seasonal water storage, the time lag between rainfall and planting and resulting insight in water resources stored in soil, reservoirs and shallow groundwater offers a window of opportunity to take management decisions regarding crop type and intensity.

3.3 METHODOLOGY AND DATASETS

We used freely available datasets for rainfall and NDVI to assess the sensitivity of the agro-ecosystem and related coping strategies. First, sensitivity to rainfall variability was assessed using data with a long temporal coverage (25 years) at medium spatial resolution (~ 8 km). Based on this analysis, sensitive regions were selected where in more detail the presence of a coping strategy in land use was studied using data with a higher spatial resolution (250 m), but with a shorter temporal coverage (10 years). Data sources, characteristics and methods will be described separately for both components in the following paragraphs.

3.3.1 SENSITIVITY TO RAINFALL VARIABILITY

3.3.1.1 DATASETS

For the sensitivity analysis, NDVI data from the Global Inventory Modeling and Mapping Studies (GIMMS) dataset, generated by the AVHRR satellite, were used. GIMMS is available at 8 km resolution for the years 1981-2006 (Tucker et al., 2005). The GIMMS dataset has been corrected for view geometry, volcanic aerosols, and other effects not related to vegetation change. The data can be downloaded as composites for the first and second half of each month. Rainfall was derived from the APHRODITE dataset for monsoonal Asia (APHRO-MA-V1003R1), a daily precipitation dataset covering most of China, South and South-East Asia (Yatagai et al., 2009). APHRODITE data are created primarily with data from between 5,000 and 12,000 rain-gauges across Asia. The rain-gauge data are interpolated at a 0.05 degree grid, using WORLDCLIM climatology data (Hijmans et al., 2005), and re-gridded to a 0.25 and 0.5 degree resolution covering the period of 1951-2007. We used the 0.25 degree resolution dataset and aggregated daily precipitation to monsoon totals (JJAS months) for all 0.25 degree grid cells.

3.3.1.2 METHODOLOGY

Sensitivity can be defined as the degree to which a system is affected, either adversely or beneficially, to climate-related stimuli (McCarthy et al., 2001). In this paper, sensitivity of the agro-ecosystem to inter-annual rainfall variability is based on the correlation between rainfall anomalies and NDVI anomalies. NDVI, derived from satellite measurement of surface reflectance, is often used as a proxy for vegetation or crop yields (Field et al., 1995; Prince and Goward, 1995; Tucker et al., 1985). It has proven suitable for detecting vegetation changes in relation to rainfall anomalies (Anyamba and Tucker 2005). Anomalies in NDVI values give information on the stability of the natural resource base of a region, catchment or farming system (Vrieling et al., 2011).

To derive annual anomalies in NDVI, data needed to be corrected for autonomous trends in crop production over the observed period. As shown by Miles et al. (2010), there seems to be a distinct slowing down in the increase in NDVI since the mid-1990s in large parts of the Indian subcontinent.

Seasonal cumulative NDVI was calculated for the *Kharif* and *Rabi* season ($cNDVI_{i,s}$, with i for years and s for season). Regression with a second-order polynomial best described the slowing down and was consequently used to determine trends in $cNDVI$ values over the observed period for all individual pixels taking the *Kharif* and *Rabi* season separately. Other approaches to describe the trend, such as simple linear regression or a combination of two simple linear regressions, one for the early period with a steep rise in NDVI and one for the later period with a slowdown, as used by (Milesi et al., 2010), were tested as well. They reduced the amount of pixels with a significant trend in $cNDVI$ and were therefore considered less suitable (results not shown). Annual anomalies in NDVI for the two seasons were then calculated per year as the difference between $cNDVI$ and the 1982-2006 seasonal cumulative NDVI trend ($cNDVI_{trend,s}$). Using maximum seasonal NDVI instead of cumulative seasonal NDVI gave similar results (results not shown).

Figure 2 shows the different time periods under consideration. The monsoon period partly overlaps with the *Kharif* season, which ends around late October after which the *Rabi* season starts. No trend in total monsoon rainfall (JJAS months) was expected over the Ganges basin for the period 1982-2006. This was verified for each meteorological grid cell individually. APHRODITE data showed a significant trend in rainfall over only 5% of the basin area, of which half was in the Himalayas, which is an area less relevant for our analysis. Annual anomalies in total monsoon rainfall ($mRain_j$) were therefore derived from a simple correction against the long-term mean for each meteorological grid cell ($mRain_{mean}$).

Sensitivity was thus interpreted as:

$$Sensitivity_s = corr\left(\left(cNDVI_{i,s} - cNDVI_{trend,s}\right), \left(mRain_i - mRain_{mean}\right)\right)$$

The relationship between annual rainfall anomalies and *cNDVI* anomalies can be either positive or negative. When the relationship is positive, more rainfall leads to higher *cNDVI*, i.e. going from drought stress to optimum plant growth and full crop cover. When the relationship is negative, more rainfall leads to lower *cNDVI*, due water logging or flooding. There will be no relationship if sufficient water resources are available each season, either from rainfall or from a reliable source of irrigation. Pearson's *r* of the simple linear regression was calculated for each *NDVI* data pixel at 8 km resolution. The sign of the correlation coefficient determines whether more rainfall resulted in a higher *cNDVI* or lower *cNDVI*. A *t*-test was used to identify pixels with a significant correlation between rainfall anomalies and *cNDVI* anomalies. We did not apply a Bonferroni correction, or a similar method, to correct for false positives which will occur to some degree when testing a correlation for thousands of pixels. The Bonferroni correction is regarded as conservative when there is a large number of tests involved. In our analysis, such a correction would reduce the expected number of pixels with a significant correlation more or less to zero. Deriving the proper correction factor is technically very complicated, especially for a spatial analysis, and beyond the scope of this paper. Instead, we show the pixels with a significant correlation between rainfall and *cNDVI* for different significance levels ($p < 0.01$, $p < 0.05$ and $p < 0.10$) and compare the spatial pattern that arises with district-level data on crop production. Results were also analysed for six sub-regions in the Ganges basin, which were defined using a combination of major land use characteristics and the sub-catchment delineation (Figure 1).

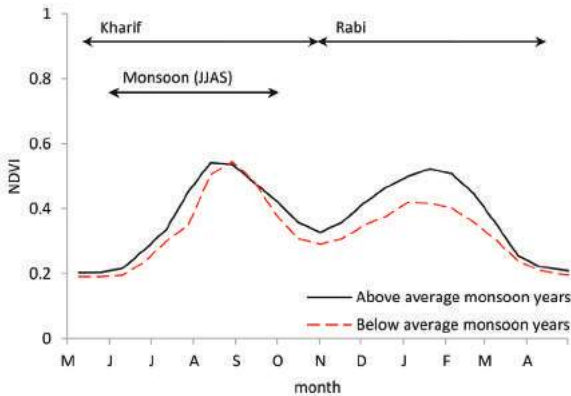


Figure 2 Seasonal variation in average NDVI in the Chambal region, part of the Ganges basin, for all years with an above-average monsoon rainfall (mean rainfall plus standard deviation) and below-average monsoon rainfall (mean rainfall minus standard deviation). Average of all pixels. Source MODIS Terra (MOD13Q1) NDVI data (Huete et al., 2002).

3.3.2 COPING STRATEGIES

3.3.2.1 DATASETS

MODIS NDVI data were used to determine whether the identified sensitivity is a result of a variation in crop growth or a deliberate adjustment of the cropping pattern. At 250m resolution, MODIS NDVI data give more spatially explicit information than the GIMMS data. MODIS Terra (MOD13Q1) NDVI is available for the year 2000 till present as 16-day composites. It has been corrected for water, clouds, heavy aerosols, and cloud shadows. Due to orbit overlap, multiple observations may exist for one day and a maximum of four observations may be collected. This can result in a maximum of 64 observations over a 16-day cycle though the final number of good quality observations is typically less than 10. With 2 or more good quality observations, the highest NDVI value is chosen as the most representative for the whole 16-day period. Otherwise, the historic average value is used (Huete et al., 2002). In the *Rabi* season, which is our main period of interest, it rains only occasionally. Never more than 2% of the pixels were influenced by cloud cover, so additional cloud correction was not necessary.

Rainfall was taken from the Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis dataset (TMPA, TRMM V7) because the APHRODITE dataset does not cover the whole period for which MODIS images are available. TRMM covers the period from 1998 to present and contains 3-hourly precipitation estimates at all longitudes from 50 degree north to 50 degree south at a 0.25 degree resolution. The TMPA product is based on a combination of passive microwave data and infrared data (IR) from different sensors. Passive microwave data from a variety of low earth orbit satellites have a strong relationship to rainfall, but incomplete 3-hourly coverage (averaging about 80% of the earth's surface in the latitude band 50°N–S). Cloud-top brightness temperatures measured by IR of geosynchronous earth orbit satellites has less correlation to precipitation at fine time/space scales and is measured at lower spatial resolution, but has complete coverage for each 3-hourly time period. The resulting rainfall estimate, rescaled to rain-gauge data, provides reasonable performance, especially at monthly scales (Huffman et al., 2007). We used the 3-hourly product, TMPA 3B42, further referred to as TRMM data. We aggregated 3-hourly rainfall to monsoon totals (JJAS months) for all pixels.

3.3.2.2 METHODOLOGY

A coping strategy to deal with inter-annual variability in rainfall is to vary the intensity of the cropping pattern from year to year. In the *Kharif* season, during the monsoon, it is assumed that NDVI is largely a direct reflection of the crop response to rainfall, with pro-

duction being supported by water management in irrigated areas. Farmers can react to varying rainfall through irrigation management if additional water resources are available, but they have less time to anticipate, e.g., by varying the cropping pattern or, more specific, the cropped area. In the *Rabi* season however, cropping starts after the monsoon when water resource availability is partly known to farmers. Differences in NDVI during this season are therefore also likely to reflect coping strategies, like leaving land fallow in this second cropping season. It is assumed that less rainfall leads to a more diverse cropped area pattern in the *Rabi* season, with both fallow land and fields fully irrigated.

The presence of coping strategies in the form of leaving land fallow in the *Rabi* season was assessed by comparing Probability Density Functions (PDFs) of maximum seasonal NDVI (*mNDVI*) between years with below-average rainfall and years with above-average monsoon rainfall. A simple crop response to lower rainfall would result in a PDF which gradually changes from a normal distribution around higher *mNDVI* values to a normal distribution around lower *mNDVI* values. In other words, in case of low rainfall, a suppressed crop growth results in lower *mNDVI* values but largely the same standard deviation and shape of the PDF. If management is involved, limited water resources could be allocated selectively. In dry years there will be areas receiving no water (highlighted by a very low *mNDVI*) and areas still receiving enough water because irrigation is specifically allocated to them (highlighted by a high *mNDVI*). In this case, the PDF would not shift, as described above, but result in a distinctly different *mNDVI* pattern during dry years.

The higher resolution of the MODIS data made it possible to distinguish between different land uses. The *Rabi* season PDFs were constructed for four main land and water management classes within the six regions within the basin. The land use classification was taken from the regional South Asia Land Use and Irrigated Area Map which is primarily based on a classification of MODIS 500m gridded data (Dheeravath et al., 2010). The 18 classes of the freely available version of this land use map were aggregated into three main groups: 'irrigated agriculture', 'rainfed agriculture', 'nature', with snow, ice and rocks in the Himalaya excluded from the analysis. As land holding sizes are on average still smaller than the MODIS grid size (Figure 1), purity of pixels cannot be guaranteed. However, land use is rather uniform in large parts of the basin, which reduces the likelihood of mixed pixels.

For each meteorological grid cell, years with above-average rainfall (defined as mean plus standard deviation, in accordance with Indian Meteorological Department standards) and below-average rainfall (mean minus standard deviation) were selected. It was not an option to pre-select single years for which all pixels experienced below-average or above-

average rainfall due to the large size of the basin and sub-regions, the heterogeneity of terrain and the spatial variation in climate. The *mNDVI* values in the *Rabi* season for the above- and below-average years of all pixels in a land use-region combination were then plotted in the PDFs. Only those pixels that showed a significant sensitivity to rainfall variability (paragraph 3.1.2) were plotted. Maximum NDVI in the *Rabi* season occurred during the second half of January. PDFs for the period before or after, i.e. the first half of January or the first half of February, gave similar results (results not shown).

3.3.3 PRODUCTION AND CROPPED AREA STATISTICS

To validate the results from the NDVI analysis, district-level statistics on production of the main staple crops were collected for three states in the Ganges basin: Rajasthan (wheat), Uttar Pradesh (rice) and Bihar (rice). Together these states cover about 50% of the Ganges area and roughly represent the main climatic regions from Rajasthan in the drier west to Bihar in the wetter east. Uttar Pradesh stretches over the central part of the Indo-Gangetic plain.

The Directorate of Economics and Statistics of the Ministry of Agriculture, Govt. of India, and the relevant state-level authorities release estimates on area, production and yield of principal crops. Yield statistics on food grain production are collected through Crop Cutting Experiments (CCEs), conducted under the General Crop Estimation Surveys (GCES), covering about 95% of villages. Area statistics are based on land records of revenue agencies and sample surveys, covering up to 20% of the villages (Government of India, Directorate of Economics and Statistics, Ministry of Agriculture, 2012). In areas with no official reporting, a more qualitative approach involving the village headmen is used to collect data.

Bihar data were collected from the Crop Production Statistics Information System (<http://apy.dacnet.nic.in>, accessed June 2012), and covers the period 1999-2011. Uttar Pradesh data were collected from the Uttar Pradesh agricultural statistics department of the Government of UP (<http://updes.up.nic.in/spatrika/spatrika.htm>, accessed April 2012), and covers the period 1990-2008. Rajasthan data were collected from the Rajasthan agricultural statistics department of the Government of Rajasthan (<http://www.krishi.rajasthan.gov.in/Departments/Agriculture>, accessed April 2012), and covers the period 1993-2006. Unlike for the other states, for which only time series of annual crop yields per district were available, Rajasthan data included besides crops yields also cropped area, for *Rabi* and *Kharif* separately, for the main staple crop wheat.

Correlation between rainfall and crop yields and rainfall and cropped area was determined in a similar way as for the NDVI analysis, de-trending seasonal crop yields and cropped area first using a second order polynomial and then applying simple linear regression. APHRODITE data were used as rainfall estimate as this dataset has a greater temporal overlap with the district statistics data than TRMM.

3.4 RESULTS AND DISCUSSION

3.4.1 TREND CORRECTION

In both the *Kharif* and the *Rabi* season there has been an increase in seasonal cNDVI over the past decades in the Ganges basin (Figure 3). For the *Kharif* season 37 % of the pixels and for the *Rabi* season 53% of the pixels ($p < 0.10$) show a significant trend in seasonal mean NDVI. Especially during the *Rabi* season this increase has been slowing down since the early-1990s, similar to the decline in growth rate as found by Miles et al. (2010). *Kharif* seasonal mean NDVI does not show a decline in growth rate when taking the mean of all pixels with a significant trend. The almost linear trend is mainly a result of a balance between pixels which still show an accelerated increase (convex regression) and pixels which show a slowing down (concave regression). Regional differences in agro-economic development in the basin might explain this variation. Regions with high-intensity agriculture and early adoption of groundwater irrigation and improved cropping practices might have experienced slower growth in recent years, while other regions are still developing. (Miles et al., 2010) observed decreases in irrigated areas and shifts in cropping patterns for more water demanding crops like *Rabi* wheat in Haryana and parts of Rajasthan in agricultural statistics. The same statistics showed a significant increase in *Kharif* production over Madhya Pradesh in the Chambal region, which they attributed to a recent expansion in irrigated area. Here we corrected for trends in cNDVI, but did not analyse them in further detail, in order to focus on the sensitivity to inter-annual rainfall variability.

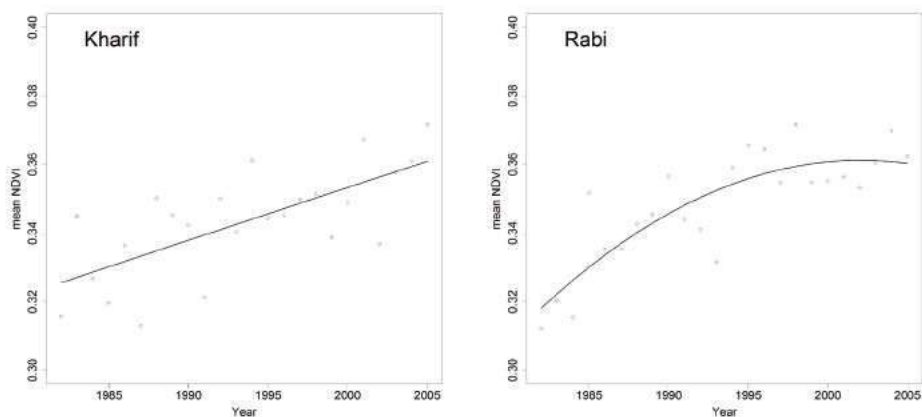
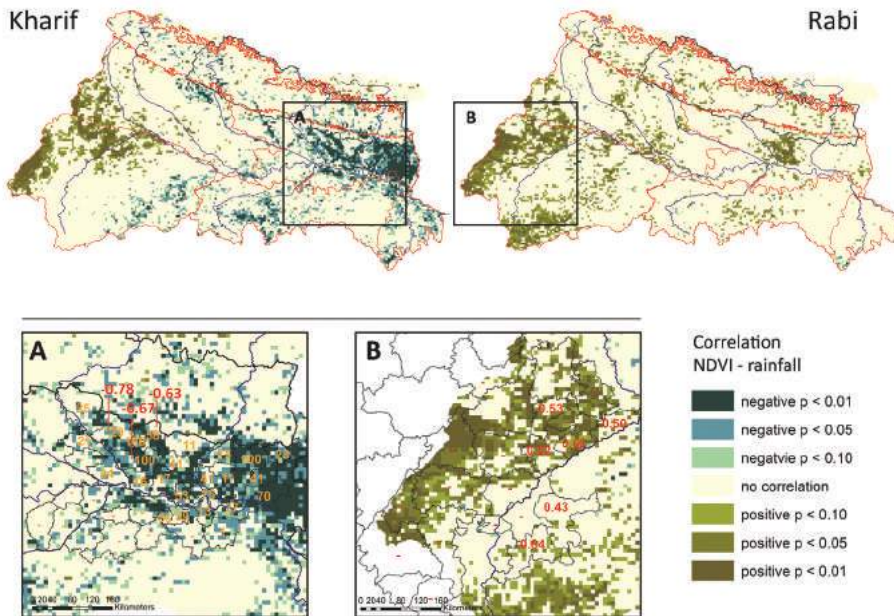


Figure 3 Trend in NDVI development for the Kharif and Rabi cropping seasons (Ganges basin mean for all pixels with a significant correlation between year and yearly mean seasonal NDVI)

3.4.2 SENSITIVITY TO RAINFALL VARIABILITY

The sensitivity analysis of cNDVI for inter-annual rainfall variability shows a significant correlation in 25% of the basin area during the *Kharif* season and 18% during the *Rabi* season ($p < 0.10$). However the direction of the relationship is distinctly different between *Rabi* and *Kharif* as is shown in Figure 4. While an increase in monsoon rainfall results in an expected increase in NDVI during the following *Rabi* season, especially in the drier Chambal region in the south-west, the pattern for *Kharif* is mixed. In the drier western part of the basin, there is a similar positive correlation, but towards the east, more rainfall seems to result in lower cNDVI. This effect is especially prevalent in the downstream part of the Kosi river basin in the northern part of the Indian state of Bihar. This region is known for its recurrent flooding (Government of India, 2008).

Figure 4 Correlation between Rainfall and NDVI for Kharif (left) and Rabi (right) based on a rainfall anomaly - NDVI anomaly regression (Pearson's r for a linear relationship), with increasing colour intensity indicating the $p < 0.10$, $p < 0.05$ and $p < 0.01$ significance intervals. In the inlays the red figures indicate the Pearson's r for significant correlation ($p < 0.1$) between Rainfall and district statistics for Bihar (A) and Rajasthan (B). The yellow figures indicate the yearly flood affected cropped area in Bihar in percentage (source: Government of India, 2008). The '-' sign indicates no significant correlation was found or no flood affected area was reported.



District-level annual crop production statistics confirm the largely positive correlations in the west and negative correlations in the east of the Ganges basin (Table 2). In Rajasthan, 30% of the districts in the Ganges basin show a significant increase in yearly crop production in years with higher rainfall. No negative correlation was found. Similar to the *cNDVI* analysis no clear pattern was detected in Uttar Pradesh with only few districts showing any correlation between production and rainfall. Yearly rainfall totals are on average higher in Uttar Pradesh than in Rajasthan, making water less limiting. In addition, a substantial part of the agricultural areas in Uttar Pradesh is supported by canal irrigation systems, bringing in snow-, ice- and rainfall-derived water from the Himalayas at times when rainfall in the plains is scarce (Siderius et al., 2013). For Bihar, district statistics on crop yields indicate a negative correlation with rainfall, though this is only significant in three districts. These three districts are all situated in the northern part of the state, a region identified as highly flood affected in a ranking by the Government of India (GoI, 2008a). According to this ranking, the flood affected area is even much larger than the district crop statistics suggest, which is also reflected in our rainfall-NDVI analysis. About 41% of the total cropped area in Bihar, mainly the northern plains, is reported to be flood prone with yields being affected due to floods, water logging and poor drainage (Figure 4, inset).

Table 2 Percentage of districts showing a positive or negative correlation between rainfall (APHRODITE) and yearly crop production based on district-wise crop statistics

State	Number of districts in the Ganges basin	Maximum number of years with data	Crop	Positive correlation		Negative correlation	
	with data (total)	n		p < 0.1	p < 0.05	p < 0.1	p < 0.05
Rajasthan	20 (20)	18	Wheat	30%	20%	0%	0%
Uttar Pradesh	54 (54)	14	Rice	6%	7%	6%	2%
Bihar	29 (40)	9	Rice	3%	0%	10%	7%

To get an indication of the loss of productivity, we calculated the percentage reduction in seasonal *cNDVI* between dry and wet years (years with a below- and above-average monsoon rainfall) (Table 3). *cNDVI* values lower than 0.2 were regarded as fallow land or bare soil and not included in the calculating the difference. The highly sensitive Chambal region shows the largest reduction in the *Rabi* season of 28% for the irrigated areas. The irrigated areas in the total Ganges basin show only a reduction of 5% in *cNDVI* between wet and dry years in the *Rabi* season. There is even a slight increase in *cNDVI* during dry years in the *Kharif* season for the Ganges basin as a whole, which can be attributed to the sensitivity to excess rainfall in the eastern and southern parts of the catchment.

Table 3 Difference (in %) in cumulative NDVI between years with a below-average monsoon and years with an above-average monsoon for the irrigated areas in Ganges basin as a whole and the Chambal region in specific

	Ganges irrigated	Chambal irrigated	Chambal rainfed
	% difference	% difference	% difference
<i>Kharif</i> season	1	-8	-12
<i>Rabi</i> season	-5	-28	-31

3.4.3 RAINFALL VARIABILITY AND CROPPED AREA DURING RABI

Figure 5 shows PDFs of MODIS *mNDVI* values at the height of the *Rabi* season for different land use classes and region combinations, for only those pixels which showed a significant ($p < 0.1$) sensitivity to rainfall variability. A distinct difference in PDFs between wet and dry years is shown for the irrigated areas of the Chambal region, the region identified as most sensitive to lower monsoon rainfall. In this drought prone area, the bulk of the irrigated area shows high *mNDVI* values in wet years (peak in *mNDVI* values around 0.8), but the shape of the PDF is almost reversed in dry years, when far more land remains fallow (*mNDVI* values around 0.2 or lower). In principle, this difference could be caused by a mixture of reflections from irrigated areas with non-irrigated areas (rainfed agriculture or nature) within one remote sensing pixel, with the latter showing a decreased natural vegetation in drier years. However, the PDFs for the rainfed agriculture and nature classes

in the Chambal region show low *mNDVI* values during the *Rabi* season in both dry and wet years, which makes such an effect in this case unlikely. A more likely explanation is that it reflects a deliberate area adjustment based on water availability at the end of the monsoon period. In dry years, land is taken out of production when soil, reservoir and shallow groundwater appears insufficient to sustain a crop during the dry *Rabi* months. Only those fields are cropped for which sufficient water is available.

Table 4 Percentage of districts in Rajasthan showing a positive or negative correlation between rainfall (APHRO-DITE) and *Rabi* season and *Kharif* season cropped area based on district wise crop statistics

Cropping season	Number of Districts	Number of seasons with data n	Positive correlation monsoon rainfall - cropped area		Negative correlation monsoon rainfall - cropped area	
			p < 0.1	p < 0.05	p < 0.1	p < 0.05
Kharif	20	18	0%	0%	0%	0%
Rabi	20	17	40%	20%	0%	0%

Statistical data on cropped area of wheat in Rajasthan confirm this inter-annual variability in cropped area in the Chambal region in response to rainfall variability. Table 4 and Figure 4 show the correlation between cropped area and rainfall of the preceding monsoon for all districts of Rajasthan within the Chambal sub-catchment. These districts cover the Chambal sub-catchment in the western part of the Ganges basin, the region most sensitive to lower rainfall. The location of districts with the highest correlation matches with the area identified to be most sensitive by our remote sensing analysis. Cropped area during the *Rabi* season shows a positive correlation to rainfall for 8 out of 20 districts ($p < 0.1$). Even in those districts without a significant relationship, the dry year of 2002/2003 is clearly reflected in the cropped area data for the *Rabi* season. Twenty-five out of 33 districts in Rajasthan, including those outside the Ganges/Chambal basin, show a below-average cropped area (cropped area of district below the mean minus standard deviation) in this year. For comparison, for the *Kharif* season no correlation between cropped area and monsoon rainfall could be found.

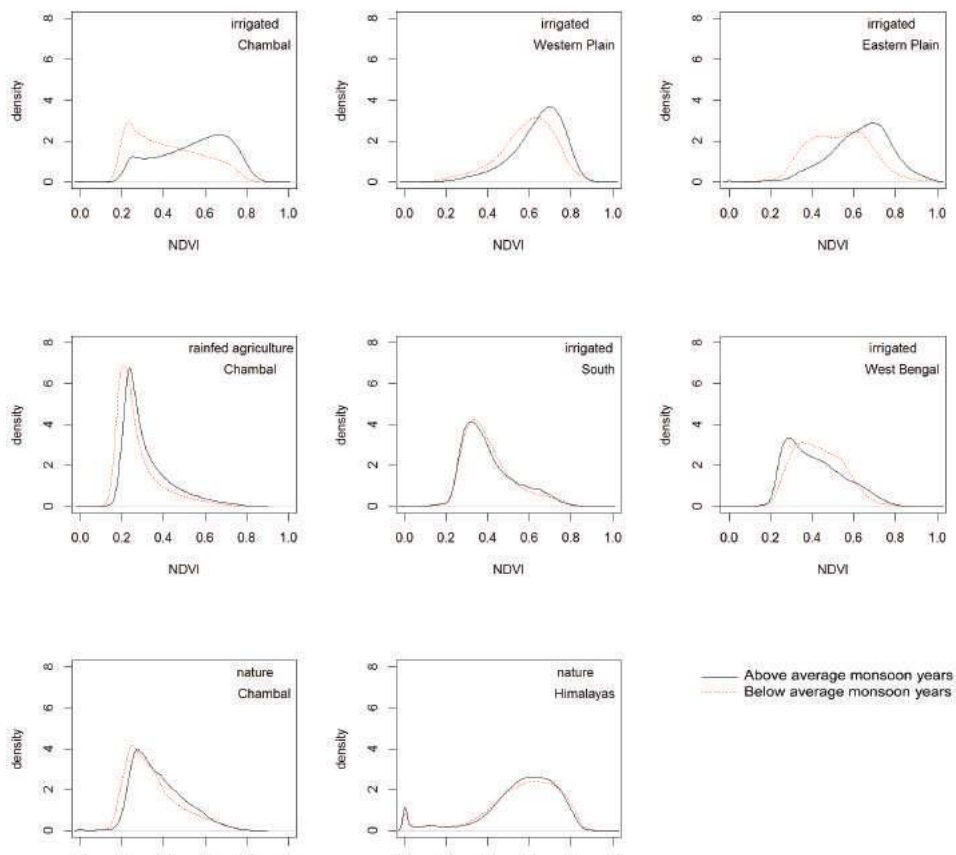


Figure 5 PDFs of NDVI at the height of the *Rabi* season (second half of January) in the different regions for years with a below-average monsoon and years with an above-average monsoon. Below and above-average are defined as the mean \pm standard deviation in accordance with Indian Meteorological Department standards.

In other regions, a variety of responses occur during the *Rabi* season (Figure 5). In irrigated areas in the Western Plain only a slight shift towards lower *mNDVI* in the dry years can be detected. This suggests water resources from canal or groundwater are sufficient to maintain a rather constant NDVI from year to year. More downstream towards the Eastern Plain the shift towards lower *mNDVI* in the dry years becomes larger, but there is no clear indication of more fallow land as in the Chambal region. In the South region, irrigated areas show lower *mNDVI* in both dry and wet years, indicating lower crop production during the *Rabi* season in most years. Interestingly, in West Bengal, irrigated *Rabi mNDVI* in a small

strip along the coast in the south was found to have a negative correlation with rain during the preceding monsoon months (see also Figure 4). This might actually have a different, though related, cause: cyclones impact this part of the basin during the *Rabi* season and both cyclones and monsoon rainfall are influenced by the El Niño Southern Oscillation (ENSO) (Choudhury, 1994). The forests of the Himalayan foothills are not affected.

The distribution of *mNDVI* at the height of the *Kharif* season (not shown) is as expected, with only a (slight) shift towards lower *mNDVI* in the Western Plain in dry years. For the South, West Bengal and Eastern Plain regions a shift towards higher *mNDVI* values in dry years was found. In these regions, too much rainfall and flooding is likely to hamper agriculture, as the correlation with rainfall anomalies during the *Kharif* season also showed.

3.5 DISCUSSION AND CONCLUSION

In this study we present a remote sensing-based method to identify areas where an inter-annual variability in rainfall has an impact on NDVI, a proxy for crop production. In the Ganges basin 25% (*Kharif* cropping season) to 18% (*Rabi* cropping season) of the land area is significantly affected. In the monsoon dominated *Kharif* season this relationship can either be positive or negative. Results show that more rainfall leads to higher *mNDVI* in the drier western parts of the basin and lower *mNDVI* in the eastern parts of the basin where too much rainfall leads to floods, which hamper crop development. For the *Rabi* season the relationship for those areas with a significant impact is mostly positive.

This variation in sensitivity shows the added value of using spatially explicit information from remote sensing over lumped cropping statistics at the catchment scale. While Milesi et al. (2010) found a higher and clearly positive correlation in grain production anomalies and rainfall for *Kharif* ($r = 0.76$) for the period 1966-2006, they looked explicitly at water-stressed regions. Revadekar and Preethi (2012) found a negative correlation between most rainfall indices and state-wise crop production for Bihar as a whole, but this approach ignored the north-south difference between drought prone and flood affected areas within the state. The Ganges basin, individual states and even individual districts contain a mixture soil and hydro-climatic conditions from being sensitive to shortage of rainfall to being sensitive to excess rainfall. Targeted policy decisions to reduce the sensitivity require a detailed site-specific analysis as can be provided with the remote sensing method developed in this study.

Overall, the small reduction of 5% in cumulative NDVI in the irrigated areas in the Ganges in below-average monsoon years during the *Rabi* season indicates that water resources

are still sufficiently available in large parts of the basin to buffer the inter-annual variability in rainfall during this second cropping season. Mainly the western part of the basin is affected in the below-average monsoon years with a reduction of 28% in cumulative NDVI for the irrigated areas during *Rabi*. The increase in fallow land in below-average years as detected with the PDFs does suggest a coping strategy during these years. This distinction between a coping strategy, in the form of more fallow land, versus a biophysical reduction in crop growth and yield is important in terms of cost and benefits. Though not optimal compared to a situation of year-round irrigation, leaving land fallow means saving inputs in the form of labour, water or investments, which are at least partially lost in the case of growth reduction or complete crop loss.

District statistics confirm that inter-annual variability in crop production is partly a result of a cropped area adjustment in the dry parts of the Ganges basin and not only a reduction in yield per hectare. This should be taken into account in analyses of the interactions between climate, water resources and food production. To the best of our knowledge, global and regional integrated hydrological vegetation models (e.g., VIC (Liang et al., 1994), JULES (Best et al., 2011), LPJmL (Gerten et al., 2004)) only simulate changes in yield per hectare but do not include algorithms to simulate inter-annual changes in cropped area. Inter-annual variability in crop production in the dry tropics is therefore likely to be underestimated. Expanding models with a management response algorithm and calibrating this using a combination of remote sensing analyses and crop statistics data could improve their validity for these water-stressed regions.

Separating deliberate management responses and coping strategies from the more biophysical responses could be further explored with remote sensing. Perry (2005) already suggested to look at resource reliability and how this affects crop production and risk strategies. The Ganges basin provided a particularly interesting case study as it has a distinct two-season crop rotation in which the second crop is for a large part depending on preceding monsoon rainfall. As such, there exists a window of opportunity in which farmers and water managers can make decisions on the allocation of resources. Using a longitudinal approach, a coping strategy of leaving more land fallow could be identified. The current analysis relied almost completely on remote sensing data with a minimum resolution of 250m. It was verified with crop production and cropped area data at district level. A combination of using more detailed remote sensing data with even more local data on specific land use, crop production and water allocation strategies, for multiple years and for both cropping seasons separately, could further enhance our insight.

As data are freely available and the presented method to calculate the sensitivity to rainfall variability is relatively simple the sensitivity analysis can be updated annually and a basin could be monitored annually. Areas currently not affected, with additional water resources like canal irrigation water or groundwater still sufficiently available, might become more vulnerable, e.g., due to a changing climate or an on-going depletion of resources. Within the Ganges basin, especially in the western states of Haryana and Rajasthan, more groundwater is used than naturally replenished (Rodell et al., 2009). A further decline in groundwater resources is likely to lead to a higher dependence on surface water resources and an increased sensitivity to rainfall variability. Contrarily, improved flood control measures might reduce the sensitivity of the agro-ecosystem to high rainfall events in the eastern parts of the basin. Coping with current climate variability is thereby considered a first step towards coping with future climate change (Glantz, 1992; Kabat et al., 2002). A better monitoring of coping strategies under current rainfall variability will also increase our understanding of the adaptive capacity of the system to deal with future change.

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4

CROP-SPECIFIC SEASONAL ESTIMATES OF IRRIGATION WATER DEMAND IN SOUTH ASIA



Especially in the Himalayan headwaters of the main rivers in South Asia, shifts in runoff are expected as a result of a rapidly changing climate. In recent years, our insight in these shifts and their impact on water availability has increased. However, a similar detailed understanding of the seasonal pattern in water demand is surprisingly absent. This hampers a proper assessment of water stress and ways to cope and adapt. In this study, the seasonal pattern of irrigation water demand resulting from the typical practice of multiple-cropping in South Asia was accounted for by introducing double-cropping with monsoon-dependent planting dates in a hydrology and vegetation model. Crop yields were calibrated to the latest state-level statistics of India, Pakistan, Bangladesh and Nepal. The improvements in seasonal land use and cropping periods lead to lower estimates of irrigation water demand compared to previous model-based studies, despite the net irrigated area being higher. Crop irrigation water demand differs sharply between seasons and regions; in Pakistan, winter (*Rabi*) and summer (*Kharif*) irrigation demands are almost equal, whereas in Bangladesh the *Rabi* demand is ~100 times higher. Moreover, the relative importance of irrigation supply versus rain decreases sharply from west to east. Given the size and importance of South Asia improved regional estimates of food production and its irrigation water demand will also affect global estimates. In models used for global water resources and food-security assessments, processes like multiple-cropping and monsoon-dependent planting dates should not be ignored.

4.1 INTRODUCTION

As global demand for food increases, water resources – one of the main resources for producing food – are becoming increasingly stressed. South Asia, home to ~25% of the world population, is often identified as one of the future water-stress hotspots (Kummu et al., 2014; Wada et al., 2011). Excess food production in recent years has obscured this bleak future; increases in both agricultural productivity and cropland extension have made the region food self-sufficient in its staple crops in recent decades. But the resources that supported this increase – surface- and ground- water extracted for irrigation, land converted into cropland, increased use of nutrients and pesticides – are not unlimited. Groundwater levels are already falling rapidly in large parts of South Asia due to over exploitation (Rodell et al., 2009; Tiwari et al., 2009) and surface-water irrigation is reaching its limits (Biemans, 2012), costly river interlinking schemes aside (Bagla, 2014; Gupta and Deshpande, 2004). On top of this, higher temperatures and an expected higher variability in climate due to global warming further jeopardizes future food production in the region (Krishna Kumar et al., 2004; Mall et al., 2006; Moors et al., 2011).

In order to understand if, when and where water availability to sustain crop production becomes critical, a more thorough understanding of the potential mismatch between seasonal water availability and demand is required. In recent years, our insight in the seasonal pattern of water availability has increased due to a better understanding of fluctuations in monsoon onset (Goswami et al., 2010; Kajikawa et al., 2012; Ren and Hu, 2014), and the variation in the active-break cycle of the monsoon, which governs intra-seasonal droughts (Joseph and Sabin, 2008), both influenced by large-scale phenomena like El Nino (Joseph et al., 1994). Effort has also gone into quantifying the seasonal availability of snow and glacier melt runoff on the regional scale (Bookhagen and Burbank, 2010; Siderius et al., 2013), with intra-annual shifts in runoff expected in the future due to climate change (Immerzeel et al., 2013; Lutz et al., 2014; Mathison et al., 2015; Rees and Collins, 2006). When it comes to estimating water demand, however, a similar detailed understanding of the seasonal pattern is surprisingly absent.

Two essential and well-known agricultural characteristics that distinguish South Asia from most other large food-producing regions in the world govern this water demand. First, South Asia's agriculture is characterized by a high degree of multi-cropping. A first crop during the monsoon season (*Kharif*) is often succeeded by a second crop during the dry season (*Rabi*) (Portmann et al., 2010). Planting dates for the *Kharif* crop are determined primarily by the onset of the monsoon rather than by an accumulation of degree days. High maximum temperatures form a constraint for crop production during the *Rabi*

season, favouring planting as early as possible. Second, with rainfall highly concentrated during June till September and significant moisture deficits occurring during the other months of the year, crop production is to a very large extent supported by a combination of canal and groundwater irrigation, especially in the dry winter season (*Rabi*) (Gol, 2013).

Many models that are used for global to regional water resources assessments still lack representation of multi-cropping (e.g. Arnold and Fohrer (2005); Best et al. (2011); Gerten et al. (2004); Liang et al. (1994)). Typically, a single cropping period per year is simulated with a degree-day based or predefined single planting date (see e.g. Elliott et al. (2014); Kummu et al. (2014)). Exceptions are the model by Wada et al. (2011) who apply multi-cropping in their estimation of water stress, but in a simplified aggregated form without distinguishing between different crops and the models of Alcamo et al. (2003) and Hanasaki et al. (2008) who apply multiple-cropping seasons using optimized planting dates. However, Hanasaki et al. (2008) note that their optimization mainly reacted to cold spells and was performed under rainfed conditions, which does not lead to optimal planting dates for the South Asia region. As a result, crop-specific seasonal estimates of irrigation water demand in South Asia are still lacking.

In this paper, we aim to provide such spatially explicit, crop-specific seasonal estimates of water demand and crop production, using a revised version of the LPJmL hydrology and vegetation model (Gerten et al., 2004), adjusted for the region. We distinguish two main South Asian cropping periods, *Kharif* and *Rabi*, and introduce zone-specific, monsoon-onset-determined planting dates for 12 major crop types, both rainfed and irrigated. We calibrate the improved model against the latest sub-national statistics on seasonal crop yields from four different countries –India, Pakistan, Nepal and Bangladesh– and explicitly evaluate the irrigation water demand and crop production for the two cropping seasons.

4.2 METHODOLOGY

4.2.1 LPJmL

We used the LPJmL global hydrology and vegetation model for bio- and agro- spheres (Bondeau et al., 2007; Sitch et al., 2003), but developed a version that contains more spatial and temporal detail for South Asia. The LPJmL model has been widely applied to study the effects of climate change on water availability and requirements for food production at a global scale (Falkenmark et al., 2009; Gerten et al., 2011) and the potential of rainfed water-management options for raising global crop yields (Rost et al., 2009). For South Asia, the model has been applied to study the adaptation potential of increased dam

capacity and improved irrigation efficiency in light of climate change (Biemans et al., 2013). LPJmL physically links the terrestrial hydrological cycle to the carbon cycle, making it a suitable tool for studying the relationship between water availability and crop production. The model includes algorithms to account for human influences on the hydrological cycle, e.g. irrigation extractions and supply (Rost et al., 2008). Production and water use for 12 different crops, both rainfed and irrigated are simulated. LPJmL is a grid-based model, run at a resolution of 0.5 degrees, and at daily time step.

Net irrigation water demand (consumption) for irrigated crops is calculated daily in each grid cell as the minimum amount of additional water needed to fill the soil to field capacity and the amount needed to fulfil the atmospheric evaporative demand (Rost et al., 2008). Subsequently, the gross irrigation demand (withdrawal) accounts for application and conveyance losses, and is calculated by multiplying the net irrigation water demand with a country-specific efficiency factor (Rohwer et al., 2007), which is different for surface-water irrigation and groundwater irrigation (as in Biemans et al. (2013); Rost et al. (2008)). Surface water is defined as the water available in local rivers, lakes and reservoirs and is calculated by a daily routing algorithm (Biemans et al., 2009). Irrigation water demand is assumed to be withdrawn from available surface water first. If surface water is unavailable, it is assumed to be withdrawn from groundwater (Rost et al., 2008).

Crop growth is simulated based on daily assimilation of carbon in 4 pools: leaves, stems, roots and harvestable storage organs. Carbon allocated to those pools depends on crop phenology and is adjusted in case of water stress on the plants. Crops are harvested when either maturity or the maximum number of growing days is reached (Bondeau et al., 2007; Fader et al., 2010).

To improve the understanding of spatial and temporal heterogeneity in irrigation water demand and crop production in South Asia, we made some adjustments to the version of LPJmL that is used for global studies. First of all, we introduced the simulation of two cropping cycles per year by developing two different land-use maps for *Kharif* and *Rabi*. Second, we applied zone-specific sowing dates related to monsoon patterns, and third, we accounted for regional differences in crop management by performing a calibration of crop yields at the subnational level. In the next three sections, those adjustments to LPJmL are explained in more detail.

In our experimental set-up, LPJmL is forced with daily precipitation, daily mean temperature, net longwave and downward shortwave radiation derived from the Watch Forcing

Data applied to Era Interim data (WFDEI) (Weedon et al., 2014). Using this dataset, all LPJmL simulations were done for the period 1979-2009 after a 1,000 year spin-up period to bring carbon and water pools into equilibrium. The calibration and all analysis presented in this paper uses the simulation results of the period 2003-2008 for comparison with available statistics. *Kharif* and *Rabi* irrigation water demand and crop production are estimated by performing two simulations using different land-use input and sowing-date input datasets. Those two runs are subsequently combined to attain the seasonal pattern for irrigation water demand and crop production.

4.2.2 DEVELOPMENT OF LAND USE MAPS FOR KHARIF AND RABI SEASONS

To derive land-use input for two separate cropping seasons for South Asia, we used the MIRCA2000 database (MIRCA, version 1.1 (Portmann et al., 2010)) on a 5 minute resolution. MIRCA is a global spatially explicit data set on irrigated and rainfed monthly crop areas for 26 crop classes around the year 2000. On an annual basis, MIRCA is consistent with other gridded datasets for total cropland extent (Ramankutty et al., 2008), total harvested area (Monfreda et al., 2008), and area equipped for irrigation (Siebert et al., 2007), but has more temporal detail. For India, MIRCA2000 includes sub-national (i.e. state-level) information on the start and end of cropping periods. The dataset explicitly includes multi-cropping.

Crop classes in MIRCA2000 were first aggregated to the crop classes available in the LPJmL model, which are fewer (12, irrigated and non-irrigated, plus one class with 'other perennial crops', versus 26 in MIRCA) but include the most important food crops for South Asia (see Figure 2 for distinguished crops). The exact period of monsoon (*Kharif*) and dry season (*Rabi*) cropping differs according to region. In India, *Kharif* sowing is strongly related to the onset of the monsoon, whereas in large parts of Pakistan – where the monsoon is less pronounced – sowing can happen earlier or later because other factors like water availability for irrigation are more important. From the monthly MIRCA cropping calendars we decided to define the cropped area of the *Kharif* season as the area under cultivation per crop as in September and that of *Rabi* as the area per crop as in January. Perennial crops were only included in the *Kharif* land-use map.

Next, a few adjustments to the obtained data were made. First, MIRCA specifies three rotations of rice in northern India, two during summer and one during winter months. We merged the two summer rotations to the *Kharif* rice area and allocated one to the *Rabi* rice area, accepting a potential minor mismatch between datasets. Second, we corrected wheat and rice areas, both of which MIRCA equally divides over *Rabi* and *Kharif*. In reality, rice is mainly cropped during the *Kharif* season and wheat is only cropped during the *Rabi*

(winter) season, when temperatures are lower and heat stress is avoided. We shifted all irrigated wheat to the *Rabi* season and made compensations where possible by shifting an equal amount of irrigated rice area to the *Kharif* season. Third, we shifted 45% of area cropped with pulses from the *Rabi* to *Kharif* season to comply with the latest agricultural statistics (Gol, 2012). In this way, consistency with other datasets was largely maintained (i.e. total cultivated area, cultivated area per crop, area irrigated), while at the same time a better match with crop phenology and regional agricultural practices was achieved.

Finally, we updated the area irrigated to the latest statistics. MIRCA represents land use and irrigated area for the period 1998-2002. Over the past 10 years, irrigated area has further increased in India alone from 76 million ha to 86 million ha (gross irrigated area), to 44% of the total area. Statistics for India show (Gol, 2012) that the increase in irrigated area occurred for all crops. By shifting 10% of rainfed area to irrigated area, while keeping the overall cropped area the same, we achieved an increase in gross irrigated area. We assumed that the all-India trend is mirrored in the neighbouring countries. Cropped area was then aggregated to 0.5 degree grids for both *Kharif* and *Rabi*, which formed the input into the LPJmL model. The resulting land use input is in good agreement with subnational statistics on cropping areas in *Kharif* and *Rabi* (see Annex III, Figure S1-S6).

Figure 1 shows the cropping intensity in the study region according to this newly compiled dataset, as well as the delineation of the river basins for which we will present our results. Figure 2 shows the total cropped area during the *Kharif* and *Rabi* seasons for all major crops in South Asia (India, Pakistan, Nepal and Bangladesh) according to the input

data compiled here and compared to the agricultural statistics (GOI, 2014; GoP, 20114).

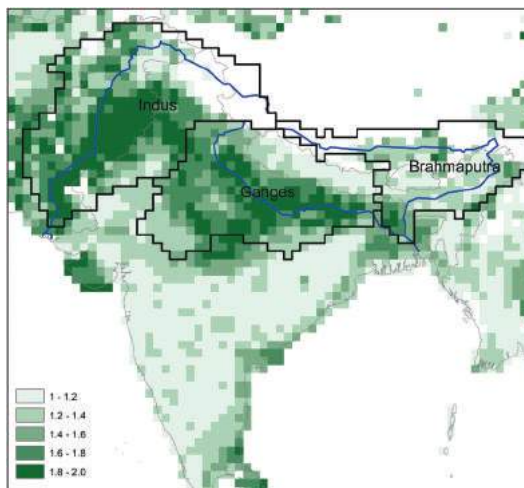


Figure 1 Cropping intensity in South Asia (land use datasets derived for this study based on MIRCA2000). Average cropping intensity is defined here as the total annual harvested area (*Kharif* and *Rabi*) divided by the maximum cropped area of the two cropping seasons. Study-basin delineations are indicated in black.

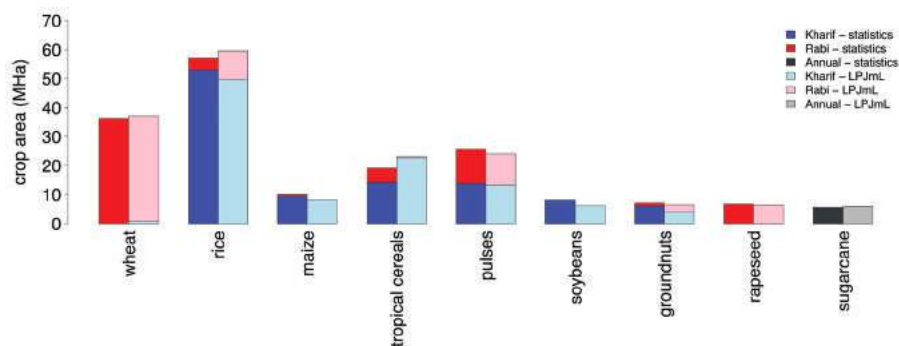


Figure 2 Total crop area in South Asia (India, Pakistan, Nepal and Bangladesh) for different crops in the two dominant growing seasons. National statistics (average of 2003-2008) versus LPJmL input data derived from MIRCA as described in section 2.2. For the spatial distribution of crops between states and provinces of India and Pakistan, Nepal and Bangladesh, see Annex III. Temperate and tropical roots and sunflower are not shown because they occupy relatively small areas; other perennial crops are not shown because there are no statistics available.

4.2.3 ADJUSTED PLANTING DATES FOR KHARIF AND RABI

Sowing dates for *Kharif* crops are closely related to the onset of the monsoon as farmers start (trans)planting rice or other crops when the first rains have arrived. Normal onset dates of the monsoon over South Asia are determined by the India Meteorological Department, at 5 to 15 day interval (IMD, 2015) (Figure 3). The onset of the monsoon starts in Kerala in southern India around the first of June (Julian day 152) and arrives in western Pakistan around mid-July (Julian day 197). For the model simulations in this study, sowing dates for *Kharif* crops were set to five days after the onset of the monsoon, because several days of rain are needed before a crop is (trans)planted (Figure 3). Inter-annual variations in the onset of the monsoon were not taken into account in this study. The perennial crop sugarcane is assumed to be planted on this date as well.

In general, the *Kharif* season ends by the end of October and the sowing of *Rabi* crops starts early – till mid-November until early January, depending on local temperatures during winter and water availability in spring. As the exact date is difficult to determine, we set the first of November as the single sowing date for the *Rabi* crops over the whole study area. Because the *Rabi* crops are generally harvested by the end of March, the irrigation water demand in the warm pre-monsoon summer months of April and May can almost entirely be attributed to perennial crops. In the analysis of seasonal irrigation

demand, we therefore distinguish three seasons: *Kharif*, from June until October; *Rabi*, from November until March; and a 'summer' season from April to May.

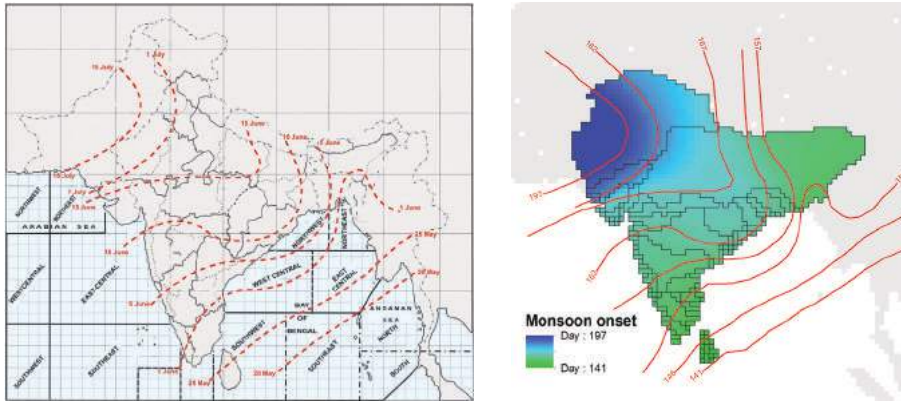


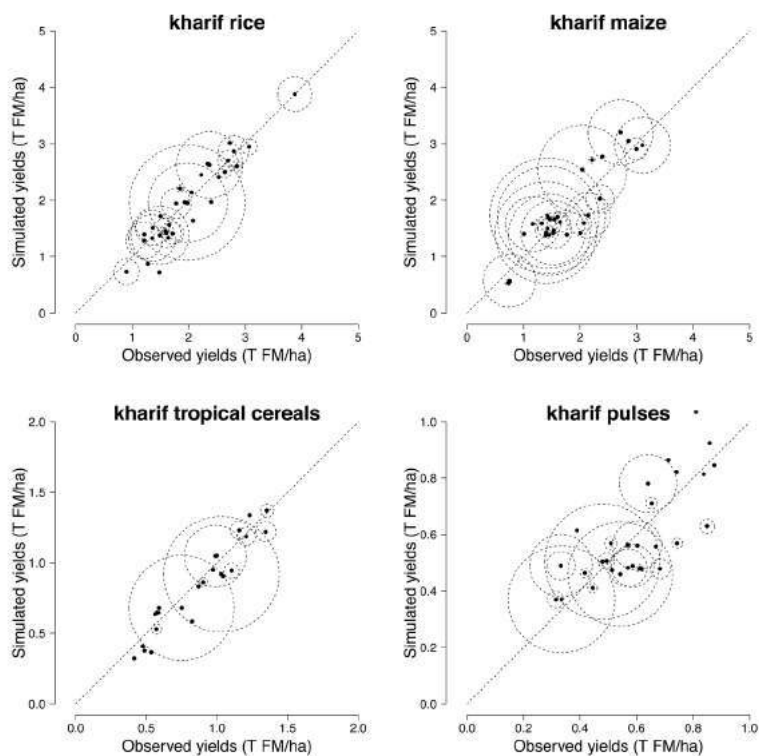
Figure 3 Normal dates for the onset of the Southwest Monsoon based on the maps presented by the Indian Meteorological Department (left) and interpolated over South Asia (right) to derive input data for LPJmL, red numbers indicating Julian days, grey lines showing basin boundaries.

4.2.4 CALIBRATION OF CROP YIELDS

Crop yields in LPJmL are calibrated by varying management intensity, which is represented by three parameters: maximum leaf-area index, maximum harvest index, and a parameter that scales leaf-level biomass production to plot level (Fader et al., 2010). The value of these management factors affects the estimated water demand, because a poorly developed crop with little leaf area will evaporate less and therefore demands less (irrigation) water and vice versa.

The calibration is performed for each crop individually, and management factors are usually determined at the country level in global applications of LPJmL. For this model version, we calibrated crop yields for *Kharif* and *Rabi* separately, as they are differentiated in the agricultural statistics. Moreover, we calibrated the management parameters at the sub-national level for India and Pakistan (state- and province- level respectively) and at the national level for Nepal and Bangladesh. By calibrating at the sub-national level, existing spatial heterogeneity in management and crop yields between regions could be better represented. We used 5-year average yield statistics, for 2003-04 till 2007-08, the most recent period for which consistent records are available from different national agricultural statistics (India: Gol, 2012; Pakistan: <http://www.pbs.gov.pk/content/agricultural-statistics-pakistan-2010-11>, last visited 1-7-2014; Bangladesh for the years from 2003-04

till 2005-06 from <http://www.moa.gov.bd/statistics/statistics.htm#3> and for 2007-08 in the 2011 yearbook (<http://www.bbs.gov.bd/PageWebMenuContent.aspx?MenuKey=234>; Nepal: (GoN, 2012)). After calibration, simulated crop yields matched well with observed yields in most regions (Figure 4). *Kharif* rice and *Kharif* maize crops show the highest variation between states and provinces. Overall, yields during the *Kharif* season are lower than yields during the *Rabi* season, when a higher percentage of the area cropped is irrigated, and temperatures are more favourable.



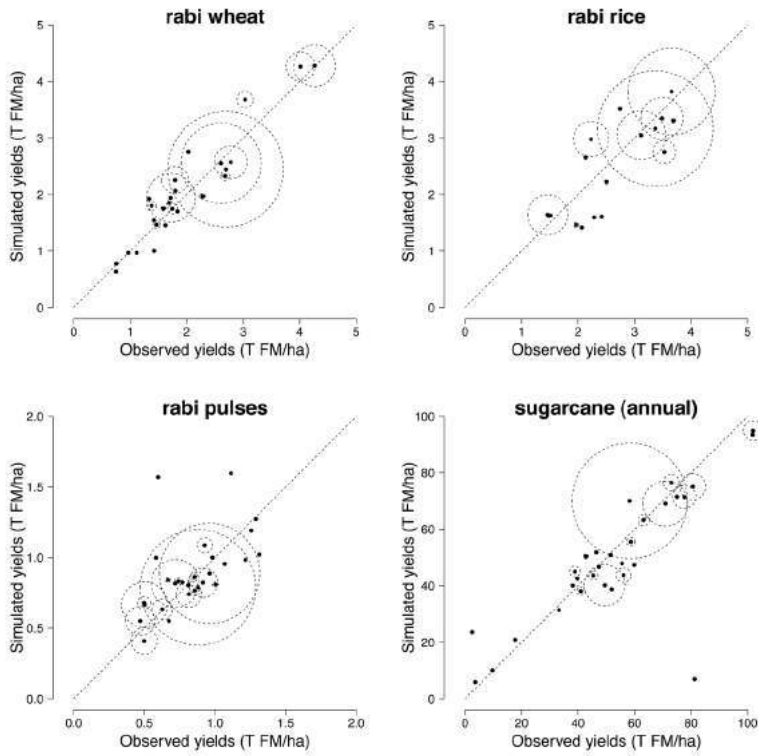


Figure 4 Observed vs simulated (calibrated) crop yields for the most important crops in the different cropping seasons. Each dot represents one state (India), province (Pakistan) or country (Nepal, Bangladesh). Size of the circle represents the relative area under that crop (for areas, see Figures S1-S6 in the Annex III).

4.3 RESULTS

4.3.1 SEASONALITY IN AGRICULTURAL WATER DEMAND

Table 1 shows estimates of seasonal net (consumption) and gross (withdrawal from surface and groundwater) irrigation water demand between the four countries. India and Pakistan have the largest water demand, both in terms of consumption and withdrawal. While Pakistan's net irrigation demand is almost equally divided over the *Kharif* and *Rabi* seasons, India's demand is skewed towards the *Rabi* season; almost ¾ of net irrigation demand in India occurs in this dry season (including summer). This difference between *Kharif* and *Rabi* is less pronounced for gross irrigation demand, i.e. water withdrawals, which include application and conveyance losses. In the *Rabi* season a much higher proportion of the irrigation water is supplied from groundwater (Table 1), which has a higher overall efficiency than surface-water irrigation from canals. Irrigation efficiency for canal water was estimated at 37.5% in India, Bangladesh, Nepal and 30% in Pakistan (Rohwer et al., 2007); efficiency of groundwater irrigation was estimated at 70% for all countries (following Gupta and Deshpande, 2004).

Table 1 Seasonal and total net and gross irrigation water demand estimates (BCM) and groundwater contribution to irrigation- water supply for individual countries and South Asia as a whole (India, Pakistan, Nepal and Bangladesh).

	net irrigation demand (consumption)				Other estimates Total	percentage groundwater irrigation					gross irrigation demand (withdrawal)				Other estimates Total
	<i>Kharif</i> (M6-10)	<i>Rabi</i> (M11-3)	<i>Summer</i> (M4-5)	Total		<i>Kharif</i> (M6-10)	<i>Rabi</i> (M11-3)	<i>Summer</i> (M4-5)	Total		<i>Kharif</i> (M6-10)	<i>Rabi</i> (M11-3)	<i>Summer</i> (M4-5)	Total	
Nepal	0.1	1.0	0.2	1.4		19%	62%	34%	54%		0.3	2.0	0.5	2.7	10 ^a
Pakistan	38	42	16	96	117 ^d	25%	68%	25%	44%		110	86	47	243	200.2 ^b -162.7 ^c
India	59	148	31	235	317 ^d	27%	79%	63%	64%		136	249	58	443	187.8 ^e
Bangladesh	0.1	11	0.3	12		10%	43%	2%	41%		0.2	24	0.8	25	575.9 ^b , 541 ^a
South Asia	97	202	48	346		26%	74%	50%	58%		247	361	106	714	558.4 ^b , 710-715 ^c

a GOI (2005). *Water Data Complete Book*, Central Water Commission, Ministry of Water Resources, Government of India.

b AQUASTAT (<http://www.fao.org/nr/water/aquastat/main/index.stm>).

c Rost et al. (2008).

d Siebert et al. (2010)

e AQUASTAT with reference to 2008 for Bangladesh and 2005 for Nepal. Approximately 79 percent of the total water withdrawal comes from groundwater (Nepal) and 21 percent (Bangladesh)

f Rosegrant and Cai (2002). 1995 estimate using a basin efficiency of 0.54.

g Water Resources Section, Ministry of Planning and Development in (Ahmed et al., 2007)

h Biemans et al. (2013)

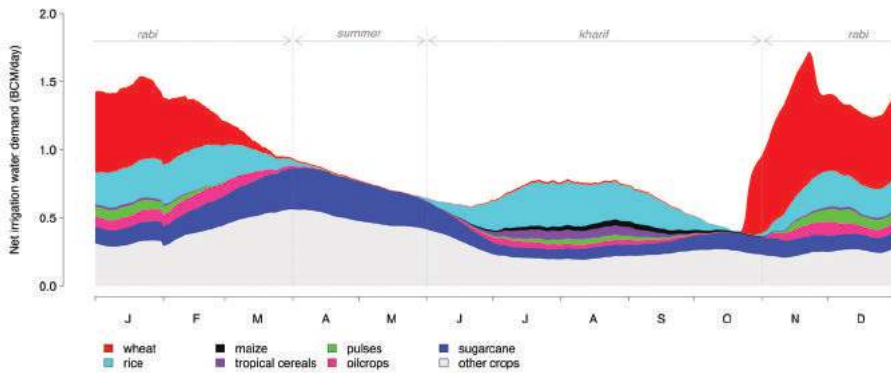


Figure 5 Mean annual cycle of net irrigation requirements for main agricultural crops in South Asia (30-day moving average).

The seasonal distribution of irrigation water demand is a result of rainfall patterns in the region. In Bangladesh and Nepal, monsoon rainfall is abundant for sustaining crop production during the *Kharif* season and irrigation is therefore concentrated in the dry *Rabi* season. Groundwater irrigation, modelled as the resultant of demand minus surface-water availability, provides most water resources during the *Rabi* season in all countries, especially in India. In Pakistan, the Indus provides annually approximately 120 BCM of utilizable runoff, of which approximately 2/3 is used during the *Kharif* (Randhawa, 2002). Our estimate of mean annual groundwater withdrawal in Pakistan is at 60 BCM, of which ¾ occurs during the *Rabi* season and summer. This is somewhat higher than previous estimates of groundwater withdrawal, which were in the range of at 47 BCM to 55 BCM (Ahmed et al., 2007; Qureshi et al., 2003; Wada et al., 2010) but still lower than the estimated total potential of 68 BCM (Randhawa, 2002). For India, the exact distribution of surface-water and groundwater withdrawal between the *Kharif* and *Rabi* seasons is not well documented. Our model estimate of 217 BCM of groundwater withdrawal per year, mainly occurring during the *Rabi* season, is in agreement with earlier groundwater studies with estimates ranging from 190 (± 37) BCM by Wada et al. (2010) to 212.5 BCM by the Government of India (Gol, 2006).

Overall, our estimates of national total net and gross irrigation water demand are in line with earlier studies and statistics, but at the lower end of the range for India. Accounting for monsoon dependent planting dates, and thereby a more effective use of rainfall during the main *Kharif* cropping season, reduced our estimate of total agricultural water demand compared to earlier regional studies, e.g. with the LPJmL model (Biemans et al., 2013). For Pakistan, our estimates are on the high side compared to other studies. Especially for

the *Rabi* season, we estimate a high additional demand from cash crops like cotton. This demand has to be met largely by groundwater abstractions, because runoff from the Indus and its tributaries is low during these months.

Evaluating the mean annual cycle of irrigation water demand per crop reveals the reason behind seasonal differences in demand (Figure 5). The single peak in net water demand for wheat during the *Rabi* season stands out, while rice peaks in both *Rabi* and *Kharif* seasons. The moderating effect of monsoon rainfall during the *Kharif* season is obvious, with net irrigation water demand during the *Kharif* season only accounting for about 30% of the annual net irrigation water demand (Table 1). So while water-use efficiency improvements in rice receive much attention, paddy fields being the epitome of excessive water consumption, rice is actually not the most water-demanding crop in the region. Because rice is grown mainly during the *Kharif* season in most states, its water demand is lower than for wheat and sugarcane, which are grown during the dry *Rabi* season. Those crops therefore depend much more on groundwater availability (see also Table 1 and Figure 6 for contribution of groundwater irrigation per cropping season). Additionally, sugarcane has an atypical demand in time, caused by its very long cultivation period of about 12 months; it requires large amounts of irrigation water in the hot dry months of March, April and May, a period when rainfall is scarce and most other fields are left fallow.

4.3.2 SEASONAL PATTERNS OF WATER DEMAND FOR DIFFERENT BASINS

As a result of varying climatological conditions and availability of spring and summer runoff from snow- and glacier- fed rivers, cropping patterns and thereby seasonal water demand pattern differ greatly between the major river basins (Figures 6 & 7). The Indus basin shows a relatively stable irrigation water demand during the year, which is primarily fed by groundwater in winter and melt runoff in summer (Figure 7). Downstream, monsoon rainfall contributes little to crop water needs. In the Ganges basin, a more seasonal pattern can be seen with demand for irrigation water being lower during the monsoon, when rainfall is sufficient over large parts of the basin, and no additional irrigation is needed. The same pattern can be seen to be even stronger in the Brahmaputra basin.

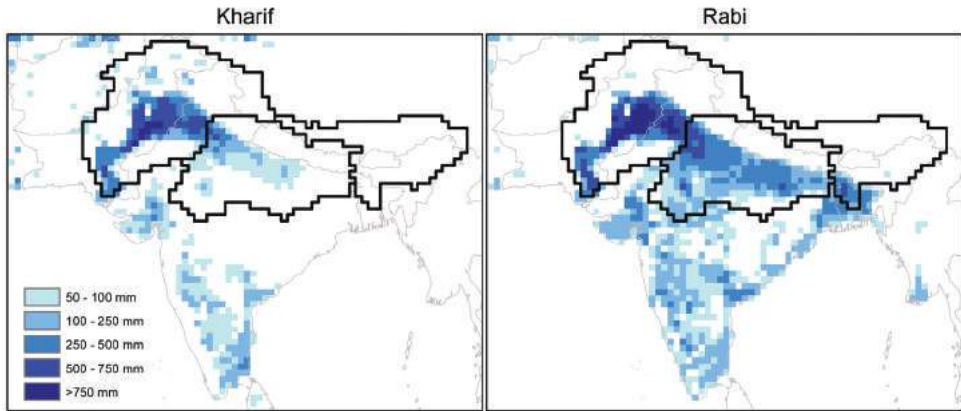


Figure 6 Gross irrigation water demand for Kharif (M6-10) and Rabi (M11-3) cropping seasons, with selected river basins (Indus, Ganges, Brahmaputra)

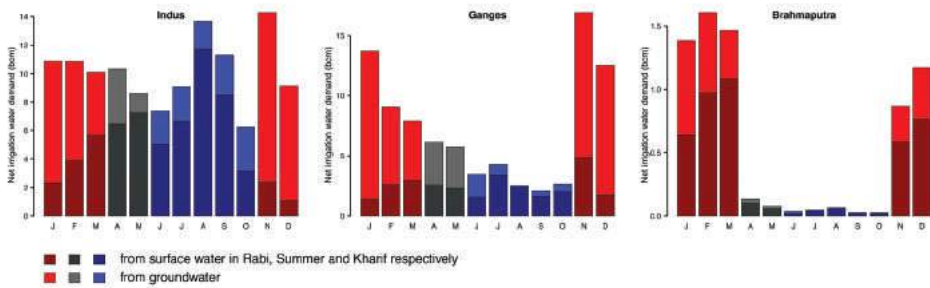


Figure 7 Monthly net irrigation water demand for three river basins. Colours indicate the different seasons (red – Kharif, grey – Summer, blue – Rabi) and the dark areas the source for supplying the irrigation water (dark – surface water, light – groundwater).

4.3.3 FOOD PRODUCTION IN SOUTH ASIA DURING KHARIF AND RABI CROPPING SEASON

Figure 8 shows the total seasonal production of only the five most important food crops (wheat, rice, maize, tropical cereals and pulses), both for the region as a whole as for the individual basins. The total area irrigated to grow these food crops is smaller in *Kharif* than *Rabi* (35 Mha vs 46 Mha total for the four counties), but total (rainfed plus irrigated) area used to grow these food crops is much larger in *Kharif* than *Rabi* (95 Mha vs 57 Mha). While the percentage of area under irrigation, productivity per hectare and sources of water used greatly differ between the *Kharif* and *Rabi* seasons, total regional food-crop production is remarkably similar in the two seasons. A lower cropped area during the *Rabi* season

is compensated for by higher yields. Of the total production of food crops in South Asia during the *Kharif* season, ~50% is supported by irrigation (Figure 8). In the *Rabi* season up to ~95% of food-crop production is supported by irrigation. We also calculated the potential rainfed yield on those areas currently irrigated. Absence of irrigation would reduce the *Kharif* food-crop production with ~15% (dark blue bar in Figure 8), against a reduction of almost 60% in *Rabi*. This stresses the importance of sufficient irrigation- water supply for achieving food security in this region.

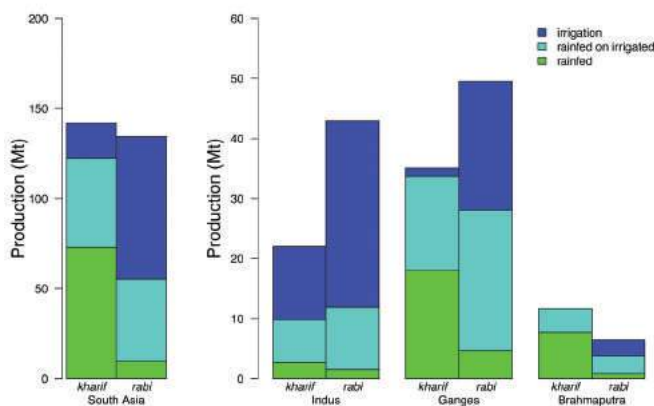


Figure 8 Seasonal irrigated (blue) and rainfed (green) production of food crops (sum of wheat, rice, maize, tropical cereals and pulses) in South Asia (Nepal, Pakistan, India and Bangladesh) and individual river basins. Light blue corresponds to potential rainfed production on irrigated land, i.e. dark blue corresponds to the increase in production due to irrigation.

A closer look into the seasonal food production in the different river basins shows clear differences. The Indus and the Ganges have a much higher annual production of food crops than the Brahmaputra. *Rabi* is the most important season for the production of food crops in the Indus. The same is true for the Ganges, although the production levels between the seasons are closer to each other. The rainfed production is much larger in the Ganges than in the Indus. In the Brahmaputra basin, the majority of food-crop production takes place during the *Kharif* season.

4.4 DISCUSSION

The seasonal estimates presented here on food production and related irrigation water demand in South Asia form a new baseline estimate of South Asian seasonal-water demand and food-crop production, as they provide more spatial, temporal and crop-specific details than previous estimates.

Incorporating seasonal cropping patterns in more detail leads to improved estimation of the timing of water demand. We show that seasonal water demand is a factor of crop-specific seasonal consumption, availability of rainfall and different sources of water supply, i.e. groundwater or surface water, and the irrigation efficiencies connected to these sources. Despite these improvements, when modelling such large basins with complex hydrology and high diversity in agricultural and water-management practices, inevitably simplifications and local inaccuracies remain.

Our estimate of gross irrigation demand, the water withdrawal, is strongly influenced by the water use efficiency value used, which is determined by a variety of factors like local irrigation practices, scale of analysis and source of water use. We used the most commonly reported values for the region, similar to other model-based studies in order to be able to compare results. Inclusion of regional, more application- and water-source-specific water use efficiency values in models would improve the estimation of gross water demand. Such detail is also necessary to gain better insight into the adaptation potential of different measures like drip irrigation and alternate wetting and drying.

More attention to seasonal cropping patterns and their water demand opens the scope for further model improvement. Double-cropping was evaluated by combining two seasonal model runs, one for *Kharif* and one for *Rabi*. Use of residual soil moisture from one season to the other was not incorporated in this way, nor could the continued depletion of groundwater be accurately modelled. An integrated double-cropping routine, with proper calibrated crop-specific planting dates and yields, would provide such necessary analysis in a region where groundwater depletion is of serious concern.

Next, estimation of planting dates should be further improved, using detailed information on local agricultural practices and local water availability. Ample information is available in the irrigation domain but it will require a form of cooperation between experts at the local to national level and the water resources modelling community. Sharing of input data might reduce costs and time expenditure, will increase its uptake and improve overall quality of water resources assessments.

Finally, cropped area and sources of irrigation used are not constants or slowly evolving properties, but can be highly variable on inter-annual time scales in response to rainfall variability (Siderius et al., 2015). These fluctuations were not assessed in the current study but are of high importance to individual farmers and the overall profitability of agriculture in regions with a variable climate. Combining an improved baseline of seasonal water demand with the inter-annual fluctuations in cropped area will lead to a more realistic assessment of both water demand and crop production, of high relevance in today's world with its volatile food commodity markets.

This paper highlights crop-specific periods of peak water demand that can form critical moments in agricultural production. Such better understanding of the size of water demand during critical moments, the crops that are responsible for this water demand, and its relative importance for food production is essential to guide sustainable development of climate adaptation measures. This analysis can support the selection of promising options to decrease irrigation water demand. When combined with information on the (un)availability of surface water and the resulting pressure on groundwater resources (Figure 7), it improves our understanding on the causes of water shortages and groundwater depletion. Finally, insight in the yield gap between rainfed and irrigated agriculture in specific regions, and between regions, can help target investments to improve irrigation practices or to increase productivity of rainfed agriculture.

4.5 CONCLUSIONS

Introducing seasonal crop rotation with monsoon-dependent planting dates in a global vegetation-hydrological model leads to better seasonal estimates of irrigation water demand. Irrigation water demand between the two main cropping seasons differs sharply both in terms of source and magnitude; gross irrigation demand during the *Rabi* season is ~30% lower than during the *Kharif* season, the traditional cropping season, when monsoon rainfall reduces the amount of supplemental irrigation water needed. Our estimate of total annual water demand is lower than that of previous studies (Biemans et al, 2013), despite the net irrigated area being higher. Overall, gross annual irrigation demand is estimated at 714 BCM; 247 BCM during the Kharif monsoon season, 361 BCM during *Rabi* and 106 BCM during the summer months of April and May.

Seasonal estimates of agricultural water demand better highlight crop-specific differences in peak water demand. Such increased temporal detail is needed for properly evaluating the impact of expected shifts in supply of water as a result of a rapidly changing climate, especially in the Himalayan headwaters of some of the main rivers in South Asia.

With temperatures rising and total precipitation fairly constant, increased melt from glaciers combined with an early melt of the snow cover is expected to shift the peak in spring runoff to early in the season (Immerzeel et al., 2010; Lutz et al., 2014). Whether this shift will affect critical moments for irrigation or the ecosystem as a whole is to be assessed.

Our study has thereby more than regional relevance. Given the size and importance of South Asia, in terms of population and food production, improved regional estimates of production and its water demand will also affect global estimates. In models used for global water resources and food-security assessments, processes like multiple-cropping and monsoon-dependent planting dates should not be ignored.

Acknowledgements: This work was carried out by the Himalayan Adaptation, Water and Resilience (HI-AWARE) consortium under the Collaborative Adaptation Research Initiative in Africa and Asia (CARIAA), with financial support from the UK Government's Department for International Development and the International Development Research Centre, Ottawa, Canada. We acknowledge the Potsdam Institute for Climate Impact Research for their support in using the LPJmL model and computational facilities.

This chapter is based on:

Siderius C., Van Walsum P., Biemans H., Van Ierland E., Kabat P., Hellegers P. (submitted).
Flexible strategies for coping with rainfall variability: seasonal adjustments in cropped
area in the Ganges basin. PLOS ONE.

5

FLEXIBLE STRATEGIES FOR COPING WITH RAINFALL VARIABILITY: SEASONAL ADJUSTMENTS IN CROPPED AREA IN THE GANGES BASIN



One of the main manifestations of climate change is expected to be increased rainfall variability. How to deal with this in agriculture will be a major societal challenge. In this paper we explore flexibility in land use, through deliberate seasonal adjustments in cropped area, as a specific strategy for coping with rainfall variability. Such adjustments are not incorporated in hydro-meteorological crop models commonly used for food security analyses. Our paper contributes to the literature by making a comprehensive model assessment of inter-annual variability in crop production, including both variations in crop yield and cropped area. The Ganges basin is used as a case study. First, we assessed the contribution of cropped area variability to overall variability in rice and wheat production by applying hierarchical partitioning on time-series of agricultural statistics. We then introduced cropped area as an endogenous decision variable in a hydro-economic optimization model (WaterWise), coupled to a hydrology-vegetation model (LPJmL), and analysed to what extent its performance in the estimation of inter-annual variability in crop production improved. From the statistics, we found that in the period 1999-2009 seasonal adjustment in cropped area can explain almost 50% of variability in wheat production and 40% of variability in rice production in the Indian part of the Ganges basin. Our improved model was well capable of mimicking existing variability at different spatial aggregation levels, especially for wheat. The value of flexibility, i.e. the foregone costs of choosing not to crop in years when water is scarce, was quantified at 4% of gross margin of wheat in the Indian part of the Ganges basin and as high as 34% of gross margin of wheat in the drought-prone state of Rajasthan. We argue that flexibility in land use is an important coping strategy to rainfall variability in water stressed regions.

5.1 INTRODUCTION

South Asia's climate is strongly influenced by land, ocean and atmosphere interconnections resulting in strong intra-seasonal (Annamalai and Slingo, 2001; Joseph and Sabin, 2008; Singh et al., 2014), inter-annual (Krishnamurthy and Shukla, 2000; Meehl, 1997) and decadal variability in rainfall (Abish et al., 2013; Krishnamurthy and Goswami, 2000). The decadal cycle is now expected to approach a thirty-year dry epoch, with probability of below-average monsoon years increasing from once in every ten to fifteen years to once in every three years (Joseph et al., 2013). Climate change seems to reinforce this decadal drying: recent research linked cooling of the Tibetan anticyclone region and warming over the equatorial Indian Ocean during the recent decades to a weaker monsoon circulation (Abish et al., 2013). Warming over the equatorial Indian Ocean might divert part of the monsoon rainfall to lower latitudes, away from the Indian subcontinent. Predictions for periods towards the end of the 21st century are as yet inconclusive (Mathison et al., 2013; Turner and Annamalai, 2012), with models generally suggesting an upward trend in regional rainfall but also an increase in inter-annual variability (Kumar et al., 2013; Sharmila et al., 2015). Whatever the long term trend, South Asia is facing a period with uncertainty in monsoon rainfall.

Food production in India, the largest country in South Asia, is highly dependent on the monsoon and inter-annual variability in monsoon rainfall. This is shown to cause large fluctuations in both monsoon-season crop production and production during the consecutive dry season (Krishna Kumar et al., 2004; Kumar et al., 2005; Parthasarathy et al., 1988; Revadekar and Preethi, 2012). Evaporative crop water demand is close to or even below mean annual rainfall in large parts of the region. Slight reductions in rainfall already lead to crop stress; when monsoon rainfall deficiency exceeds 10% compared to the long term average and consequently more than 20% of the country's area is affected, the year is categorized as an all-India drought year (IMD, 2015). However, at the local level sensitivity of food production to inter-annual rainfall variability can differ strongly. Whether a meteorological drought leads to an agricultural drought depends on local rainfall distribution and management practices for land and water like irrigation. Siderius et al. (2014) showed that in the Ganges basin, the drier west is more affected than the wetter east, with the highly irrigated middle part of the Indo-Gangetic plain hardly showing any sensitivity.

Irrigation forms a buffer against rainfall variability and almost 30% of the cultivated area in India is now equipped for irrigation; more than half of this area is supported by groundwater, the rest by canal water and local reservoirs (Gol, 2012). Presence of irrigation infrastructure alone, however, does not guarantee a continuous water supply from year to

year. Large scale irrigation systems are not always effectively managed (Chambers, 1988; Meinzen-Dick et al., 2002), with water often being over-allocated and supply insufficient for meeting total crop demand in the command area. Local storage facilities like shallow aquifers or village reservoirs (tanks), from which part of the irrigation water is drawn, are not always completely replenished during years with low rainfall (Siderius et al., 2015). As a result, in years of shortage a proportion of farmers will not have access to irrigation water and have to skip planting altogether. Others will have to choose: either they spread available water over a large area, facing a reduction in yield levels, or else they concentrate irrigation, maintaining high yield levels on a smaller area (Siderius et al., 2014), and optionally supplementing income with rainfed crops (Kelkar et al., 2008; Venot et al., 2010b). Being flexible in leaving land fallow is a common coping strategy for dealing with water shortage. Between purely rainfed and fully irrigated agriculture there is a grey area where cropped area, irrigated area and type of crops planted are dynamic variables depending on annual water availability and the cost of irrigation.

Such land and water use dynamics are usually not incorporated in hydro-meteorological and land surface models (e.g. Arnold and Fohrer (2005); Best et al. (2011); Gerten et al. (2004); Liang et al. (1994)). Global and regional models used to assess the impact of water availability on food production typically focus on the impact of rainfall on yield, keeping the cropped area constant. Mostly, these models are calibrated and validated using long term average production values. Only recently did Kummu et al. (2014) analyse the global impact of inter-annual rainfall variability on food production, indicating South Asia as one of the food security hot spots. In their study, as in many other studies, however, yields are simulated for a fixed land use pattern, without any inter-annual variation in cropped area or area irrigated. On those areas irrigated, optimum water supply is guaranteed, with water generally taken from an unlimited groundwater reservoir if surface water resources were insufficient (as e.g. in LPJmL (Gerten et al., 2004) or VIC (Liang et al., 1994)). Only in some applications groundwater abstractions are restricted to a predefined volume (Wada et al., 2010), the size of which is hard to assess, however. Using this kind of optimal irrigation on a fixed land use pattern will probably lead to an underestimation of production variability and an overestimation of unsustainable groundwater use.

In this paper we explore the impact of flexible land use strategies for coping with rainfall variability. Flexibility in land use is in this paper defined as deliberate, seasonal adjustment of cropped area, by leaving land fallow or not. First, the contribution of cropped area variability to overall variability in rice and wheat production was assessed by applying hierarchical partitioning (ANOVA) on time-series of agricultural statistics (as explained in

section 5.2.1). Cropped area was then introduced as an endogenous decision variable in a hydro-economic optimization model and subsequently we analysed to what extent the model is capable of simulating the assessed inter-annual variability in cropped area and overall crop production, taking into account costs of irrigation and land use and the prices of crop produced (as explained in Section 5.2.2). Finally, with the improved model, we quantified the value of flexibility, i.e. the foregone costs of choosing not to crop in years when rainfall is scarce. This value was assessed under current costs and price conditions, with and without cost of family labour. We focused on the Indian part of the Ganges basin, one of the world's major food producing regions, and a region where groundwater depletion and seasonal water stress are major issues of concern.

5.2 METHODOLOGY AND DATA

5.2.1 ASSESSING THE NATURE OF CROP PRODUCTION VARIABILITY USING AGRICULTURAL STATISTICS

We first determined how area and yield contribute to variability in production, using long-term time series on annual crop production, yield and cropped area for the whole of India and the Indian part of the Ganges basin, from the Department of Agricultural statistics. To distinguish year-to-year variation from long-term trends, time-series of crop production, area and yield were de-trended using 3rd order polynomial regression, which best describes the increase in production since the 1950s and the slow-down since the 1990s. De-trended cropped area and yield vary due to yearly management decisions and climatic variability. Annual crop production is the product of both. Logically, a linear regression that seeks to explain production as a function of area and yield has a predictive power of 100% (i.e. $R^2 = 1$). However, possible correlations can exist between area and yields (e.g. anticipated high yields lead to an increase in cultivated area). In order to determine the relative importance of area and yield in explaining production, the method of 'hierarchical partitioning' (Chevan and Sutherland, 1991; Grömping, 2006) was used. The method was applied at the national level to India, to the Ganges basin and to all districts within the Ganges basin.

As an indicator of variability of production of different crops at different spatial scales, the relative standard deviation (%RSD) was used,

$$\%RSD = \frac{\sigma_{prod}}{\mu_{prod}} * 100$$

where μ_{prod} is the mean production and σ_{prod} is the standard deviation of production. %RSD was calculated at district, state and basin level. A single value of variability for all districts (states) was obtained by aggregating %RSD's of the individual districts (states), applying weighted averaging on the basis of production. State-level production, aggregated from district-level production values of districts within the Ganges basin, does not represent the area of the state outside of the Ganges basin. Model grid cells are, at ~50km by ~50 km resolution, similar in size to administrative districts, which warrants direct comparison of modelled %RSD based on grid cells, with observed %RSD based on district values.

For the Ganges basin we could use district-level production statistics for 1999 till 2008, the most recent period for which consistent records are available from the Department of Agricultural statistics website of the Government of India (<http://apy.dacnet.nic.in/>). Data for all-India rice and wheat were retrieved from the same source. For Rajasthan, additional data on wheat production came from the website of the Indian Directorate of Wheat Development (http://dwd.dacnet.nic.in/wheat_prod1/wheat-annx3.pdf). Data on rice production before 1999 came from the Indian Directorate of Rice Development (<http://drdpat.bih.nic.in/>). Rainfall data which we used for the correlation with all-India production were taken from the 1 by 1 degree gridded data product from the Indian Meteorological Department (Rajeevan et al., 2006).

5.2.2 MODELLING VARIABILITY IN CROP PRODUCTION

5.2.2.1 THE HYDRO-ECONOMIC MODEL WATERWISE

While traditional climate-driven crop models are proven to be well capable of simulating average crop yields, i.e. productivity per hectare (e.g. Asseng et al. (2013); Biemans et al. (2015)) they lack the capacity to vary the size of the area cropped based on available water resources. The hydro-economic model WaterWise (WW) can assess variability in crop yield as well as cropped area. WW optimizes the total gross margin (total yield-over-cost), choosing the optimal combination of land use and water management options, given available water resources:

$$Y_{TOT} = Y_{LU} - C_{LWM}$$

with

$$Y_{LU} = \sum_{z,u,y,s} (Prod_{z,u,y,s} * P_{y,u} - C_{LUu} * Ac_{z,u,y,s})$$

$$C_{LWM} = \sum_{z,u,y,s} (C_{IRRIZ,u} * Ac_{z,u,y,s})$$

where Y_{TOT} represents total gross margin (in Indian Rupee (Rp) /yr), Y_{LU} the profit from land use (Rp/yr) based on production ($Prod$, in ton) multiplied by price of product (P , Rp/ton) minus non-water costs (C_{LUu} , Rp/ha) multiplied by the cropped area (Ac , in ha), in season s of year y per land use u in hydrotope z . C_{LWM} are the costs of local water-management measures for supporting land use, i.e., the variable costs of local irrigation measures ($C_{IRRIZ,u}$, in Rp/ha), depending on the amount of water used, multiplied by the cropped area (Ac , in ha).

WW is a hybrid holistic model; production and water fluxes per ha of all land use and water management options are pre-processed by an off-line hydrology-vegetation model (here LPJmL (Biemans et al., 2015; Gerten et al., 2004); see Figure 2 and next subsection). Land use is an endogenous variable in the WW model which allows for optimization of seasonal variability in land use. Unlike other hydro-economic models (Cai, 2008; Cai et al., 2003; Yang et al., 2013), WW does not contain a crop-water production function. In WW, the (sometimes extreme) nonlinearities between water and crop production are dealt with in the off-line column model. Crop productivity and water fluxes from the offline hydrology-vegetation model are then attached to continuous decision variables in WW that represent the area fraction for which a land and water management option is actually applied: associated with these variables are all the (time-dependent) water balance variables and crop production variables. By decreasing cropped area, production decreases, but also water demand is reduced and cultivation costs are avoided.

In this study we defined four land and water management options: i. leaving land fallow, resulting in no costs (only for *Rabi* season); ii. rainfed cultivation resulting in fixed costs of cultivation; iii. irrigation from surface water and; iv. irrigation from groundwater. Access to irrigation was derived from Portmann et al. (2010), corrected uniformly for each crop for the increase since 2000 using government statistics (Gol, 2012). Groundwater irrigation on this irrigated area constrained to a maximum of 66% (FAO, 2015) (see also next subsection). The latter two options add additional costs depending on the amount of irrigation water supplied and the source of irrigation water. While WW does not contain a

crop production function in the code itself, the combination of fallow, rainfed and irrigated crop production does mean WW (in the here used schematization) has a choice between 3 discrete options along the crop-water production curve; zero production, 'suboptimal' rainfed production and optimum production at maximum water supply. As rainfall varies between the different grid cells, at the aggregated level of a subbasin the model does have, in effect, a whole range of options to choose from at different intervals along the crop-water production function, each with a different marginal return on water.

Because we were interested in present-day coping strategies, we blocked permanent land use conversion from one crop to the other in this study and instead focused solely on seasonal land and water management decisions. To realistically mimic only those seasonal land and water use decisions which are actually a farmers' response to monsoon rainfall, the choice of leaving land fallow was restricted to the second cropping period, the so-called *Rabi* season. At the time of planting the *Rabi* crop, just after the monsoon, farmers usually have knowledge of available water resources. This in contrast to the first cropping period, the *Kharif*, when the monsoon has just started at the moment of planting and the availability of water resources over the growing season is still unknown (Siderius et al., 2015; Siderius et al., 2014). As a result, monsoon rainfall totals could not be used as a decision-determining variable for the *Kharif* period. In this period, the model was only allowed to switch between irrigation and rainfed conditions. In the Ganges basin, about 60% of food crops are produced during *Rabi* (Biemans et al., 2015).

In terms of runoff routing and reservoir routines, WW is similar to other hydro-economic models like the Nile Economic Optimization Model (Whittington et al., 2005), Ganges Economic Optimization Model (Wu et al., 2013), and the Indus Basin Model Revised (Yang et al., 2013). WW has been previously applied to the Nile basin for quantifying the contribution of rainfed and irrigated agriculture to overall food security and, at a more local level, for solving complex issues of flood mitigation and water quality management in basins in Europe (van Walsum et al., 2008). The WW model code is formulated within a Mixed Integer Linear Programming framework (MILP). The WW model equations have been implemented in Xpress-Mosel (FICO, 2014) and are summarized in ANNEX I. The complete formal description of the model, the model code and input and output documentation are available at www.waterwijs.nl.

5.2.2.2 CROP PRODUCTIVITY, WATER FLUXES AND LAND USE DATA

For the Ganges application, the hydrology-vegetation model LPJmL (Gerten et al., 2004) was used as the off-line pre-processor of crop productivity and water fluxes at the grid

cell level (0.5 degree resolution) (Fig. 1). LPJmL has been widely applied in global and regional studies on water availability and food production (Biemans, 2012; Biemans et al., 2013; Bondeau et al., 2007; Falkenmark et al., 2009; Gerten et al., 2004; Kummu et al., 2014; Rost et al., 2008; Sitch et al., 2003). LPJmL provided seasonal production, $Prod_s$, per hectare for all crops and all four land and water management options in all gridcells of the LPJmL model for the Ganges domain (Figure 2). Associated with each combination was a daily irrigation water demand and all other day water fluxes; runoff, drainage and recoverable irrigation return flows to determine water availability and precipitation, evapotranspiration, soil moisture for both upper and lower soil compartments to complete the water balance for a check on consistency. We used the regional LPJmL model application described by Biemans et al. (2015), which has seasonal crop productivity for the major food crops extensively calibrated and water demand validated at state level for both the *Kharif* and *Rabi* cropping seasons for the whole of South Asia.

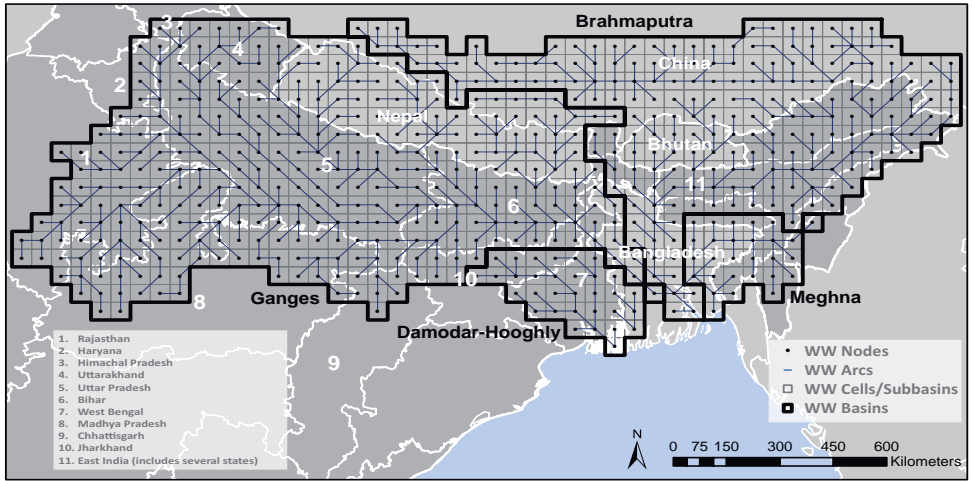


Figure 1 Model domain, with Indian states (dark grey) and other South Asian countries (light grey).

WW was set-up for the Ganges-Brahmaputra-Meghna basin with a similar surface water and land surface grid structure as LPJmL, including the main reservoirs. The topological schematization of WW involves nodes k , arcs j , subbasins r and hydrotopes z , the latter representing agro-climatic zones with a certain soil type. In the Ganges application, subbasins are analogous to LPJmL gridcells (Figure 1), with hydrotopes analogous to the various crop classes in each LPJmL gridcell. While we set-up and ran the WW model for the whole Ganges-Brahmaputra-Meghna basin, our analysis focused on the Indian part of the Ganges basin for which consistent observed data are available. In the remainder of

the article we will refer to this domain simply as 'Ganges'. The model was run for a 10-year period, from 2000-2009, overlapping with the observed data.

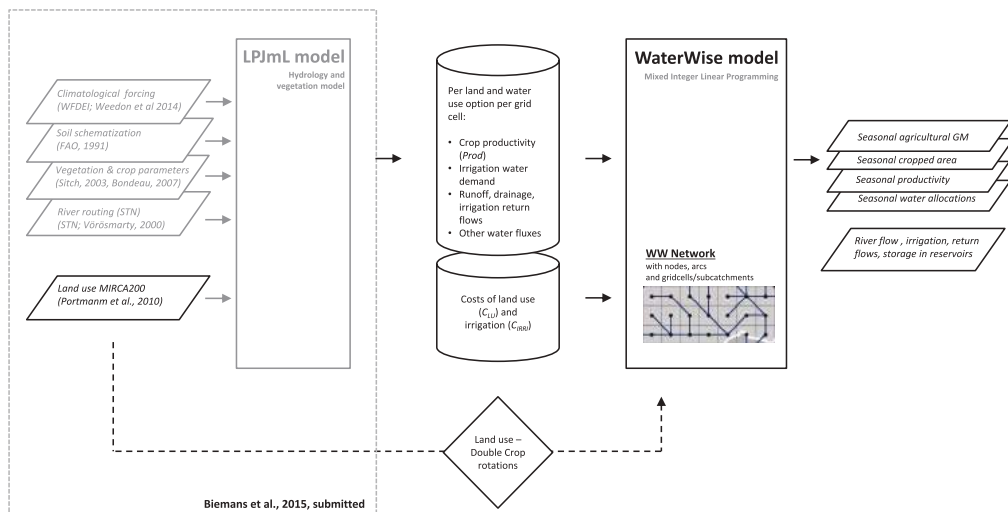


Figure 2 Model linkages between WaterWise and LPJmL. Climatological forcing is taken from WATCH ERA INTERIM. Schematization of soil, vegetation and river routing is based on global datasets. Land use is based on MIRCA. For the WaterWise model, MIRCA's monthly land use was compiled into consistent double-crop rotations for WaterWise. Costs of land use per hectare and costs of irrigation per m³ of water used per ha are attached to crop productivity and water fluxes of each crop in each grid cell.

The land use pattern was based on MIRCA2000 (Portmann et al., 2010), which gives irrigated and rainfed cropped area for a total of 26 crops per month at a spatial resolution of 5-arc minutes. For the LPJmL South Asia application MIRCA's monthly pattern was already aggregated to seasonal cropping patterns for *Kharif* and *Rabi* at 0.5 degree resolution (Biemans et al., 2015). To derive from these seasonal patterns the specific double-crop rotations in a gridcell, which are required in WW, we clustered *Kharif* rice, tropical cereals and maize with *Rabi* wheat, rice and pulses in each gridcell, according to the commonly used priority order in table 1 (adapted from (Yadav and Rao, (2001))). This lead to a total of 13 single crop rotation options (for *Rabi* or *Kharif*) and 5 double crop rotations in our model. Non-agricultural land use (nature, bare soil, rocks and glaciers, urban area) covers 59 % of total area. In our analysis we focused primarily on rice and wheat in the Indian part of the Ganges basin, the two staple crops. Rice is grown mostly during *Kharif*, whereas wheat is grown only during *Rabi* from November to April, being less resilient to high temperatures.

Table 1 Cropping pattern for the complete Ganges-Brahmaputra-Meghna basin, as adapted from MIRCA (Portman et al., 2010; Biemans et al., 2015) and their priority order

<i>Crop id</i>	<i>Cropping period</i>	<i>Area (km²)</i>	<i>Area percentage</i>	<i>order</i>
Rice _k	Kharif	127043	7%	
Maize _k	Kharif	27502	2%	
Pulses _k	Kharif	25750	2%	
Oil crops _k	Kharif	33105	2%	
Roots _k	Kharif	60116	4%	16%
Rice _r	Rabi	13640	1%	
Maize _r	Rabi	27502	2%	
Pulses _r	Rabi	30596	2%	
Wheat _r	Rabi	75674	4%	
Oil crops _r	Rabi	41630	2%	
Roots _r	Rabi	2077	0%	11%
Rice _k Wheat _r	Kharif - Rabi	103504	6%	1
Rice _k Maize _r	Kharif - Rabi	40183	2%	2
Rice _k Pulses _r	Kharif - Rabi	30596	2%	3
Tropical cereals _k Wheat _r	Kharif - Rabi	15106	1%	4
Maize _k Wheat _r	Kharif - Rabi	6317	0%	11% 5
Sugarcane	Whole year	23743	1%	
Other	Whole year	17824	1%	
Pasture	Whole year	4774	0%	3%
Non-agricultural land	Whole year	1005965	59%	59%

Irrigation is only supplied in WW when total demand over the whole season can be realized. Irrigation water is taken from river flow, from groundwater and local runoff within the subbasin. In addition, cells within the main irrigation schemes of the basin can withdraw irrigation water from surface water not only from flow through the arc that directly crosses the cell but also from the main tributaries Yamuna, Upper Ganga and Ramganga, from which the large irrigation canals originate. Minimum flows to the Hooghly branch and to Bangladesh were inserted as minimum flow boundary conditions, each at 500 m³s⁻¹.

5.2.2.3 COST AND FARM-GATE PRICE DATA

Costs of cultivation and farm gate prices for the principal crops in India were derived from the Directorate of Economics and Statistics for the cropping year 2011/2012, the latest for which data was available (<http://eands.dacnet.nic.in>, last visited 31-10-2014). We did not intend to make a detailed full-scale analysis of India's agro-economic performance, nor of the difference in profitability of agriculture between different states and therefore modified the data to single, simplified, crop-specific values for yields and prices for the whole basin (Table 2). In this way, crops competed for water, with differences in market conditions between states being neutralized. No distinction between *Kharif* and *Rabi* costs and prices was made.

Table 2 Costs and farm gate prices per hectare for 2011/12 and WW parameterization (average costs and average prices from statistics represent the mean of all states, with minimum and maximum state-level values in between brackets; source <http://eands.dacnet.nic.in>)

	Costs (Rp ha ⁻¹)				Prices (Rp ton ⁻¹)		Break-even production (Ton ha)	
	Statistics		WaterWise		Statistics			WaterWise
	Average total costs		Land Use	Irrigation	Total costs	Average prices		
Rice	19584	(12544 - 29356)	15000	5868	20868	10888 (8970 - 13840)	12500	1.8
Wheat	17498	(11613 - 25538)	15000	5008	20008	11666 (10520 - 12790)	12500	1.5
Tropical cereals	10467	(6385 - 19081)	7500	3532	11032	11992 (8070 - 22000)	12500	0.9
Pulses	10211	(6678 - 13580)	7500	3544	11044	35030 (24870 - 61930)	37500	0.3
Maize	11777	(9192 - 16151)	7500	4038	11538	9898 (9100 - 10810)	12500	1.2
Oil crops	11675	(8618 - 15049)	7500	6314	13814	24206 (17460 - 33220)	25000	0.5
Sugarcane	39274	(31961 - 52947)	30000	19215	49215	2205 (2200 - 2100)	2500	17.8
Other			30000	16543	46543		2500	

note 1: Cost and prices averages are not area-based. States included: Haryana, UP, Rajasthan, Uttarakhand, Bihar, Madhya Pradesh, West Bengal and Assam.

note 2: Irrigation costs are based on maximum irrigation requirement (as calculated by LPJmL) multiplied by irrigation costs of 0.01 USD (which is about 0.6 Rupees at autumn 2014 exchange rates).

Costs are comprised of land use costs (C_{LU}) per hectare and variable irrigation costs (C_{IRRI}) based on the m³ of water used per ha. C_{LU} includes all actual expenses in cash and kind like fertilizer costs, irrigation charges and value of machinery, but excludes rental value of the land and value of family labour (A2 class, (GoI, 2008b)). CIRRI accounts for irrigation charges and hired machinery, diesel and electricity costs needed for irrigation. Applying a generally used value of 1 USD cent per m³ (~0.6 Rp) multiplied by the maximum amount of irrigation water applied as calculated by LPJmL gave maximum C_{IRRI} ranging from 3500 Rp per ha for pulses and tropical cereals to almost 20000 Rp for sugarcane. Cost of irrigation for sugarcane are so high as it also requires water in the hottest and driest months of the year. The ratio between C_{LU} and maximum C_{IRRI} is approximately 3 to 1 for rice and wheat. The same ratio was found in state-level statistics for states in the Ganges basin with high irrigation water use (i.e. Haryana, UP).

Prices at farm gate level of rice (paddy), wheat, tropical cereals and several others crops vary around 12500 Rp ton⁻¹. Oil crop prices are on average double and the price of pulses almost triple that amount. Yields in ton/ha are on average considerably lower for these crops, though, reducing their comparative advantage. Sugarcane prices are only a fifth of those for staple crops, but yield in ton per hectare for the raw product is a factor 10 to 20 higher. Due to its long growth period (12 months in the model, in reality sometimes longer) its water demand is high, though, and a stable water supply is required for a successful yield.

5.2.2.4 SCENARIOS

As a baseline, we ran WW in simulation mode, mimicking the production of rice and wheat as simulated by the LPJmL model ('WW-baseline' variant). In simulation mode, variation in area cropped is not allowed ($Ac_{z,u} = \text{constant}$) and groundwater resources are unlimited. Production is described as:

$$Prod_{z,u,y,s} = yld_{z,u,y,s} * Ac_{z,u} \text{ and}$$

$$yld_{z,u,y,s} = f_1(Crop, Soil, T, Rad, RH, Prec, Ir)$$

where $yld_{z,u,y,s}$ is seasonal crop yield (in ton per ha). Seasonal crop yield is influenced by the crop (*Crop*), soil conditions (*Soil*) and the meteorological variables temperature (*T*), incoming solar radiation (*Rad*), relative humidity (*RH*), precipitation (*Prec*) and access to irrigation (*Ir*); the latter is a binary condition and based on the MIRCA land use database, which indicates how much of the area for each crop is equipped for irrigation (Portmann et al., 2010; Siebert et al., 2007). If equipped for irrigation, water demand is met either from surface water or from groundwater.

To explicitly allow for adjustment of cropped area in our model, we switched to running the model in optimization mode, including seasonal costs of land and water use and benefits of crop production. The seasonal decision to crop (or leave land fallow without any costs involved) or to irrigate then becomes an economic decision, influenced by costs of land and water use and economic yield of production ('WW-flexible' variant). Cropped area is now calculated as:

$$Ac_{z,u,y,s} = f_2(yld_{z,u,y,s}, P_{y,u}, C_{LU,u}, C_{IRRI}, qsupply_{y,z,y,s})$$

with $P_{y,u}$ the price per ton yield (in Indian Rupee (Rp)/ton), $C_{LU,u}$ is the cost of cultivation (in Rp/ha) and C_{IRRI} the cost of irrigation (in Rp/ha, depending on the m³ of irrigation water required per ha) and $qsuppl_{y,z,y,s}$ is the available supply of irrigation water. Gross margin, i.e. production multiplied by prices minus costs, is optimized for the basin as a whole. This means, if given the flexibility to leave land fallow, an area is only cropped when benefits per ha exceed costs per ha, and when also, basin-wide, water cannot be used more productively elsewhere.

Finally, to further constrain the model and better mimic variability as observed, we restricted access to unlimited groundwater reserves by replacing part of it with virtual local storage reservoirs (VLSRs), representing shallow groundwater aquifers and storage

in local reservoirs (ponds, village tanks) that are seasonally recharged by local runoff. Water availability in areas depending on VLSRs will fluctuate from year to year, limiting crop production in dry years, so that cropped area and production variability will increase. The decision to crop or to irrigate then becomes an economic decision influenced by seasonal water scarcity ('WW flexible-limited' variant).

The exact size and number of all open wells, ponds, tanks and water harvesting reservoirs and area that is irrigated by them is unknown. Groundwater irrigation in South Asia is largely unregulated with only limited government control and monitoring (Shah, 2010). In a sensitivity analysis, we varied the volume of these VLSRs in combination with the area of cropland irrigated by them. The separate types of storage facilities are lumped in the model per subbasin. Volumetric capacity of a VLSR was calculated as the assumed depth of the reservoir multiplied by the area of cropland in a subbasin depending on it. For the depth of reservoirs we used a range from 0.01m to 1m. The area irrigated from VLSRs ranged from 0% to 66%, with area irrigated from deep groundwater reduced accordingly to maintain a total area irrigated from groundwater and VLSRs of 66%. We then compared the resulting range of production variability with observations and selected the parameter combination for which simulated variability approached observed variability.

5.3 RESULTS

5.3.1 VARIABILITY IN PRODUCTION OF RICE AND WHEAT

Trend-corrected cropped area, yield and production data for rice and wheat are shown for India in Figure 3. Both yield and area have increased over the past decades. While area has increased rather linearly, yields have increased more rapidly since the mid-sixties as a result of new high-yielding varieties and improved irrigation supply and nutrient inputs of the green revolution. From the 1980s the trend has continued mainly due to additional groundwater exploitation (Kannan and Sundaram, 2011). As a result of these increases, production has risen fourfold for rice and fifteen-fold for wheat; India has thus become self-sufficient in both commodities despite its rapid population growth. While the trend in yield and production increases seems to slow down since the end of the 1990s, favourable weather conditions still led to bumper crop yields in recent years.

After de-trending, the yearly anomalies in crop production, yield and area remain. Anomalies at all India level are presented in Figure 3, which also contains examples for the drought-prone state of Rajasthan and separately for its Bundi district, an important rice

and wheat producing area. Clearly, variability in all three variables increases when going to a lower level of scale for both rice and wheat production. This is to be expected as variations in districts average out at state level, and variation between states average out when totalized at all-India level. For instance, annual rice production in a drought prone state like Rajasthan is influenced differently by rainfall anomalies than rice production in a cyclone prone state of West Bengal. Overall, at all-India level, fluctuations have increased over time in absolute terms, but decreased in relative terms. This is a result of the large increase in area, yield and production over the past decades (ANNEX IV).

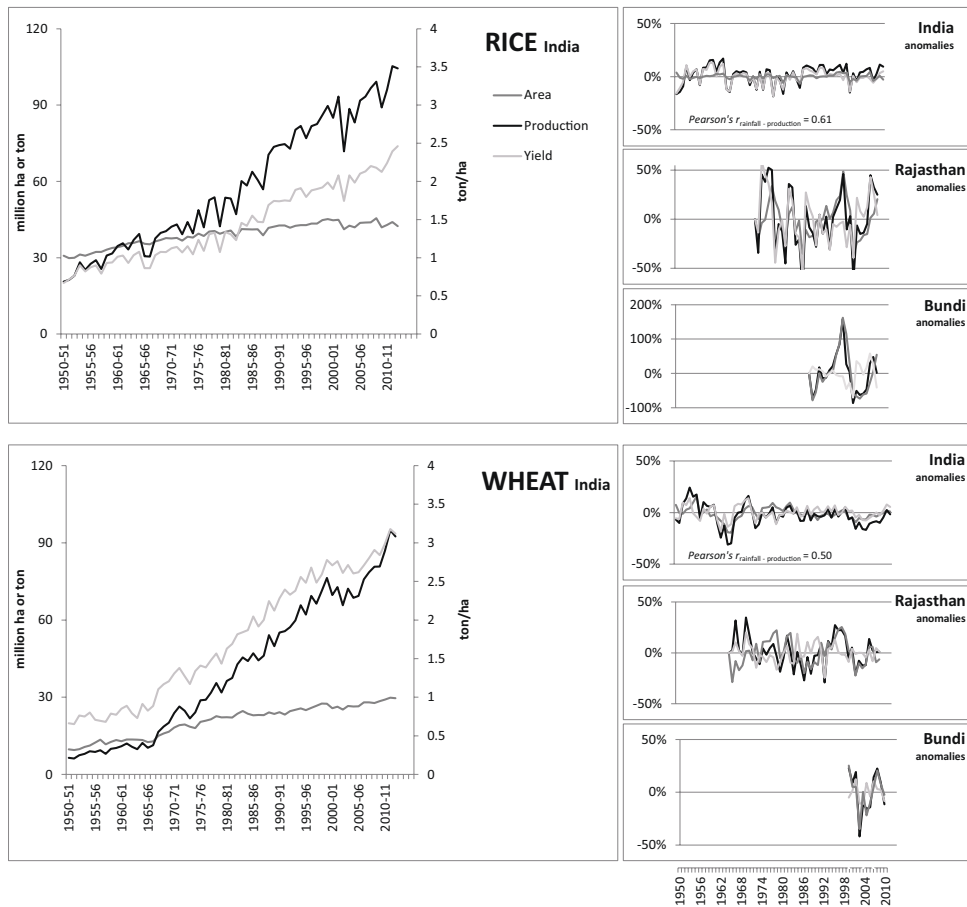


Figure 3 Crop production, yield and area for rice and wheat for India (left), and anomalies for India, state (Rajasthan) and district level (Bundi district in Rajasthan) (right) (data source: GoI, 2012).

The relative contribution of cropped area fluctuations to overall production variability, as determined by the hierarchical partitioning method, also seems to increase when moving to the more local scale (Table 3). At all-India level, production anomalies are caused mainly

by yield fluctuations and only partly by a fluctuating cropped area. Zooming in on Rajasthan and on Bundi, the influence of area fluctuations increases. The same pattern can be seen when analysing all districts in the Ganges basin over the period 1999-2009 and comparing district-level variability against basin variability. Overall, these figures show that cropped area adjustments are almost as important as fluctuations in yield in explaining production variability.

Table 3 Relative importance of cropped area and yield in explaining variability in production

	<i>rice</i> <i>Area</i>	<i>Yield</i>	<i>time period</i>	<i>wheat</i> <i>Area</i>	<i>Yield</i>	<i>time period</i>
India	31%	69%	1950 -2012	44%	56%	1950 - 2012
Rajasthan	39%	61%	1974 - 2009	69%	31%	1966 - 2009
Bundi district	92%	8%	1990 - 2009	74%	26%	1999 - 2009
Ganges basin total	39%	61%	1999 - 2009	34%	66%	1999 - 2009
Ganges district average *	51%	49%	1999 - 2009	43%	57%	1999 - 2009

* for all districts in the Indian part of the Ganges basin

5.3.2 MODELLING VARIABILITY

5.3.2.1 A MATTER OF COSTS AND BENEFITS

Variability in crop production simulated by a hydro-meteorology-driven model should fall within the bandwidth of observed variability caused by rainfall (see ANNEX V for how this bandwidth was determined). With WW in simulation mode, using the exogenous land use from the LPJmL model and no costs attached to land or water use (the “WW baseline” variant), variability in production is clearly underestimated (Figure 4). As water resources are unlimited in this variant, production is optimal for all irrigated crops, resulting in a stable and overall very uniform production from year to year. The %RSD mainly reflects variability in rainfed yields or minor fluctuations in yield from irrigated areas due to fluctuations in agro-climatic parameters other than rainfall. The decreasing trend in variability in observations from district to basin level is hardly resembled.

Making seasonal land and water use an economic decision based on costs and benefits in WW, and allowing the model to choose the amount of land under cultivation in the *Rabi* season (“WW flexible” variant, Figure 4), improves simulated inter-annual variability in production considerably for rice, but hardly for wheat. A stronger increase in variability for rice is to be expected; yields per ha are on average lower than for wheat, especially in poorer states like Bihar, while costs of cultivation are in the same order and the amount of irrigation water required is often higher. Adding costs to land and water use and giving

(the model) the opportunity to restrain from irrigation or planting a second crop when rainfall is scarce, thus, mainly affects rice production in states with low productivity. For wheat, which is more than 90% irrigated, the benefit of irrigation far exceeds the costs of irrigation. With sufficient irrigation water available, either from surface water or groundwater, the value of water will not be a limiting factor for wheat production under current price conditions.

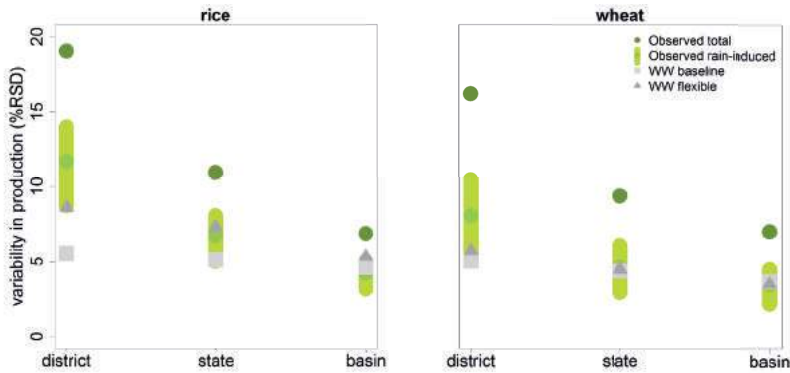


Figure 4 Variability in production (%RSD), averaged for district and states in the Ganges basin and the total basin, with observed total variability ('Observed total,' source MOA, 2012), variability correlated to rainfall ('Observed rain-induced', expressed as a range) and variability as simulated by WW without costs ("WW baseline" variant) and with costs and flexible land and water use ("WW flexible" variant).

5.3.2.2 A MATTER OF GROUNDWATER ACCESS

In order to increase simulated variability in wheat production, limiting access to water, rather than introducing a price to water use seems a necessary option to explore. Figure 5 shows variability in wheat production as a function of the volumetric capacity of local storage reservoirs (VLSR) and the dependency of wheat production on this local storage (rather than on unlimited ground water). At district level, variability increases to up to 30% (%RSD), when the volumetric local storage capacity approaches zero and deep groundwater irrigation absent. In this extreme case, only surface water irrigation on the remaining 34% of irrigated area is available. District level results also show that even when there is a large VLSR capacity, deep groundwater is indispensable for buffering rainfall variability, as without it variability will not get below 10%. In regions with high cropping intensity and/or low rainfall, additional runoff to be stored in the local storage reservoirs is simply insufficient for providing enough water for all crops. With maximum access to groundwater, a constant production can be maintained and any remaining variability is caused mainly by variability of the small area under rainfed production and from climatic param-

eters other than irrigation water supply, like temperature. Variability at state and basin level show similar patterns of variability in production, but at a lower level.

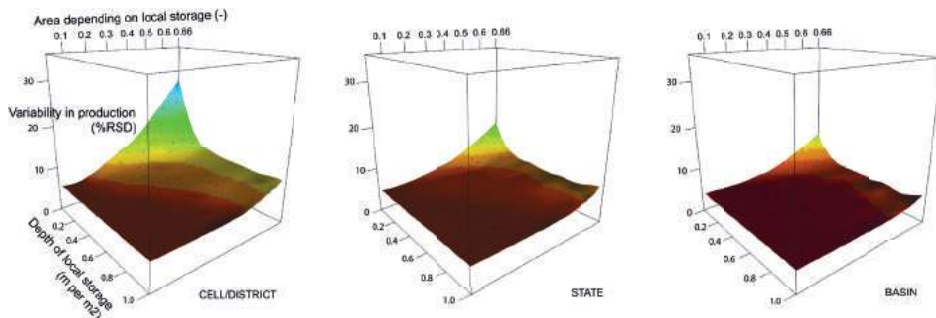


Figure 5 Variability in wheat production (%RSD) as function of size of virtual local storage reservoirs (expressed in m per m² of area irrigated from the reservoirs) and area depending on them (as a fraction of total irrigated area, with the area with access to deep groundwater lowered accordingly to maintain a constant area irrigated from deep groundwater and virtual local storage reservoirs), at district/cell, state and basin level. Labels of axis at state and basin level are identical to those of cell/district level.

To improve our model, parameter values for VLSR depth and area irrigated by them should be chosen such that district variability for wheat approaches the expected %RSD of ~9%. With two parameters there is, however, a whole range of combinations possible that approach this variability in production (the yellow gradient in Figure 5a). As a best guess estimate, we simply assumed that the area having continuous access to VLSR will be half the stated area from statistics (so 33% of the total irrigated area, with deep groundwater serving the other 33%). Local storage on this area should then be 150 mm per m² to match observed variability in wheat at the district level. Simulated %RSD approaches, as Figure 6 shows, the mid of the range of expected variability in wheat production as caused by rainfall for all levels in this “WW flexible-limited” model variant. Rice production is hardly affected by any combination of these parameters and simulated variability remains, at district level, at the lower end of the expected observed variability (Figure 6).

In Figure 6B variability for all individual cells, clustered per state, is shown. For rice, the average variability is rather constant over all states except for Bihar, a downstream state with a relatively low productivity. For wheat, the most extreme variability is found in the two more drought-prone states Rajasthan and Madhya Pradesh in the south-western part of the Ganges basin. Variability in wheat production in Uttarakhand is high as well, mainly because of a high percentage of rained wheat production in this mountainous state.

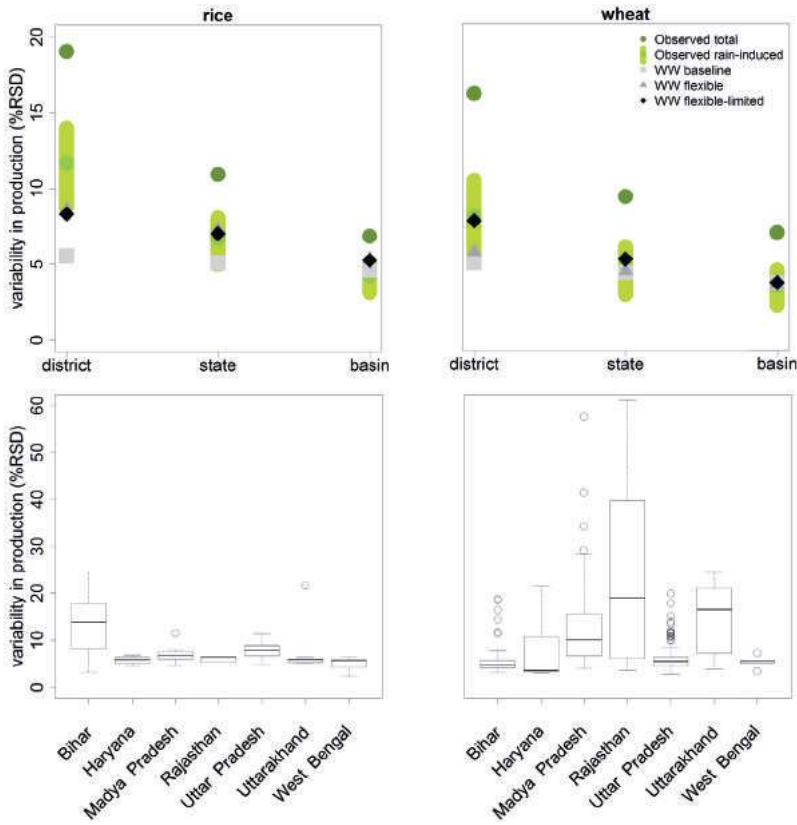


Figure 6 (A) Variability in production with limited deep groundwater (top) and (B) box-whisker plots of simulated variability in production (%RSD for the “WW flexible-limited” model variant) for the various cells within each state within the Ganges basin (bottom).

While simulated variability improved by introducing flexibility in cropped area, average production of rice and wheat was hardly affected (Table 4). Total rice yields in the Indian Ganges basin were reduced by less than 4%, while wheat production was reduced by just over 6%, despite introducing constraints on deep groundwater availability during the wheat producing season. While introducing more inter-annual variability, average simulated production, thus, remains close to official estimates with ~60% of Indian wheat and ~26% of rice produced in the Ganges basin. Overall, results in Table 4 show that variability in rice production can largely be explained by yield fluctuations, while variability in wheat production is a result of both area and yield fluctuations, which depends on the location in the basin. In upstream rainy Uttarakhand, variability in production is mainly due to fluctuations in yield, while in dry Rajasthan, with its high reliance on irrigation, fluctuations in area start to dominate once the model is given the freedom to vary it.

Variability in yield decreases between the scenarios when area is allowed to vary; the model prefers to maintain high production per ha and to reduce costs by decreasing the amount of hectares during periods of shortage. This behaviour appears to match reported coping strategies of farmers (Kelkar et al., 2008; Siderius et al., 2015; Venot et al., 2010b).

Table 4 Impact of model improvements ("WW baseline", "WW flexible", "WW flexible-limited") on average rice and wheat production, cropped area, yield and gross margin per hectare, and their variability (%RSD), at state level and basin totals – Ganges basin domain only.

rice												
	production (million tons)			area (million ha)			yield (tons/ha)			gross margin (Rp/ha)		
	baseline	flexible	flex limited	baseline	flexible	flex limited	baseline	flexible	flex limited	baseline	flexible	flex limited
AVERAGE												
Bihar	6.4	5.9	5.7	4.7	4.3	4.2	1.4	1.4	1.3	-	32	30
Haryana	2.0	2.0	2.0	0.7	0.7	0.7	3.0	3.0	3.0	-	362	362
Madhya Pradesh	1.1	1.1	1.1	1.2	1.2	1.2	1.0	1.0	1.0	-	-49	-49
Rajasthan	0.0	0.0	0.0	0.0	0.0	0.0	1.3	1.3	1.3	-	29	28
Uttar Pradesh	12.0	11.9	11.9	6.2	6.2	6.2	1.9	1.9	1.9	-	146	146
Uttarakhand	0.5	0.5	0.5	0.2	0.2	0.2	2.9	2.9	2.9	-	343	343
West Bengal	2.7	2.7	2.7	1.0	1.0	1.0	2.7	2.7	2.7	-	303	298
TOTAL	24.9	24.2	24.0	14.0	13.6	13.5						
VARIABILITY	production			area			yield			gross margin		
	baseline	flexible	flex limited	baseline	flexible	flex limited	baseline	flexible	flex limited	baseline	flexible	flex limited
Bihar	2.7	10.8	9.6	-	8.4	7.3	2.7	3.4	3.3	-	28.9	29.7
Haryana	5.3	5.3	5.3	-	0.0	0.0	5.3	5.3	5.3	-	8.9	8.9
Madhya Pradesh	5.8	5.9	5.9	-	0.0	0.0	5.8	5.9	5.9	-	23.8	23.8
Rajasthan	5.3	5.1	4.8	-	0.0	0.0	5.3	5.1	4.8	-	49.6	47.4
Uttar Pradesh	6.8	7.1	7.1	-	0.2	0.2	6.8	7.1	7.1	-	19.0	19.1
Uttarakhand	4.2	4.2	4.2	-	0.0	0.0	4.2	4.2	4.2	-	7.3	7.3
West Bengal	3.2	3.2	3.4	-	0.0	2.8	3.2	3.2	3.1	-	5.7	5.6
TOTAL	47.1	46.4	44.2	18.3	18.0	17.3						
wheat												
	production			area			yield			gross margin		
	baseline	flexible	flex limited	baseline	flexible	flex limited	baseline	flexible	flex limited	baseline	flexible	flex limited
AVERAGE												
Bihar	6.1	6.1	5.9	2.7	2.7	2.7	2.3	2.3	2.2	-	223	208
Haryana	5.2	5.1	5.1	1.2	1.2	1.2	4.3	4.3	4.3	-	627	627
Himachal Pradesh	0.0	0.0	0.0	0.0	0.0	0.0	1.7	1.7	1.7	-	99	99
Madhya Pradesh	5.3	5.1	4.6	2.4	2.3	2.1	2.2	2.2	2.2	-	208	195
Rajasthan	4.1	3.8	2.8	1.6	1.5	1.1	2.6	2.6	2.5	-	284	273
Uttar Pradesh	24.9	24.8	24.3	10.0	10.0	9.8	2.5	2.5	2.5	-	264	261
Uttarakhand	1.2	1.2	1.2	0.3	0.3	0.3	4.4	4.4	4.4	-	661	661
West Bengal	0.3	0.3	0.2	0.1	0.1	0.1	2.1	2.0	1.9	-	173	138
TOTAL	47.1	46.4	44.2	18.3	18.0	17.3						
VARIABILITY	production			area			yield			gross margin		
	baseline	flexible	flex limited	baseline	flexible	flex limited	baseline	flexible	flex limited	baseline	flexible	flex limited
Bihar	4.1	4.1	3.8	-	0.1	1.4	4.1	4.1	4.4	-	8.7	9.5
Haryana	3.2	3.3	3.6	-	0.4	1.4	3.2	3.2	3.2	-	4.4	4.4
Himachal Pradesh	3.7	3.7	3.7	-	0.0	0.0	3.7	3.7	3.7	-	13.0	13.0
Madhya Pradesh	4.1	4.5	7.3	-	2.9	5.9	4.1	4.1	3.7	-	9.0	8.4
Rajasthan	4.7	5.8	15.7	-	3.1	14.9	4.7	4.6	4.3	-	8.6	8.1
Uttar Pradesh	4.3	4.3	4.1	-	0.1	1.1	4.3	4.3	4.2	-	8.3	8.1
Uttarakhand	11.7	11.7	11.7	-	0.0	0.0	11.7	11.7	11.7	-	16.0	16.0
West Bengal	4.9	4.8	3.8	-	0.0	4.7	4.9	4.8	5.1	-	11.6	14.3

5.3.3 VALUE OF FLEXIBILITY

The importance of being flexible in land use, i.e. being able to leave land fallow and reduce cropped area, differs for both rice and wheat and for the different states as Table 4 and Figure 7 show. Leaving land fallow is a strategy most relevant for wheat production, where especially in the state of Rajasthan the area left fallow is simulated to be high. In our model we find that in the drought year of 2002 the area cropped in Rajasthan was reduced by 34% compared to the maximum over the modelled period (2000-2009) – a percentage very similar to the reduction found in the statistics for the whole state of Rajasthan (minus 33%). For rice, only downstream Bihar and to a lesser extent West Bengal show comparatively small fluctuations in fallow area. In both states, rice is planted in a double crop rotation, so also during the *Rabi* cropping season in which we allowed the model to vary cropped area.

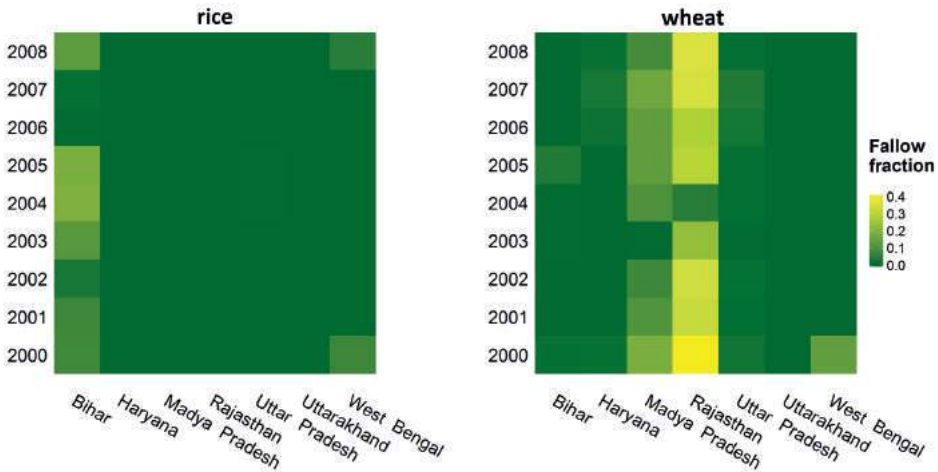


Figure 7 Annual fallow land fraction per state for rice (left) and wheat (right) in the "WW flexible-limited" variant.

The 'value of flexibility' (VoF) becomes clear if we zoom in on wheat production in Rajasthan and we compare our final, WW flexible-limited variant to an alternative run with identical parameters settings, but without allowing the model to leave land fallow. Without this strategy of leaving land fallow during dry years, average crop productivity would go down by 20% to less than 2 ton/ha and economic yield per ha would be reduced by almost 40% to 168 USD/ha. Total gross margin from wheat production would be reduced by 12%.

This 12% can be considered the lower estimate of the VoF. In our validated model, we did not include the cost of labour as we assumed this was not a major decision factor in Indian agriculture over the past decades. However, with increased mobility and ongoing

demand for labour in urban areas providing alternatives for on-farm family labour, and with rural employment and minimum wage schemes by the Indian government limiting the availability of hired labour in rural areas, costs of labour is rising (GoI, 2013) and likely to become a more prominent factor in farm-level decision making. If we would include the cost of labour, our expectation is that VoF will increase. To quantify this effect we increased cultivation costs by a third, the increase resembling the median costs of labour in major rice and wheat producing states, as calculated by the Indian Ministry of Agriculture for the year 2011/12 (<http://eands.dacnet.nic.in>, last visited 31-10-2014). In this scenario, up to two-thirds of the area is now left fallow in Rajasthan during years of water stress, while yield still remains at 2.6 ton/ha on those areas that are cropped and receive irrigation water. Compared to an alternative variant without flexibility, this leads to a difference in total gross margin from wheat in Rajasthan of 34%, a value that could be considered the VoF corrected for cost of labour. While important in drought prone states like Rajasthan, at basin level the VoF is limited, at 4% for wheat. Especially in the largest wheat producing state, Uttar Pradesh, wheat production remains fairly constant over the years in all scenarios (Figure 8).

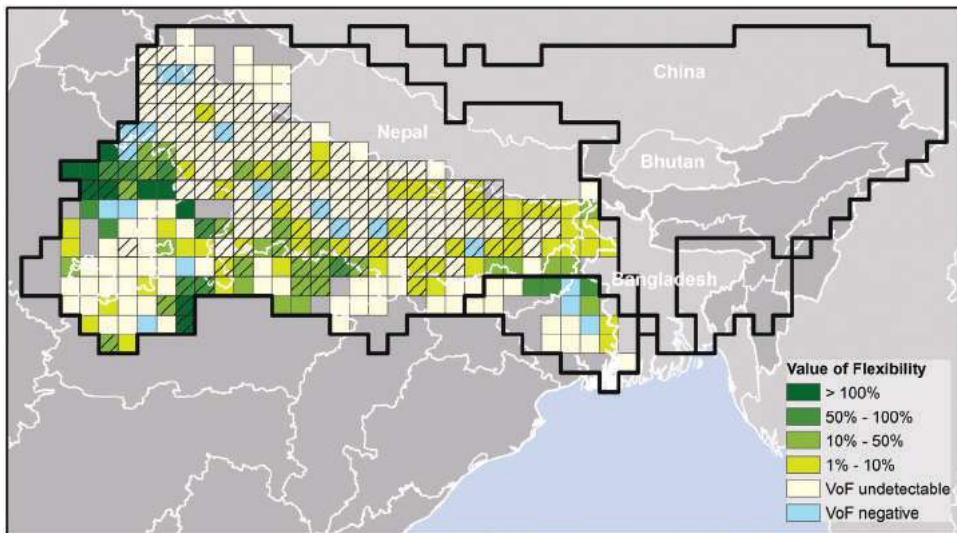


Figure 8 Value of flexibility for wheat production in the Indian part of the Ganges basin (as percentage of gross margin). Shading indicates major wheat producing area (cells in which at least 20% of the area is cropped with wheat during the Rabi season). In regions without cells, wheat is cropped on less than 2% of the area according to MIRCA2000.

Flexibility is beneficial for farmers' gross margin, but it does come at a societal cost. When farmers are able to leave land fallow in order to maximize their returns, overall production decreases, potentially increasing the costs for consumers. In Rajasthan the decrease in production was 17%. At basin scale this effect on production was limited to a decrease of 4%.

For rice, with our current model setup and labour costs included, the VoF is close to zero as the largest share of production occurs during the monsoon season, for which we assumed land use is fixed. When we exclude labour costs, the VoF for rice is even slightly negative (-1%); if the model is not allowed to vary land use per season, more crops (e.g. wheat, sugarcane) are irrigated upstream against high costs and return flows, also from groundwater, become available for rice cropping downstream. This slightly benefits rice production during the dry season especially in downstream Bihar. If farmers can choose they would, however, still largely avoid rice production during dry years; for rice production in the *Rabi* season alone the VoF is 21%, indicating that in this season it can be a relevant coping strategy.

5.4 DISCUSSION

Simulation of agricultural production was improved by including seasonal decision making on cropped area in the hydro-economic model WaterWise. With the improved model we analysed the impact of rainfall on the production of rice and wheat in the Indian part of the Ganges basin. The value of flexibility in cropped area was quantified for scenarios with and without costs of labour. While being high for wheat production in a drought prone state like Rajasthan, the value of flexibility was found to be limited for the Ganges basin as a whole, indicating that water resources are overall still largely sufficient, but unequally distributed.

We focused solely on the relationship between monsoon total rainfall and crop production variability, separating natural causes of inter-annual variability from socio-economic ones. The observed variability in production, and the fraction influenced by rainfall, can be regarded as the benchmark for the hydro-economic model. Inevitably, there are shortcomings in our approach, which make that simulated variability deviates from observed, such as:

1. We only considered decision making on cropped area for the second cropping season, *Rabi*, which starts after the monsoon. In order to better match observed variability in rice production, flexibility in planting during the *Kharif* season should be included. Climatic factors that trigger planting decisions during the *Kharif* season are, however, less straightforward. At the time of planting

it is quite uncertain how the monsoon will unfold, so monsoon rainfall totals cannot be used as a decision-determining variable in a model. A more detailed assessment of the impact of late monsoon onset on cropping decisions or the use of seasonal forecasts would be required;

2. We focused on annual anomalies in production and rainfall. A drought, however, can have a prolonged effect, as the statistics on Rajasthan suggest. The area cropped with rice is suppressed for several years after the 2002 drought. Farmers might become more risk averse, or have less room for investments after an adverse weather year. Our model does not consider such inter-annual relationships. An option would be to expand the model with a farm-level budget, dependent on each year's gross margin, from which land and water use investments in the next year have to be paid;
3. Our model inevitably oversimplifies a complex reality in which people might continue to grow crops based on cultural preferences, issues of food security or absence of alternatives (to mention a few of possible factors), rather than applying an economic logic solely based on cost and benefits and the availability of water. Farmers with less entitlement or access to water might refrain from planting a second crop when rainfall is not far from the mean, while others irrigate too much. While this would show up in the statistical data, the model does not consider this aspect.
4. In addition, we used fixed prices for agricultural output, independent of total production. In theory, prices will rise during years of shortage, favouring planting rather than leaving land fallow. Farmers with access to additional irrigation or other inputs might anticipate such higher prices and plant more, rather than less in adverse climate years. Locally, this would reduce flexibility. That said, in India prices are controlled by the government, so this incentive is expected to be less prominent in our case study area.
5. Finally, we did not allow our model to switch to other crops in this application, though this is a relevant strategy in dealing with rainfall variability. Farmers sometimes shift from food to fodder crops, for example, during drought to increase their income from dairy production. Incorporating such shifts, including their costs, would enable evaluating a combination of strategies, including both diversification and flexibility.

Despite these shortcomings, our improved model was capable of simulating existing variability at different spatial aggregation levels, especially for wheat. The model mimics the strategy of farmers to concentrate cultivation and irrigation on a smaller area in years

of shortage, especially during the second growing season. In a sense this is a second-best strategy: farmers prefer a constant maximum use of land. But when water is not sufficiently available at reasonable costs, avoiding loss of investments becomes the main strategy.

Improved understanding of seasonal variability in food production is important for policy makers and planners dealing with food security, both regionally and globally. While India is largely food self-sufficient now, a major question is to what extent variability will affect it in the future, when a growing population will put more pressure on limited land and water resources. Understanding variability is thereby not only of relevance for coping with shortages, but also for efficiently managing surpluses; both the amplitude of fluctuations in production and the frequency of extremes influence the stocks that need to be kept and the volume that can be exported.

Flexibility in land use should be seen as a vital coping strategy for dealing with water shortages due to rainfall variability. Coping with current variability is often considered as a first step towards coping with future climate change (Glantz, 1992; Kabat et al., 2002). With rainfall variability expected to increase due to climate change and costs of groundwater irrigation likely to rise due to falling groundwater levels and/or a reduction in subsidies on diesel or electricity, a higher variability in production can be expected. An analysis of how increased variability in rainfall might lead to permanent changes in cropping pattern, or a permanent reduction in cropped area, would remain a relevant next step to explore.

5.5 CONCLUSIONS

Seasonal adjustment in cropped area can explain almost 50% of variability in wheat production and 40% variability in rice production in the Indian part of the Ganges basin. This makes these adjustments almost as important as variability in yield. The distinction matters economically; while changes in cropped area represent a coping strategy for adverse conditions, a reduction in yield is merely a response of the crop. In both cases production and income are reduced. But when a farmer can decide not to crop, costs can be avoided as well.

Our improved hydro-economic model, with the capacity to seasonally adjust cropped area and irrigation application, is capable of reproducing observed rainfall-induced variability in wheat production at district, state and basin level, but is at the lower end of observed variability for rice. Wheat production is most influenced by limitations to the availability of groundwater. Rice production reacts mainly to increased costs of cultivation.

The value of flexibility, i.e. the benefit of being able to adjust cropped area, was estimated for wheat at 34% (increase in gross margin) in the drought prone state of Rajasthan and at 4% for the basin as a whole. For rice, the area cropped was largely stable in our model, and variability in rice production was at the lower end of the expected observed variability. A better understanding of the impact of seasonal forecasts, monsoon onset and break-monsoon periods during transplanting time, a critical moment in crop management, could improve our assessment of the variability and the value of flexibility in rice production and other crops grown during the monsoon.

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6

THE ROLE OF RAINFED AGRICULTURE IN SECURING FOOD PRODUCTION IN THE NILE BASIN



A better use of land and water resources will be necessary to meet the increasing demand for food in the Nile basin. Using a hydro-economic model along the storyline of three future political cooperation scenarios, we show that the future of food production in the Basin lies not in the expansion of intensively irrigated areas and the disputed reallocation of water, but in utilizing the vast forgotten potential of rainfed agriculture in the upstream interior, with supplemental irrigation where needed. Our results indicate that rainfed agriculture can cover more than 75% of the needed increase in food production by the year 2025. Many of the most suitable regions for rainfed agriculture in the Nile basin, however, have been destabilized by recent war and civil unrest. Stabilizing those regions and strengthening intra-basin cooperation via food trade seem to be better strategies than unilateral expansion of upstream irrigation, as the latter will reduce hydropower generation and relocate, rather than increase, food production.

6.1 INTRODUCTION

Major socioeconomic and geopolitical transformations are affecting the allocation of one of the world's most disputed resources: the water of the Nile River. At present, most water in the Lower Nile is being utilized, mainly for irrigation by downstream Egypt. Attempts to convert existing water allocation, primarily based on the 1959 treaty between Egypt and Sudan, to a more equitable share for all countries have not been successful (Nicol and Cascão, 2011). The regional balance of power is, however, changing: (i) the political upheaval after the Arab spring has weakened the dominance of Egypt (Nicol and Cascão, 2011); (ii) in an increasingly multi-polar world, access to infrastructure loans to build dams and irrigation infrastructure upstream has diversified (Broadman, 2008; Foster et al., 2009); and (iii) foreign investors have taken a renewed interest in the basin's agricultural resources, buying and leasing agricultural land all over the basin (Cotula et al., 2009; von Braun and Meinzen-Dick, 2009). Amid these transformations, reallocation of Nile water is a hot issue (Cascão, 2009; Waterbury, 2002; Whittington et al., 2005), with many countries seeking to utilize more water for hydropower and food production.

Increased food availability in the basin is urgent. According to the 2012 report of the United Nations, "The State of Food Insecurity in the World" (FAO et al., 2012), 100 million people in the countries of the basin are undernourished, which amounts to almost a third of the local population. Undernourishment has increased in northern and sub-Saharan Africa over the past decade, bucking the world-wide trend. Except for Egypt, none of the 11 Basin countries is self-sufficient in food (Omiti et al., 2011). Within the context of high and volatile commodity prices that favour net producers over buyers (Breisinger et al., 2010; Swinnen and Squicciarini, 2012), this reliance on global markets is a dangerous gamble: recent political instability in the Nile region has been directly linked to food price hikes (Arezki and Bruckner, 2011), and these risks will only increase. The population of the Basin countries is expected to grow by a third, from 367 million in 2012 to 488 million in 2025 (UNDP, 2011). At the same time, world-wide competition for land, water, energy, and, ultimately, food is increasing (Godfray et al., 2010). Developing countries like those in the Nile, with purchasing powers much lower than that of other major food importing countries, are most vulnerable to global shortages (Rutten et al., 2013).

We aim to support the complex policy challenge of the Nile basin by clarifying the science behind the discourse on water, energy and food security, exploring the possibility of national to regional food self-sufficiency as alternatives to an increasing reliance on global markets. We approach this from a hydro-economic perspective and argue that with the water resources of the Nile itself almost fully and productively allocated, the real solution

to future food self-sufficiency for the Basin lies outside the domain of water allocation and irrigated agriculture and in the rainfed areas of South Sudan and the Lake Victoria region. According to the United Nations Food and Agriculture Organization (FAO), the potential area suitable for cultivation in South Sudan alone is as high as 30 million hectares, which is ten times the cropped area of Egypt. Only about 10% of that potential is currently being used for agriculture. Recent world-wide assessments of food production have stressed intensification in existing areas, rather than expansion to new areas, as the best way of increasing food production (Foley et al., 2011; Godfray et al., 2010; Tilman et al., 2011). The Nile basin seems to be an important exception, with a combination of both intensification and expansion being warranted.

6.2 METHODS

6.2.1 APPROACH

For our research, we derived a baseline of water use (Figure 1), agricultural crop production and gross margin (GM) in the Nile basin around the year 2005, using an area-based hydro-economic model in simulation mode (WaterWise; ANNEX II). For this, a present-day spatial distribution of land use systems (FAO, 2009b) was made consistent with country-specific FAO crop statistics (FAO, 2004) on actual cropped area. Crop production and GM of the water-limited production was then calculated for both rainfed and irrigated crops.

Next, we estimated food requirements in the basin for the year 2025. Future food self-sufficiency correction factors per country were based on the projected population increase up to 2025 (UNDP, 2011) and a population-average calorie requirement of 2300 kcal/person per day (Tontisirin and de Haen, 2001). As such, a minimum intake was imposed, without regard for household access, dietary preferences, or nutritional value. We assumed that agricultural production in the Nile catchment part of each country will grow at the same pace as each country's average. Future food self-sufficiency targets for the Nile basin could then be derived by multiplying baseline agricultural production with these correction factors (table 2).

Finally, we applied the hydro-economic model in optimization mode, to select those investments in agriculture (area-wise expansion or intensification of rainfed agriculture and new irrigation schemes) and hydropower (new reservoirs) that generate the highest GM using the available land and water resources. We explored where and how food production can best be increased and whether food self-sufficiency for the basin and its individual countries can be achieved by the year 2025.

6.2.2 WATERWISE MODEL

Our model resembles existing hydro-economic models developed for the Nile (Block and Strzepek, 2010; Block et al., 2007; Jeuland, 2010; Whittington et al., 2005; Wu and Whittington, 2006). Similarly to the model of Whittington et al. (2005) it describes the whole Nile basin, including all existing irrigation schemes and hydropower reservoirs, and most of the proposed hydropower plans. Water gets transmitted through the river network using a routing scheme in combination with the variable storage method for the dynamics of large water bodies (swamps, reservoirs), with use in one location limiting options elsewhere. Economic parameters, like the pricing of hydropower, are like those in earlier optimization studies. However, in contrast to the latter we did not limit our analysis to the river system alone, i.e. optimizing hydropower and irrigation yields, but included yield from rainfed land use. Land use is an endogenous variable in our model and land-use changes and the impact on downstream flows are thereby integrated into the optimization; the model optimizes GM by choosing the optimal combination of land and water use options for each of 1371 so-called hydrotopes, units of similar soil and meteorological characteristics (ANNEX II), given available water resources:

$$Y_{TOT} = Y_{LU} + Y_{HP} - C_{LWM}$$

with

$$Y_{LU} = \sum_{z,u,y} (Prod_{z,u,y} * P_{y,u} - C_{LU,u} * Ac_{z,u,y})$$

$$C_{LWM} = \sum_{z,u,y} (C_{IRRIz,u} * Ac_{z,u,y})$$

where Y_{TOT} represents total gross margin (in USD /yr), Y_{LU} the profit from land use (USD/yr) based on production ($Prod$, in ton) times price of product (P , USD/ton) minus non-water costs (CLU , USD/ha) times the cropped area (Ac , in ha), in year y per land use u in hydrotope z . Y_{HP} is the GM of hydropower (USD/yr). C_{LWM} are the costs of local water-management measures for supporting land use, i.e., the variable costs of local irrigation measures (in USD/ha), depending on the amount of water used. These variable costs relate to pumping costs, which is a combination of labor, capital and energy costs. For the variable costs of water we used a regional estimate of 0.01 USD/m³ (Hellegers and Perry, 2006) .

Crop production and related water fluxes for all land and water use options in each hydrotope are pre-processed by water-crop modules run in an offline mode (ANNEX II). In the Nile application a soil moisture accounting model of the bucket type is used, very similar to the AQUACROP model of the FAO (Raes et al., 2011), but more advanced in simulating soil storage and drainage, while simplifying the dynamic crop growth. Rainfall can contribute to runoff,

drainage, or groundwater storage, after correcting for evapotranspiration. The calculation scheme for the evapotranspiration follows the FAO single crop coefficient method (Allen et al., 1998), applied separately to the vegetated and non-vegetated part. Crop production is simulated with a slightly modified form of the Ky approach of FAO (Doorenbos and Kassam, 1979), where the ratio between actual and potential evapotranspiration is translated into a mean yield ratio. Actual yield in each hydrotope is then calculated by multiplying this mean yield ratio with a predefined potential yield. This relatively simple method has the advantage of being robust and requiring a minimum of data.

WaterWise optimizes GM of food production by i. converting non-arable land into arable land, by ii. converting existing arable land into high-intensive variants and/or iii. by increasing the area under irrigation in predefined existing and new large-scale irrigation areas, depending on irrigation water availability and availability of investments. GM from hydropower can be increased by routing more water through existing hydropower schemes, if turbine capacity allows, or by investing in new ones.

Investment costs for the conversion to irrigated area were based on a comprehensive study on the cost of irrigation by IFPRI (Inocencio et al., 2007). We took the value for ‘success’ projects, under the optimistic assumption that new irrigation systems will be designed, constructed and maintained according to the latest knowledge and standards. There is a clear difference between north Africa and sub-Saharan Africa: the latter having, at 3552 USD/ha, only about half the conversion costs as North Africa. Conversion to arable land was made possible at an investment of 2174 USD/ha, assuming that conversion to rainfed arable land is similar to land preparation for irrigation, but without the additional hardware costs. Investments costs in new hydropower were mainly based on grey literature (see ANNEX II). All major planned hydropower plants, including Ethiopia’s highly controversial Grand Renaissance Dam, were offered as options.

The optimization was performed on the basis of two representative climate years—a relatively wet year (1999) followed by a dry year (2000). We did not explicitly include water demand from other sectors like household and industry, being relatively small compared to agricultural demand, nor the economic benefits of flood or sediment control, or environmental flows. Climate change was left out from the analysis. Within the time-frame considered, we expect that any climate change trend will be overshadowed by existing natural variability. However, rainfall projections for East Africa do show a large spread between climate models for the periods beyond 2025, adding considerable uncertainty to any long-term investment decision.

6.2.3 DATA AND SCHEMATIZATION

Rainfall from the tropical rainfall measurement mission (TRMM) (Kummerow et al., 1998) and daily reference evapotranspiration from ECMWF (Uppala et al., 2005) were used as meteorological inputs, with soil properties coming from FAO-UNESCO's 1974 Soil Map of the World(1:5,000,000). Soil classes were aggregated based on maximum soil moisture storage and surface slope. A present-day spatial distribution of land use systems (FAO, 2009b) at 5 arc minutes spatial resolution was made consistent with country-specific Food and Agriculture Organization crop statistics (FAOSTAT)(FAO, 2004) on actual cropped area by correcting for fallow area. Estimations of arable land were only available at national level. Simply correcting based on land area would lead to an underestimation of arable land within the Nile basin, the Basin part being wetter, in general. A Nile basin estimate was derived by multiplying the national average with the relative proportion of humid zone within the Basin area, as proposed by the FAO (Appelgren et al., 2000). A more detailed mapping of the irrigated areas was achieved by a supervised classification of Landsat images in combination with a FAO map indicating regions with a certain percentage of irrigation (Occurrence of irrigated areas (FGGD); (FAO, 2007; Siebert et al., 2005)).

For arable land in each country we defined one unique country-specific cropping system CCSs, representing a range of crops. Only crops that occupy each at least 10% of the arable area in at least five countries according to FAOSTAT (FAO, 2004) were included. This resulted in seven main crops: bananas, beans, maize, sorghum, sweet potatoes, vegetables and wheat. Because of the importance of groundnuts for Sudanese agriculture and rice for Egyptian agriculture these two crops were added. For each country, five dominant crops were selected from this subset and based on these five crops an average price per ton produced and cost per ha were derived for each country-specific cropping system. This resulted in a total of seven rainfed and two irrigated CCSs for the basin as a whole (Table 1). Crop growth periods and monthly crop factors, to multiply the daily reference evaporation with, were derived from Allen et al. (1998).

Table 1 Cropping system characteristics for the dominant crops as derived from FAOSTAT (current) and estimates for future

	<i>Current Yield</i> ton/ha	<i>Potential yield</i> ton/ha	<i>Price</i> US\$/ton	<i>Cost</i> US\$/ha	<i>Potential GM</i> US\$/ton	<i>Dominant crops in the</i> <i>cropping system</i>
Current						
Burundi	3.6	4.0	216	122	736	Beans - Bananas
Egypt (irrigated)	19.5	19.5	122	183	2197	Wheat - maize
Ethiopia	1.5	4.0	149	92	499	Sorghum - wheat
Kenya	2.4	4.0	125	106	390	Beans - maize
Rwanda	3.9	4.0	218	136	730	Beans - Bananas
Sudan	0.6	4.0	152	92	510	Sorghum
Sudan (irrigated)	9.7	9.7	122	183	1007	Sorghum - wheat
Tanzania	1.7	4.0	147	96	486	Maize - s. potatoes
Uganda	2.9	4.0	218	123	743	Beans - Bananas
Future						
Future intensive		4.0	218	123	743	Not specified
Ethiopia (newly irrigated)		19.5	122	123	2256	"
Sudan (newly irrigated)		19.5	122	183	2196	"

A uniform region-specific potential yield of 4 ton/ha was derived by correlating country-specific crop yields on rainfed arable land (in ton/ha, from FAOSTAT, 2004) with the ETa/ETp ratio of each country (AQUASTAT) ($R^2 = 0.7$). While this is a gross simplification of the diversity in crop production, a potential yield of 4 ton/ha does corresponds well with earlier estimates (e.g. Penning de Vries et al., 1997). By using a region-specific potential yield, limiting factors other than water, for example, phosphate shortages, pests, or Nile region-specific restrictions in the agro-food chain infrastructure, are implicitly taken into account. Economic parameters in terms of crop prices and costs per hectare do differ per country. Average costs and prices for each CCS were calculated using area averaging of the FAOSTAT data.

Large scale irrigation was separately schematized and parameterized. This type of irrigation in the Nile Basin is currently concentrated in Egypt and Sudan. Especially in Sudan and Ethiopia there is the land potential to increase the area irrigated (Block and Strzepek, 2010; Block et al., 2007). Irrigation from the main water courses was only allowed in pre-defined large-scale irrigation schemes, currently located in Egypt and Sudan. Yield, price and cost data per hectare for Egypt could be derived directly from FAOSTAT data (FAO, 2004), but for Sudan these were available only as an average of irrigated and rainfed areas combined. Sudan's irrigated agriculture is known to underperform because of the siltation of irrigation canals, waterlogging, and general deterioration of operation and maintenance (Plusquellec, 1990). Sudan's yield per hectare was assumed to be half that of Egypt, but with the same costs, and cropping intensity at only half of its potential. With regard to new irrigation schemes in Sudan and Ethiopia, we assume that investors, water managers and irrigation engineers have learned from past mistakes and that productivity will match that of irrigated agriculture in Egypt.

6.2.4 SCENARIOS

We evaluated the target of food self-sufficiency under three transformative scenarios with varying degrees of cooperation, which are currently under debate. A hydro-economic model like WaterWise searches, if unrestricted, for a basin-wide optimum, thus reflecting complete cooperation and sharing of GM. This cooperation can then be restricted by specific boundary conditions or objective targets. With the model we focus on the allocation of land and water resources. The third production factor, labour, is assumed to be available and was not taken into account.

The background of the “National Food Self-Sufficiency” scenario is a future where cooperation and trade of agricultural produce is limited and food self-sufficiency is a target of each country individually; GM will drop once supply exceeds demand since transaction costs will increase once products have to be transported to other markets. To mimic this behaviour to the extreme in the model, the weight of land use revenues above a country’s target is reduced to nil in the objective function. In the “Upstream Hegemony” scenario, Ethiopia and Sudan maximize their agricultural GM for international export, irrespective of any downstream demands. All new irrigation schemes and the rehabilitation of existing irrigation schemes in Ethiopia and Sudan are forcefully implemented in the model at the investment cost required. In addition, the model maximizes agricultural GM of the major irrigation schemes in these two countries via the objective function. The “Basin Cooperation” scenario represents a future of enhanced trade in agricultural commodities within the basin, underpinned by infrastructural developments and political, economic, and financial cooperation. In the model this is implemented by solving the objective function for the basin as a whole, giving total freedom to maximize land use throughout the basin to reach the food self-sufficiency target for the basin as a whole. One country can offset shortages in another.

Our model includes both expansion of agricultural area and intensification with higher profits and costs per hectare, with investments in agriculture competing with investments in hydropower. The difference between expansion and intensification in the model needs to be interpreted with care. Especially small-scale agriculture is likely to be clustered with non-agricultural land uses in the present day land use classification. In addition, in war-torn regions, many fields have been temporarily abandoned or left fallow. In these areas, ‘expansion’ will refer more to a leap in production from low-yield agriculture to a form of commercial agriculture connected to regional markets, rather than an agricultural development from scratch.

We focused on the near future, in which we assume gradual autonomous technological progress in rainfed farming practices in those countries currently producing at a GM level below the regional maximum (Uganda, according to FAO). Such productivity-based growth, currently estimated at 1.3% for Sub-Saharan Africa (Fuglie and Rada, 2013), was represented by an optional ‘future intensive’ cropping system, activated under conditions of sufficient water availability (ANNEX II). No investments were required for conversions to more intense cropping systems, as they are assumed to be an autonomous development within the boundaries of current agronomic practices in the Basin.

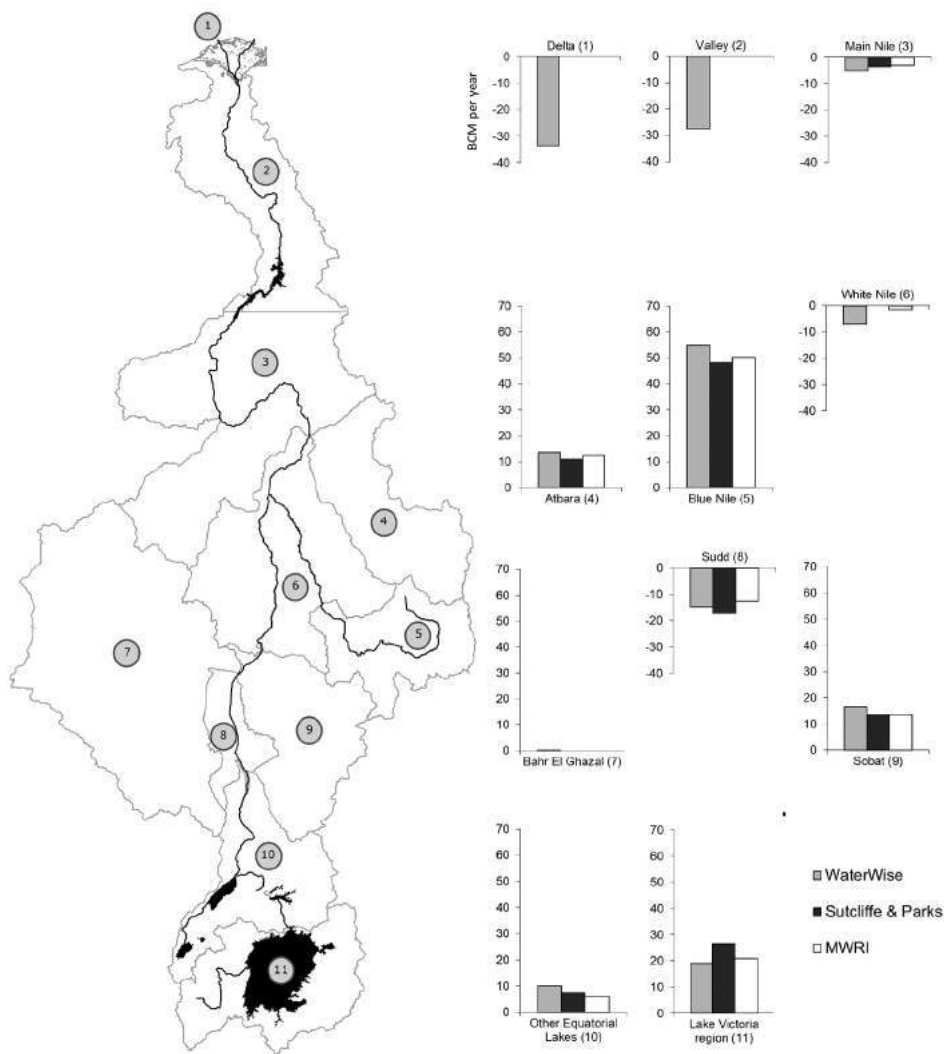


Figure 1 Comparison of WaterWise-Nile runoff contribution and abstraction with modelled runoff (MWRI, 2005) and runoff derived from water balance estimates (Sutcliffe and Parks, 1999) for the main water balance areas of the Nile (in billion m³/yr). The water demand of the Delta and Valley was not available for the latter two studies and therefore omitted. No figures for the White Nile are available from Sutcliffe & Parks because of the different catchment schematization. WaterWise-Nile was validated on the wet, average, and dry years of 1999-2001; Sutcliffe and Parks have determined the runoff based on measurement data of the period 1905-1995. The period of the MWRI study represents 1991-2001. Water abstractions of 70 billion m³ to Egypt support unofficial estimates, suggesting that actual releases at Aswan are higher for the period evaluated than the, often reported, officially allocated 55.5 billion m³ (Nicol and Cascão, 2011) even after correction for return flows.

6.3 RESULTS

Our baseline value of annual agricultural GM of 15.4 billion USD per year is about 35% lower than the single available FAO estimate for the basin (Appelgren et al., 2000). The inclusion of livestock in the latter figure, estimated at 18-35% of African agricultural GDP (Ehui et al., 2002; Sansoucy, 1995), can explain a large part of the difference. To accommodate the growth of the population, total food requirements are expected to rise by 75% over the 2005-2025 period, according to our calculations. A major shift occurs in Egypt, which goes from food surplus to shortage.

Our results show that under the “National Food Self-Sufficiency” scenario, when none of the countries is stimulated to have surpluses due to lack of trade, investments shift towards generating higher hydropower revenues and the basin as a whole will fail to become food self-sufficient (Table 2). Egypt, Rwanda, and Eritrea are unable to produce enough food for their growing populations because of the restricted availability of water or agricultural lands. Under the “Upstream Hegemony” scenario, when there is no restriction on trade within the basin, food self-sufficiency can be realized in 2025 in the Nile basin at a total investment cost of 100 billion USD. As imposed in the scenario, Ethiopia and Sudan expand their irrigated agriculture. However, this is achieved at the expense of increasing the vulnerability of Egypt, with the flow of water downstream being reduced by almost 40%, as Sudan and Ethiopia fully develop their irrigation potential. Egypt will be able to produce only half its needed food requirements, increasing inequality in food self-sufficiency among countries.

Under the “Basin Cooperation” scenario, the basin attains self-sufficiency in a manner that is profoundly different from that of “Upstream Hegemony.” Here, the Lake Victoria region and South Sudan are responsible for the bulk of the increase in food production through intensification and expansion of the areas of rainfed agriculture (Figure 2), while allowing

Egypt's highly productive irrigation schemes still to receive a large amount of water. Interestingly, Ethiopia can be food self-sufficient, but does not need to be so under the "Basin Cooperation" scenario, where climatic circumstances for rainfed agriculture are more favourable in South Sudan and investments there are prioritized. A limited reallocation of irrigation water toward Ethiopia is warranted though, as the country has the comparative advantage of more favourable rainfall and temperature conditions than Egypt or Sudan. Rehabilitating the currently underperforming schemes of Sudan is also prioritized, but additional expansion further north near the Merowe Dam is not, as irrigation there has no advantage over the existing schemes in Egypt. Water allocations of 59 billion m³ to Egypt remain above its share of 55.5 billion m³ of the 1959 treaty, a number often quoted. The construction of large hydropower reservoirs, like the Grand Renaissance Dam, does not affect Egypt's share, neither does conversion of land to rainfed agriculture.

Table 2 Food self-sufficiency and the contribution of irrigated agriculture to food self-sufficiency targets for the main food-producing countries in the Nile basin (Nile basin area); baseline (2005) and three future scenarios. (Sudan includes both Sudan and South Sudan, but changes in the contribution of rainfed production to GM refer mainly to South Sudan, while changes in irrigation are restricted to Sudan, which contains all the large-scale irrigated areas)

Country	Baseline		Future Target 2025 Needed increase in agriculture CM	National Food Self-Sufficiency		Upstream Hegemony		Basin Cooperation	
	Contribution of irrigation to food self- sufficiency	Overall food self- sufficiency		Contribution of irrigation to food self- sufficiency	Overall food self- sufficiency	Contribution of irrigation to food self- sufficiency	Overall food self- sufficiency	Contribution of irrigation to food self-sufficiency	Overall food self- sufficiency
Egypt	100%	135%	17%	85%	85%	57%	57%	78%	78%
Ethiopia	0%	78%	117%	16%	100%	16%	80%	16%	80%
Sudan*	28%	92%	83%	~0%	100%	122%	237%	93%	223%
Uganda	0%	102%	91%	0%	100%	0%	111%	0%	111%
Other	0%	75%	165%	0%	66%	0%	96%	0%	98%
Basin	48%	111%	74%	27%	92%	36%	103%	38%	107%

*Sudan includes both Sudan and South Sudan, but changes in the contribution of rainfed production to GM refer mainly to South Sudan, while changes in irrigation are restricted to Sudan, which contains all the large-scale irrigated areas

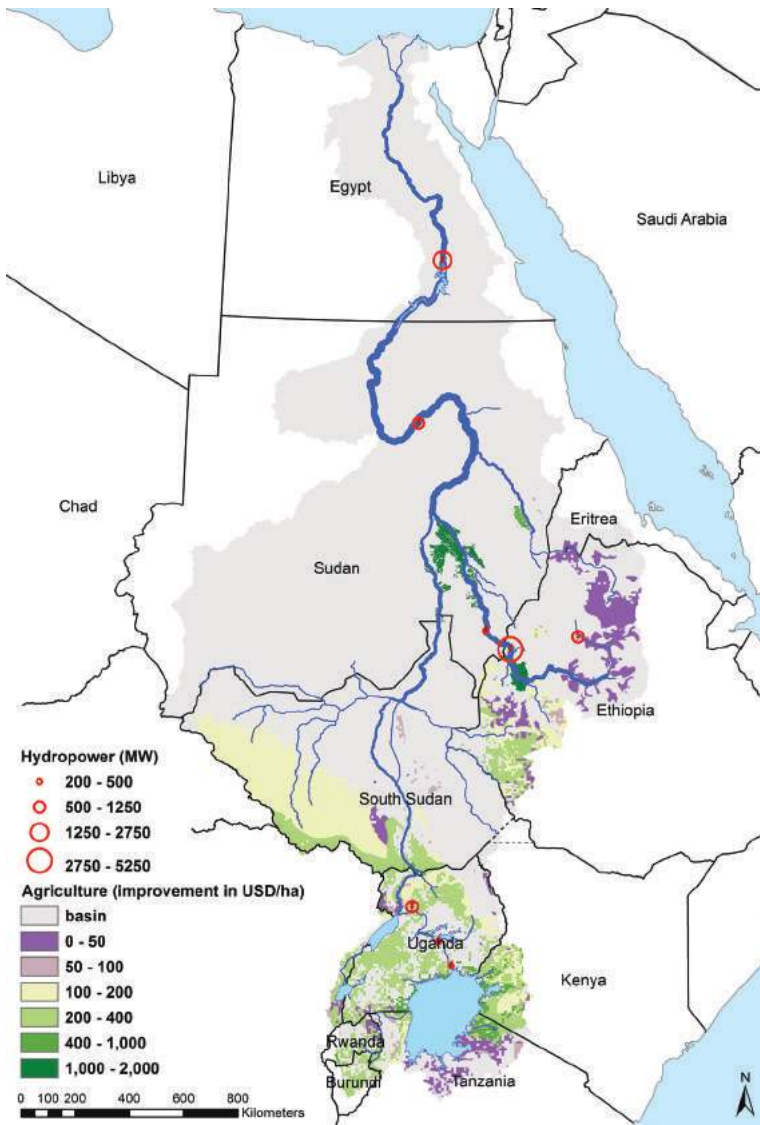


Figure 2 Increase in annual agricultural gross margin (in USD/ha) between baseline (2005) and 2025 (in a scenario of full "Basin Cooperation" on investments in land use change and water resource allocation for agriculture and hydropower). The regions in dark green represent increase in gross margin in the rehabilitated irrigated areas of Sudan and the new irrigated areas in Ethiopia, under the assumption that they reach the same productivity as Egypt's irrigated areas. The drawn river width is proportional to annual mean discharge in this scenario, with a maximum of 2622 m³/s after confluence of the main Nile with the Atbara in Sudan.

Rainfed agriculture contributes over 75% of the additional food requirements in all scenarios. Expansion of rainfed agriculture is suggested primarily in unstable regions of South Sudan and northern Uganda, where the causes of underdevelopment are largely socio-political as opposed to biophysical. Many parts of Africa are characterized by high inter-annual and intra-annual variability in rainfall (Cooper et al., 2008). A reliable rainfed agriculture will require investments in local water harvesting and site-specific supplemental irrigation (Rockström and Falkenmark, 2015), in the long run supported by more accurate regional weather forecasting and smart forms of crop, water and soil monitoring and management. However, the pessimistic view of the whole of East African agriculture being drought-stricken needs refinement as well. Figure 3, which compares seasonal rainfall totals with crop water demand, indicates suitability for rain-fed agriculture, with country regions lying within the Nile basin being wetter than the countries' total averages. Potential new agricultural areas identified in this study have a total crop season precipitation of about 900 mm, more than double the country's average and well above crop water requirements. Our model suggests investments in a total area of around 11 million ha in South Sudan, about a third of the potential identified.

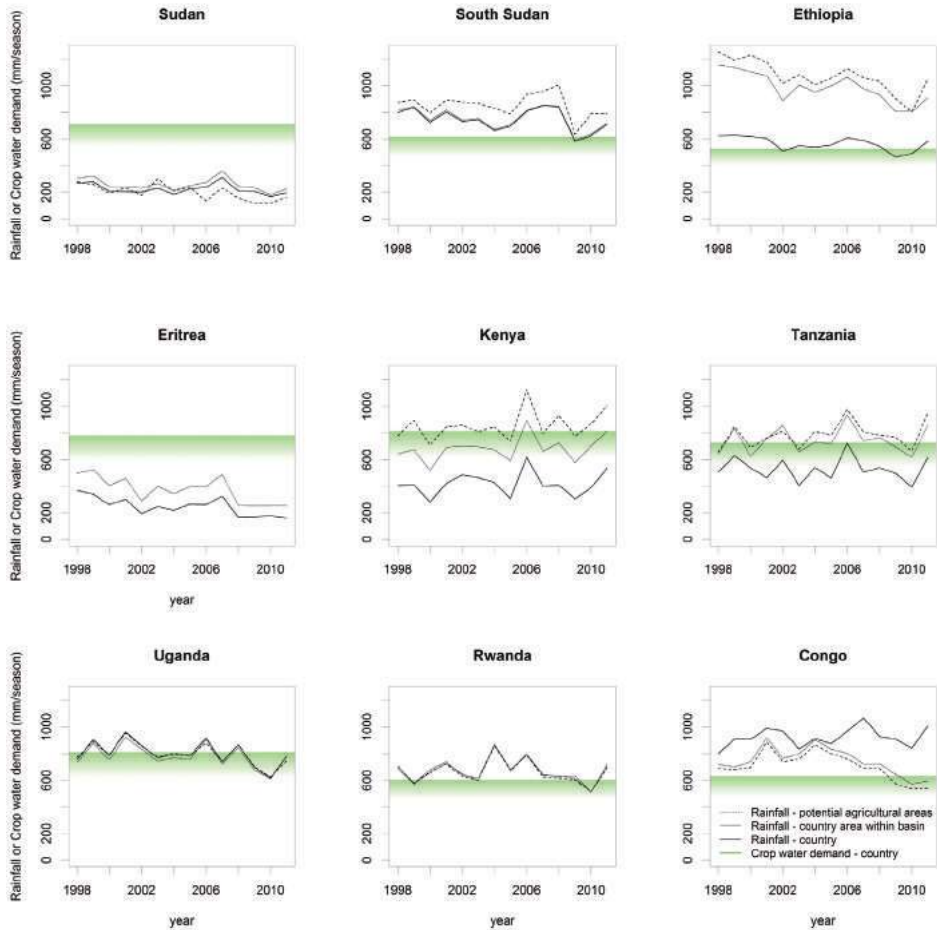


Figure 3 Satellite-derived country-specific rainfall (source: Tropical Rainfall Measurement Mission [TRMM] data (Kummerow et al., 1998)) for various spatial delineations for the main cropping seasons (JJASO for Sudan, South Sudan, Ethiopia and Eritrea; MAM and SON for all other countries) in relation to average crop water requirements of rainfed agriculture during these months (set equal to potential crop evapotranspiration, based on ECMWF reference evapotranspiration (Uppala et al., 2005) and FAO crop factors, see SI). Green shades indicate a range between 75% and 100% of crop water requirements.

If not all countries are self-sufficient in food, as is the case under the “Basin Cooperation” scenario, then regional trade is required to deliver food to where it is needed. Food surplus regions in the basin are situated in the south, whereas the largest shortages will occur in the north: in Egypt and Eritrea. While basic transport infrastructure is present in the form of river connections and railroads, historic trade routes need to be revived. To make optimal

use of comparative advantages, staple food suitable for long-distance transport to Egypt could be produced in upstream areas, while Egypt could specialize in fresh produce for its urban population and European markets (Wichelns et al., 2003). Export of agricultural produce from South Sudan, which, according to our calculations, could amount to 1.8 billion USD a year at farm-gate level, will provide diversification to this young economy, lessening its dependence on oil. Ethiopia's hydropower revenues could give the country access to food markets, should it choose not to develop its vulnerable highland regions to the maximum. The recent integration of energy grids in the region shows that such cooperation is possible.

6.4 DISCUSSION

This study focusses on the potential to reach national to regional food self-sufficiency in the Nile basin, as an alternative to an increasing reliance on global markets. This focus on food self-sufficiency gave us a framework to assess the contribution of rainfed agriculture compared to that of irrigated agriculture and the impact of different scenarios on the allocation of Nile waters. We do not, however, wish to advocate self-sufficiency as the only solution or criticise a reliance on global markets. For this, a different type of study including an analysis of the costs and benefits of regional to global food imports and exports would be required.

An integrated analysis of this kind faces numerous data uncertainties. Several (price of hydropower, yield of the current irrigation system in Sudan schemes and the investment cost of land cover change) were assessed in a partial sensitivity analysis (ANNEX II). Inevitably, caveats remain. Our study aims to explore different solutions from a hydro-economic perspective, thereby simplifying the diversity of crop production. Limitations in terms of soil nutrient conditions, farmers' knowledge levels and access to markets, were not explicitly addressed. They are, though, implicitly included in a potential rainfed yield that is lower than what would be expected from crop and soil and meteorological characteristics alone. This potential yield of 4 ton/ha is based on actually reported yields and in line with earlier studies.

For agriculture in the political and socio-economic unstable regions of South Sudan and north Uganda to approach this potential yield requires considerable effort in creating the infrastructure to make knowledge, technology and inputs - seeds, fertilizers and pesticides - available to farmers. This study did not assess the likelihood of such developments, but rather advocates increased effort to make this happen. Environmental consequences of such development should be thoroughly assessed. We did not include environmental limitations to agricultural intensification or expansion. But a sustainable intensification

(Godfray et al., 2010), with proper land management to reduce negative externalities of increased production will be required in the Nile basin as much as elsewhere.

Agricultural intensification and expansion did not lead to significant changes in downstream runoff. We found that seasonal evapotranspiration from arable lands was quite similar to that of the original vegetation in most locations. In literature, an increase in runoff after deforestation is often reported, but for temperate regions. Results from the tropics are mixed (Brown et al., 2005; Bruynzeel, 1988). In addition, any change in land use on less than 20% of the catchment area appears hard to detect in runoff (Bosch and Hewlett, 1982; Brown et al., 2005; Stednick, 1996). Still, further study on the local and regional impact of upstream land use changes using a model with a more detailed vegetation and land management parameterization would be useful to verify these initial findings.

Finally, a more detailed analysis of the impact of intra-seasonal droughts on food production is needed to further verify whether rainfed agriculture is sustainable. This should ideally be supplemented with an analysis of the robustness of agriculture and hydropower development under a range of future climate scenarios, given the diversity in both magnitude and direction of change in projections for this part of the world. Ultimately, a comparison of regional versus global climate variability would shed more light on whether the region would be better off cooperating rather than depending on volatile global markets. Although regional cooperation makes countries more vulnerable to regional climate extremes, the region would still have a safety net during such periods of basin-wide scarcity: the global market. If the Nile region were to rely on the global market in the first place, it could no longer act as a safety net.

6.5 CONCLUSIONS

Similar to earlier studies that focused solely on irrigated agriculture and hydropower (Whittington et al., 2005; Wu and Whittington, 2006), we find that basin cooperation will provide the most benefit to the basin – a result to be expected given the nature of the model used. Integration of rainfed agriculture in the objective function, however, greatly changes the solution space available. Earlier (non-)cooperation studies with their strong focus on Nile water allocation tend to emphasize potential conflicts between Egypt, Sudan and Ethiopia and highlight the role of Egypt as the main hegemon and the unequal distribution of water (Cascão, 2008; Cascão, 2009; Whittington et al., 2005; Wu and Whittington, 2006). In our study we show that a different distribution will merely shift production, which will not be sufficient to feed a growing population. We argue that rainfed agriculture in the unstable regions like South Sudan and North Uganda is key to food self-sufficiency in

the basin and that the heated debate on water allocation should be put into perspective. Conflicts over allocation, can only hinder cooperation on food production and trade thereby hampering the Basin's development.

Egypt's policy stand in particular seems to resemble a risky strategy: obstructing cooperation within the basin and hindering upstream water infrastructure development, as it has done in the past, gives Egypt the most water. But if this lack of cooperation leads to unilateralism, increased and uncoordinated upstream abstractions will have serious consequences for Egypt's agriculture and hydropower sectors. The resulting more unequal distribution of food self-sufficiency among basin countries will jeopardize regional stability. However, we also show that a more equitable solution is available, should countries choose to cooperate on basin-wide food production and trade, albeit with some, but rather limited, loss of water allocations for Egypt. This will require old policy dogmas to be relinquished and a change of perspective both on the basin itself and on the utilization of its land and water resources.

Such a change in perspective asks for a different, more integrative approach to basin governance and investments, away from the current focus on large water infrastructure projects. Investments for supporting a transition towards a climate-smart sustainable agriculture are needed, with technology improvement and technology adaptation and transfer essential to reduce the environmental impacts of increased production in the basin. The alternative is an increased dependence of Nile basin countries on volatile global food markets.

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7

SYNTHESIS



7.1 SYNTHESIS

A major global challenge will be to produce enough food in a changing climate. Food production requires a lot of water. Whether the freshwater planetary boundary, a single average global estimate of sustainable water use, has been exceeded is the topic of current debate (Jaramillo and Destouni, 2015; Rockström et al., 2009b; Steffen et al., 2015). This thesis leaves this global debate to others. Instead, it contributes to the literature by exploring on a more regional scale how to cope once one gets closer to this boundary, when rainfall variability cannot be buffered anymore by water supply measures alone, growing water demand cannot always be met and water stress increases. In a recent analysis of inter-annual variability of water scarcity in food production at the global level Kummu et al. (2014) identified North and East Africa and South Asia as hotspots of frequent water stress. This thesis explores the link between rainfall variability and food production in two major basins in these hot spots; the Ganges basin and the Nile basin.

In the introduction a general question is posed: “How can the world cope with increased rainfall variability?”. Four more detailed research questions were defined, each of which is addressed in one or more chapters in this thesis. In answering these questions this thesis focuses on a specific form of coping with rainfall variability: using flexibility in land and water use.

Flexibility here refers to the ability of farmers and local water managers to seasonally anticipate variations in water availability by changing the cropping type or overall land use practices resulting in a dynamic system of land and water use modifications. Rainfall variability and resulting water availability are the main uncertainties, and land and water the production factors that can be varied. This thesis thereby introduces an economic perspective on the impact of rainfall variability on crop production, by including the costs of land and water use and the benefits of production.

A multiscale approach is followed; first, an empirical study on conjunctive use of rain, tank and groundwater in a small-scale tank irrigation site provides insight into the magnitude of variability in rainfall that farmers and water managers are exposed to and into the type of flexibility, in adjusting cropped area and water applications. Next, the usefulness of remote sensing to sense adjustments in cropped area in response to inter-annual rainfall variability is tested at the larger scale of the Ganges basin. Finally, an existing hydro-economic model, WaterWise, is further developed to include flexibility in cropped area after which it is applied to the Ganges basin. With the same model, the impact of changes in land use and water allocations on future food production in the Nile basin is explored.

In section 7.1 the research questions, which were presented in the introduction, are answered. Section 7.2 reflects on data and methods used to derive these results. In Section 7.3 contributions to the scientific debate are summarized. In Section 7.4 overall policy conclusions are drawn. Recommendations for further research are presented in the last section.

7.2 ANSWERS TO THE RESEARCH QUESTIONS

Q1 Can conjunctive use of water from rain, tank and groundwater reserves buffer rainfall variability and thereby improve water productivity and overall food production of traditional irrigated agriculture in South Asia?

The results in Chapter 2 indicate that conjunctive use of water from rain, tanks and groundwater reserves can improve the resilience and productivity of traditional tank irrigation systems, provided proper monitoring of the use of water is included. Tank rehabilitation with such monitoring requires little additional investment compared to traditional tank rehabilitation with its exclusive focus on technical interventions; the developed approach was based on low-cost and low-maintenance monitoring techniques. Using these techniques, farmers could themselves do the monitoring, requiring only limited guidance from external agricultural extension workers or irrigation experts. Strengthening this capacity of farmers and local extension workers should be promoted as part of a climate-smart agriculture.

Three indicators were used in the analysis of conjunctive use of rainfall, tank water and groundwater: cropping intensity, economic water productivity and net agricultural income. For a total of twelve cropping seasons over a period of six years the actual volume of water supplied was compared with crop water requirements, and linked to crop yields. This long term monitoring is essential to understand and properly attribute the impact of any changes under conditions of high inter-annual rainfall variability.

The monitoring revealed that high rainfall variability leads to considerable inter-annual fluctuations in cropping intensity, income and water productivity. Farmers exhibit large flexibility in dealing with this rainfall variability; their main source of water from tank, rain or groundwater varies each year, as does the cropping intensity. Overall, this lead to a high variability in production. However, results suggest that improved conjunctive use resulted in a more stable cropping intensity, increased economic water productivity and lead to a higher net agricultural income. Groundwater tables were not negatively affected. With yields almost double regional and all-India yields, improved conjunctive tank irrigation in this region appears to be economically viable, despite the small landholding size.

Q2 How can we observe and measure flexibility in land use in the Ganges basin in response to rainfall variability?

Remote sensing can be used to detect flexible strategies for coping with rainfall variability. Using a longitudinal remote-sensing based method, a coping strategy of leaving more land fallow during below average monsoon years was observed primarily in the drier western part of the Ganges basin (Chapter 3). District statistics confirmed that inter-annual variability in crop production is partly a result of a cropped area adjustment in the dry parts of the Ganges basin and not only a reduction in yield per hectare.

Regions sensitive to rainfall variability were identified first, using the correlation between inter-annual rainfall anomalies and anomalies in Normalized Difference Vegetation Index (NDVI), a proxy for crop production. Whether this sensitivity results from a variation in crop growth or from a deliberate adjustment in the cropped area by leaving land fallow, reflecting a flexible coping strategy, was determined next. The method to distinguish flexibility in land use using remote sensing was based on a comparison of the probability distribution of NDVI values at peak crop development during the second cropping period between wet and dry years. In regions where only a slight shift occurs in the probability distribution of vegetation cover, a crop yield response is expected; the crop has grown overall less well in dry years. In regions where a distinct bimodal pattern is observed between dry and wet years, which is different from that of natural vegetation, a coping strategy of leaving land fallow is expected. Farmers anticipate shortages in the dry season rather than that they wait for crops to perish.

Q3 What factors influence flexibility in land use and how can we determine the value of this type of flexibility as a coping strategy?

Flexibility in land use, i.e. seasonal adjustment in cropped area, can explain almost 50% of variability in wheat production and 40% variability in rice production in the Indian part of the Ganges basin. This makes these adjustments almost as important as variability in yield. Chapter 5 shows that variability in crop production can be simulated well if cropped area is allowed to vary, and is made dependent on the costs of cultivation and the amount of groundwater available.

Climatic factors that influence flexibility in land and water use are a strong seasonality and inter-annual variability in rainfall, seasonal shortages in water resources availability and a certain level of predictability in the amount of available water resources. This predictability can either be through accurate seasonal weather forecast or arise from the fact that in monsoon-dominated regions rainfall has occurred before the start of the second

cropping season. Agro-economic factors that further affect flexibility are costs of water, land and labour and prices of crops produced.

The value of flexibility, i.e. foregone costs of choosing not to crop in years when water is scarce, was assessed using the hydro-economic model, WaterWise, which was expanded to seasonally vary cropped area. The model showed that flexibility in wheat production, grown during the dry season, is influenced most by restricting access to unlimited groundwater from deep aquifers. Rice production reacts mainly to increased costs of cultivation. Including costs of (family) labour increased flexibility, especially in wheat production. While being high for wheat production in a drought prone state like Rajasthan, the value of flexibility was found to be limited for the Ganges basin as a whole, indicating that water resources are overall still largely sufficient in most parts of the basin.

Q4 Will reallocation of water in the Nile be sufficient to achieve water and food security in the Nile basin, given the basin's high rainfall variability?

With the water resources of the Nile itself almost fully and productively allocated, Chapter 6 shows that the real solution to future food self-sufficiency for the basin lies outside the domain of water allocation and irrigated agriculture. Instead, it lies in using the potential of agricultural production in upstream rainfed areas. These areas can contribute over 75% of the additional food requirements in all modelled scenarios. Expansion of rainfed agriculture is suggested primarily in unstable regions of South Sudan and northern Uganda, where the causes of underdevelopment are largely socio-political as opposed to biophysical. The model also indicates that developing upstream rainfed agriculture through intensification and expansion does not drastically affect downstream runoff. Egypt's highly productive irrigation schemes will still receive an amount of water exceeding its official share.

In conclusion, strengthening intra-basin cooperation via food trade seems to be a better strategy than unilateral expansion of upstream irrigation, as the latter will reduce hydro-power generation and relocate, rather than increase, food production. A reliable rainfed agriculture will require investments in local water harvesting and site-specific supplemental irrigation, with similarities to the conjunctive water use and monitoring system as described in Chapter 2, in the long run supported by more accurate regional weather forecasting and smart forms of crop, water and soil monitoring and management.

Overall, I conclude in this thesis that:

- Fluctuations in food production in the Ganges basin are as much a result of

- deliberate seasonal decisions on the area to crop as they are a result of variations in yield;
- A conceptual or applied model that tries to explain these fluctuations in food production should include economic factors, in terms of costs of land and water use and benefits of production;
 - Flexibility, by deliberately adjusting cropped area, is a local coping strategy, but also a regionally relevant phenomenon – the value of flexibility can be quantified; in the Ganges basin it appears to be higher for wheat than for rice;
 - Re-allocation of Nile water for irrigation to countries upstream will not solve the food security problem in the Nile basin; large-scale investments in rainfed agriculture supported by supplemental irrigation can.

7.3 DISCUSSION ON DATA AND METHODS

This thesis covers a range of spatial scales. Empirical data from a local case study site (Chapter 2) was complemented with remote sensing data covering the basin scale, even up to a 250m by 250m resolution (Chapter 3). Model-based scenario analysis (Chapters 4-6) covered the district to basin level scale. Remote sensing and model-based studies were validated with statistics on crop production, yield and cropped area, covering district, state, basin and the national level. The impact of rainfall variability on food production remains largely hidden when one studies only the catchment scale. Its relevance becomes clear when one observes the lower scales as well.

While the coverage of multiple spatial scales is presumably one of the strengths of this thesis, the lack of longer time series remains one of the main constraints, when analysing variability and strategies to cope with it. Such analysis requires time series of considerable length. Despite collecting data over 12 cropping seasons in six years in the assessment of flexibility and conjunctive use of water in a tank irrigation site (Chapter 2), results remain indicative rather than conclusive. Each year is unique, maybe not so in terms of total rainfall, but certainly in the distribution of rainfall over the year. Still, the longitudinal assessments as presented in Chapters 2 (tank monitoring) and 3 (remote sensing) are a step forward compared to comparative analyses based on two random years.

In the introduction an expanded conceptual model of the impact of rainfall variability on food production was proposed (figure 3), which was tested with the WaterWise hydro-economic model in Chapter 5. Costs of land and water use and benefits of production were introduced as additional variables. Inclusion of flexibility in model assessments does not

necessarily need to be through hydro-economic optimization as presented in this thesis; more simple decision rules, based on empirical correlation between rainfall and cropped area, could be applied to existing models. Many of these models already have the opportunity to annually vary land use via input variables. A hydro-economic model as applied and further developed in this study, however, does give the possibility to include economic decision making, introducing additional versatility and diversity, potentially with better forecasting skill.

Inevitably, there are several caveats or limitations to the applied approach to assess the relationship between rainfall and food production using a hydro-economic model, which can be clustered into temporal, spatial and conceptual limitations:

- **Temporal scale limitation:** the inclusion of double cropping and flexible cropped area adjustments in the hydro-economic model, WaterWise, improves simulation of variability in crop production as compared to standard global hydrology-vegetation models in areas where climate is variable. In this thesis, I focus mainly on flexible strategies in the second cropping season, the *Rabi*. A more detailed assessment of decision making at the start of the monsoon would be a next step in understanding variability in production and the overall value of flexibility. The here presented Value of Flexibility for rice and wheat production in the Ganges should be regarded as a first indication and a basis for further quantification.
- **Spatial scale limitation:**
A) neither in the remote sensing study (Chapter 3), the statistical data nor in the WaterWise model application (Chapter 5) is it possible to distinguish whether flexibility as observed, i.e. the reduction in cropped area in response to reduced water availability, is equally distributed amongst farmers. Land holding sizes in the study regions are on average much smaller than the units of analysis in the remote sensing study or the model application. It is likely that some farmers can continue to crop all their land, having better access to water resources, while others have to skip planting all together in years of below average rainfall. Remote sensing data series with even higher resolution are increasingly available, with pixel size matching the plot size of (smallholder) farms to detect flexible coping strategies in more detail. Such a detailed remote sensing analysis should be combined with field studies, that not only validate the type of crop or vegetation, but also the land ownership and management practices. More detail would, however, not necessarily alter the conclusions in Chapter 3 or the Value of Flexibility as derived in Chapter 5; but it could inform whether locally it is a coping strategy that should be promoted,

or whether it also leads to inequality that should be remediated, e.g. by imposing uniform restrictions on land use in years of drought.

B) by applying a basin hydro-economic model, this thesis is constrained in its analysis of food security with international trade beyond the basin borders not included in the model. Whether regional food self-sufficiency is better than a reliance on global trade is depending on the stability and reliability of the global food system. This cannot be judged with a model as used in this thesis. An alternative would be to use a partial equilibrium global agricultural sector model such as IFPRI's IMPACT model (Rosegrant et al., 2002), which weighs a local decision of increasing food production against international trade. The trade-off, however, is a reduction in biophysical schematization and parameterization detail.

- **Conceptual limitation:**

A) For the Ganges basin application an existing crop-vegetation model was first improved, calibrated and validated and output of the most important food crops was used as input into the hydro-economic modelling. This allowed for comparison between rice and wheat, the two major food crop in the region. In the Nile basin application such a detailed validated crop model was not yet available; the diversity of the various agro-ecosystem was aggregated to country specific cropping systems. Differences in crop-water response, costs of cultivation or price of crops were thereby averaged out. Results should be judged in light of these simplifications. The main conclusion- that rainfed agriculture contains the main potential, is however robust.

B) last but not least, in this thesis I look mainly at economic performance in terms of efficiency. Other societal or ecological values like poverty alleviation, equity, employment or ecosystem functioning were not included in the hydro-economic model, nor was the wider economic impact of e.g. increased hydropower availability or (in)stability in food supply accounted for. Such values and impacts are difficult to quantify and vary due to many external factors. Modelling results should be interpreted keeping in mind these limitations.

Finally, while this thesis focuses in detail on the impact of rainfall variability in the Ganges basin, in the Nile basin model rainfall variability was simplified into a dry and a wet year, with a verification of results against a 10 year time series of rainfall. As the Nile basin shares many characteristics with the Ganges basin, like a double-cropping pattern and a strong seasonality in rainfall, a similar thorough analysis is warranted though. A deeper understanding of the value of flexibility could furthermore be gained by studying even more water stressed basins than the Ganges basin, like the Krishna basin in Southern India.

7.4 SCIENTIFIC CONTRIBUTIONS

This research represents a step forward in understanding flexible strategies for coping with rainfall variability. In the individual chapters the conceptual model (figure 3) was further explored from different angles and placed within existing research. Overall, the contribution of this thesis to the scientific debate can be clustered under four themes:

1. This thesis explores the impact of inter-annual rainfall variability on variability in crop production. This focus on variability is timely. With climate change now generally perceived inevitable, the policy attention is shifting from mitigation to adaptation, and beyond, to a discussion on how to deal with loss and damages if adaptation fails. In this light, research on rainfall variability and extreme rainfall events, their impact and how to cope with them becomes increasingly relevant. This is expressed by the recent special IPCC report on extremes (Field, 2012), a research program like 'FutureWeather' of the Dutch meteorological institute, which looks in detail at representative weather patterns that cause extreme conditions (Hazeleger et al., 2015), or the development of proxy weather generators (Fatichi et al., 2011; Supit et al., 2012; Yiou, 2014), that aim to better capture weather variability and extremes at specific time-slices in future. Translating this into impacts is a next step, which requires adjustments in the way impact models are being used and their data is analysed. Not many of such studies exist. This thesis adds to recent research, that looks into the impact of (changing) rainfall variability on food production (Kummu et al., 2014). It shows that inclusion of double cropping and seasonal adjustments in land use should be part of such analyses.

2. In response to variability, farmers take decisions on what and where to crop. This thesis treats farmers not as passive observers simply waiting for climate events to unfold, but highlights their coping and decision making capacity. Rainfall variability not only affects crop yield, but also affects the area cropped (Chapters 2, 3 and 5). Flexibility is postulated as a coping strategy in agricultural water management next to diversification. In many case-studies flexibility by varying area cropped in response to rainfall variability is mentioned in one way or another (Kelkar et al., 2008; Molle et al., 2010; Pandey et al., 2007; Venot et al., 2010a), but the cause-effect mechanisms behind it are not explained; it is simply reported as 'a form of coping'. In this thesis I show how inter-annual variations in rainfall can explain adjustments in cropped area, and how this is influenced by economic factors like cost of land and water use. Flexibility, and the interaction between the biophysical system (rainfall) and the socio-economic system (land use, resource allocation and food production) thereby fit well in the upcoming discourse on socio-hydrology (Sivakumar, 2012; Sivapalan et al., 2012) and the ongoing, underlying, discourse on

co-evolution of socio-ecological systems (Norgaard, 1981; Rammel and van den Bergh, 2003; van den Bergh and Gowdy, 2000), studying how men alter their natural environment and how these alterations again shape society.

3. Variability and the value of flexibility are explored with a hydro-economic model, WaterWise, which was further developed in this thesis. The inclusion of seasonal variations in cropped area in a (distributed) hydro-economic catchment model is, to the best of my knowledge, not validated and presented at this scale and with this level of detail. WaterWise thereby does not contain an endogenous crop-water production function like many other hydro-economic models, but allocates water by varying the area under different, pre-defined water management options. This means either no irrigation or full irrigation, in the here used schematization⁴. The alternative approach of optimizing water productivity along the production curve, i.e. making best use of the concept of diminishing marginal returns of water supply close to the maximum, theoretically leads to a better, optimal, allocation of water resources and is enthusiastically promoted by the scientific community (the 'deficit irrigation' discourse). There are, however, many constraints to its actual adoption by farmers. Farmers have often limited options to assess actual water needs during the growing season, have limited say over timing of water delivery and little financial buffer to take risks. In addition, for an individual farmer there is often no economic incentive for risking valuable yield by saving 'cheap' water, if the water will then be used by somebody else. The model as developed in this thesis offers a different and, arguably, more realistic sub-optimal approach for describing how farmers deal with variability in rainfall and varying availability of water resources.

4. This thesis contributes relevant regional case studies to the 'green' versus 'blue water' discourse (Kummu et al., 2014; Rockström et al., 2009a; Rockström et al., 2010), which is resulting in renewed attention for rainfed agriculture with its inherent vulnerability to rainfall variability. In basin-oriented hydro-economic model analysis, this integration of rainfed with irrigated agriculture is still less common. For example in the Nile basin, the water management debate centres largely around the allocation of Nile water, the blue part, while at the same time crop production studies address the yield gap in African agriculture and how to close this, mainly focussing on the 'green part'. In this thesis I bring those two schools of research together and show how allocation of water is affected, when also rainfed agriculture is taken into account. For the Ganges basin I show that there is no clear-cut line between rainfed and irrigated agriculture.

⁴There is no restriction to the amount of pre-defined water management options in WaterWise. Different water supply options, say at 80%, 90% and 95% capacity compared to full demand, could be pre-processed. In combination with the freedom to vary the area under different land and water management options this gives a very versatile model.

7.5 POLICY IMPLICATIONS

Despite impressive increases in crop productivity and food production over the past decades, the Ganges and Nile basin have been, are and will be hotspots of water and food insecurity. Food price hikes in 2008 exposed the vulnerability of the global food system to variability. Major geo-political changes followed with countries in and around the Nile basin particularly affected.

National policies around water and food security have tended to focus on grand water schemes; the Nile Valley project in Egypt, the Renaissance Dam in Ethiopia or the River inter-linkages project in India. Local solutions and strategies for smallholder farmers to deal with rainfall variability center around creating increased local storage, with varying success. This thesis aims to increase our knowledge of the impact of rainfall variability on regional food security and on the possibilities to adapt locally to increased rainfall variability due to climate change, by being flexible. It highlights the decisions farmers make in their allocation of land and water resources in response to rainfall variability and the impact this has on food production.

Flexibility in land and water use is a relevant strategy for coping with increased rainfall variability in regions where there is a strong seasonality in rainfall, where a second crop is cultivated using water stored in reservoirs, soil or shallow aquifers, and/or where seasonal rainfall is highly predictable. Such conditions occur in much of the monsoon-dominated subtropics. Whether flexibility is a more appropriate strategy than diversification or whether agriculture is sustainable in the long run will be location dependent and farm specific. Flexibility as a strategy has the potential to allocate available resources best under conditions of high rainfall variability. There are, thereby, several policy options that can support it:

- **Access to information:** Access to better information is required to improve the capacity of individual farmers to be flexible and to take the right decisions in time. Skill in seasonal climate forecasting is improving with the continued interest in climate and the development of weather and climate models. These predictions are made available to farmers with increasing detail and lead time, often by commercial companies. The challenge for extension services lies in making this information available to smallholder farmers in South Asia and Eastern Africa who have, individually, limited capacity to invest in such services. While the hardware component seems to develop almost autonomously, with mobile coverage increasing rapidly, the software component, e.g. the accuracy, local relevance, type and reliability of information products could still be improved.

- **Safety net:** Better availability and use of information is not enough. Flexibility, by following forecasts, also brings risk as weather remains variable. In both regions farm holdings are small and farmers have limited financial buffer and therefore limited possibility to take risks. Governments, in cooperation with the private sector, should continue to develop and support innovative agricultural insurance schemes through which also individual small-holder farmers can share these risks. Insurance schemes thereby contribute to a form of aggregation in an agro-ecological system that is highly fragmented.;
- **Land policies:** Stimulating larger farm structures, e.g. by removing land ceiling acts, loosening land lease restrictions or stimulating cooperatives, would be a more structural form of aggregation. Small-holder farming, with its low degree of mechanisation, is considered a desirable future neither by many farmers nor their children despite their strong emotional connection with land and livelihood. Larger farms or cooperatives make it easier to be flexible, to leave land fallow if necessary or to plant more if possible. Land reform, however, is a very sensitive issue in South Asia and East Africa and issues related to equity, social justice and the consequences for rural employment should be taken well into account.
- **Subsidies:** Agricultural inputs are heavily subsidised in South Asia and East Africa, but connectivity to markets and timely availability of subsidized seeds, nutrients and pesticides should still be improved to enable farmers to be flexible. At the same time, market-distorting policies should be revised. In India, current minimum support prices or procurement prices for rice, wheat and other crops safeguard farmers from low prices in excess years, but hamper the development of markets and thereby the transmission of price signals. This might actually lead to less area being planted and less crop being harvested in drought years, when costs of irrigation rise. Again, a reassessment of government subsidies should naturally be placed in a much broader socio-economic context.

In promoting flexibility, the conflicting interests between producers and consumers should be kept in mind. As is illustrated in Chapter 5, by being flexible farmers maximize gross margin rather than production. While this is beneficial for farmers' welfare, it potentially comes at a societal cost; when farmers leave land fallow in order to maximize their returns, overall production decreases slightly, especially during dry years, potentially increasing the costs for consumers. The challenge for policy makers is to give farmers the capability and freedom to be flexible, while at the same time safeguarding the stability of food supply to consumers.

In order to stabilize food supply to consumers, better storage and regional transport and trade of food crops are required. In both the Nile and Ganges basin, this has one of the highest priorities. Understanding variability in food production is thereby not only of relevance for coping with shortages, but also for efficiently managing surpluses; both the amplitude of fluctuations in production and the frequency of extremes influence the stocks that need to be kept and the volume that can be exported.

Finally, this thesis supports pleas for a different, more integrative approach to basin governance and investments away from the current focus on large water infrastructure projects. Rockström and Falkenmark (2015) advocate it as a “radical rethink of global water-management strategies and policies”, to more attention to ‘green water’ rather than ‘blue water’. Rainfed agriculture supplemented with irrigation from local water harvesting structures and storage reservoirs – in various ways similar to the tank system in southern India – can boost food production in both Asia and Africa. In several areas it might be the only option. Investors and politicians should still think ‘big’; large investments in transportation, storage and market facilities and in knowledge and expertise are needed. A reduction of trade barriers is thereby essential. Above all, lasting stability and peace, fostering cooperation, is a necessity for these regions to become more resilient to future rainfall variability and fluctuations in production.

7.6 RESEARCH RECOMMENDATIONS

Local scale

In this thesis variability in rainfall and food production under current climate conditions was studied. A next step would be to assess scenarios of climate change. In light of an expected increase in climate variability (Field, 2012) not only random variability and extreme events, but also the risk of possible sequences of extreme events becomes relevant. A farmer might be able to cope with a single drought year, but two consecutive adverse weather years could form a turning or tipping point and lead to a more permanent transition. A more extensive economic analysis, including better insight into farm-level budgets and price variability would be needed to assess the impact of such changes. Whether flexibility in land use remains a suitable strategy to cope with variability and risks under future climate variability is thereby an interesting question to answer.

A closer look at what triggers flexibility, i.e. what weather events, weather expectations or other factors that influence seasonal decisions on land use and water allocation, would be another opportunity for further research. There is still little understanding of these

triggers, and the exact moments at which they occur and how they might be influenced by climate change. A research challenge is to further improve seasonal weather forecasts to match information requirements during these critical moments. Improved skill in seasonal forecasts and increased availability of commercial and non-commercial climate and adaptation services alone is not sufficient, though. It is imperative that also smallholder farmers, such as those in the Ganges or Nile basin will be able to use the information and combine it with their own observations.

Regional scale

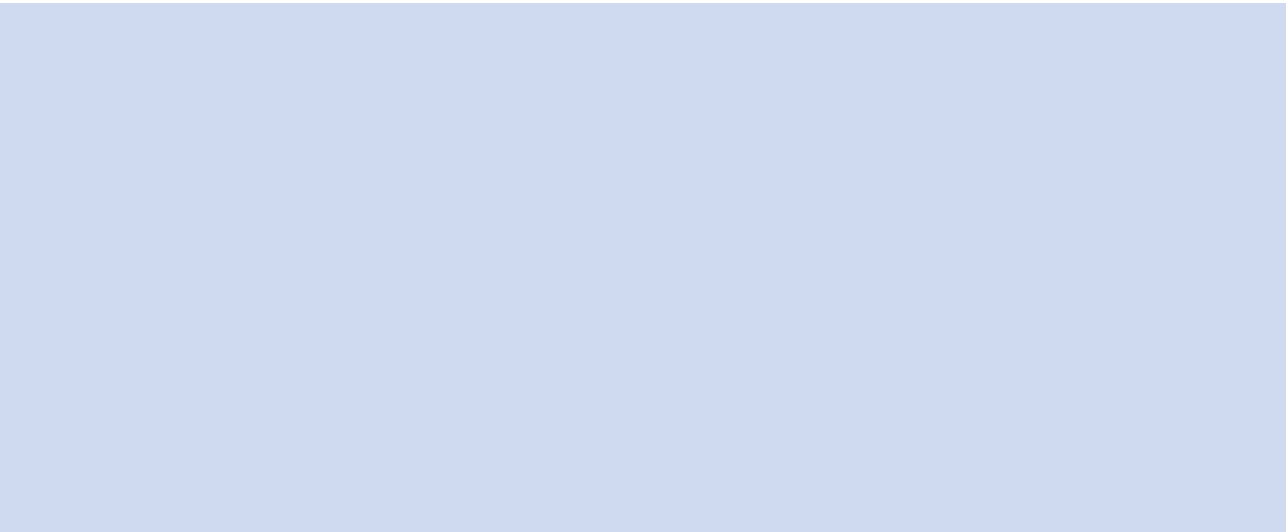
At the regional level, future food security in the Nile and Ganges basins and surrounding regions will depend on the success of a number of development options; an intensification or expansion of agricultural production (i); a better connectivity through regional (ii) and/or global trade (iii), an increase in food storage (iv) besides the necessity to reduce waste of crops and food (v). The first two options were explored in the Nile basin in Chapter 6. Which option or, more likely, which mix of options would work best within this broader development context remains a pressing and important question in both regions. The expected increase in rainfall variability makes it an even more complex puzzle to solve. Large investment decisions with far-reaching and heavily disputed welfare consequences are depending on it. The recent dispute on opening Indian retail to foreign investments is just one example. Better regional hydro-economic studies are needed, that include the impact of rainfall variability in considerable detail, to test the different development options and to explore different combinations.

The recommendations in this thesis, e.g. concerning the various development options in the Nile basin, are only a first exploration, of a scientific nature, and require further follow-up in the form of detailed feasibility studies. A robustness analysis of different regional development projects, like the large Renaissance Dam in Ethiopia or the river inter-linkages project in India, against different regional climate change scenarios with specific attention to rainfall variability should be part of such a feasibility study. Especially the climate change signal for the Great Lakes region around Lake Victoria remains highly contested amongst different global and regional climate models. With renewed interaction between upstream and downstream riparian countries, and given the regions pressing development challenges, the potential trade-offs between flood protection and drought mitigation, within the context of higher food demand, should be explored.

Global scale

Ultimately, a better understanding of the future volatility of the global food system would shed more light on whether countries in a region like the Nile basin would be better off cooperating rather than depending on global markets. Regional cooperation leaves countries more vulnerable to local rainfall extremes. On the other hand, globalization tends to reduce resilience to drought, as optimization of the food network leads to a loss of redundancy (D'Odorico et al., 2010; Walker and Salt, 2012). A highly connected food system may thus results in the more widespread propagation of perturbations (Godfray et al., 2010). In recent years science has advanced in its understanding of the global climate system, both in terms of teleconnections as well as how variability and extreme events will change. Within this context the probability of - potentially correlated - events, like simultaneous droughts in major food producing regions, will be interesting to explore. A better understanding of such extreme events could help to create a more resilient global food system.

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ANNEX I SHORT DESCRIPTION OF WATERWISE MODEL EQUATIONS



INTRODUCTION

The WaterWise model has the specific ability to suggest investments that make best use of the available land and water resources. It solves the problem of economic scarcity, with the implementation of local investments having consequences for the physical possibility of investments elsewhere. Like most hydro-economic models, WW describes the hydro-logic and crop growth processes in considerable detail, whereas the economic optimization algorithm is relatively simple.

WaterWise is a hybrid-holistic model: separate water-crop modules are run in an offline mode as part of the pre-processing. The results are imported into the optimization model through continuous decision variables on the interval $[0,1]$ that represent the area fraction for which the option is actually applied: attached to these variables are all the (time dependent) water balance variables and crop production variables of a certain crop management option. The attached variables can have any kind of nonlinear interaction with each other, since this does not have to be formally represented in the hybrid holistic model. In this manner the (extreme) nonlinearities between water and crop production in the column model are modelled with linear variables in the hybrid holistic model.

The Waterwise model code is formulated within a Mixed Integer Linear Programming framework (MILP). The model equations have been implemented in Xpress-Mosel (FICO, 2014) . The MILP technique is for instance used in representing discrete options like the building of a reservoir. There are many examples in literature of this usage, e.g. Gillig et al. (2001) . Less common is the use of MILP for representing nonlinear hydrologic relationships and thresholds in the economic evaluation. In comparison to nonlinear techniques involving a gradient search, mixed integer linear programming has the advantage that when the optimum is found one can be sure it is the global optimum, without any further analysis required.

⁵ FICO, 2014. FICO Xpress optimization suite. <http://www.fico.com/en/products/fico-xpress-optimization-suite>

⁶ Gillig, D., B. A. McCarl and F. Boadu 2001. An economic, hydrologic, and environmental assessment of water management alternative plans for the south central Texas region, *Journal of Agricultural Applied Economics* 33:59–78.

ECONOMIC MODEL

WW optimizes the total Gross Margin (total yield-over-cost), choosing the optimal combination of land use and water management options, given available water resources:

$$Y_{TOT} = Y_{LU} - C_{LWM} + Y_{HP} - C_{RWM}$$

with

$$Y_{LU} = \sum_{z,u,y,s} (Prod_{z,u,y,s} * P_{y,u} - C_{LUu} * Ac_{z,u,y,s})$$

$$C_{LWM} = \sum_{z,u,y,s} (C_{IRRIZ,u} * Ac_{z,u,y,s})$$

where Y_{TOT} represents total gross margin (e.g. in Indian Rupees [Rp] /yr), Y_{LU} the profit from land use (Rp/yr) based on production ($Prod$, in ton) multiplied by price of product (P , Rp/ton) minus non-water costs (C_{LU} , Rp/ha) multiplied by the cropped area (Ac , in ha), in season s of year y per land use u in hydrotope z . C_{LWM} are the costs of local water-management measures for supporting land use, i.e., the variable costs of local irrigation measures (in Rp/yr), depending on the amount of irrigation water used for each hydrotope z and land use and water management option u . Y_{HP} are the gross margin of hydropower (Rp/yr), based on flow through the hydropower arc (QSOUTJ) multiplied by the hydropower-station specific yield (in Rp /m³). C_{RWM} the costs of regional water management (i.e. maintenance costs for large canals and the costs of flow-through connections that involve pumping to support the river, canal, and reservoir system [Rp/yr]). Y_{HP} and C_{RWM} were not used in the Ganges-Meghna-Brahmaputra application.

In addition, investment costs can be inserted for modifications to the land use and water management system:

where I is total investment (in e.g Rp), I_{LU} is investments in transitions of land use (Rp), I_{LWM} is investments in improving local water management (Rp), I_{HP} is investments in

$$I = I_{LU} + I_{LWM} + I_{HP} + I_{RWM}$$

hydropower (Rp) and I_{RWM} is investments in regional water management (Rp). These investment costs can be annualized and added to the yield term or kept separate and given an upper bound. In the Ganges-Meghna-Brahmaputra application, no investment costs were used as we assessed present-day variability and the overall cropping pattern and water management structure was kept constant.

LAND USE MODEL

The land use and management options are modelled with decision variables on the interval [0,1]. The constraint for the choice between land use options reads as:

$$\sum_u XU_{z,u} = 1$$

where $XU_{z,u}$ is the decision variable for the fraction of land use option u in hydrotape z (-). The model contains possibilities for constraining the total fraction of the hydrotape area that can be converted, limiting it to e.g. 20%. It is also possible to set a constraint on the fraction of the area that can be converted to a certain land-use type. In addition, the land use options can also be clustered into groups, e.g. of 'cereals' and 'other' crops. The model is then forced to keep the total area of the group the same, within each hydrotape or within a certain region.

For estimating the costs of transitions, the land use changes that the model is generating are compared with the current situation by:

$$\sum_{u2} XU2XU_{z,u2,u} - \sum_{u2} XU2XU_{z,u,u2} = XU_{z,u} - aluref_{z,u}/A_z$$

where $XU2XU_{z,u2,u}$ is the decision variable for conversion of land-use type $u2$ to u in hydrotape z , $aluref_{z,u}$ is the area of land use option u in a hydrotape in the current situation (ha), and A_z the area of hydrotape z (ha). By attaching cost coefficients to the changes, the model is encouraged to select values of variables involving minimal changes; this resolves the problem of indeterminacy due to the presence of more variables than equations.

WATER MODEL

In the water model the decision variable $X_{z,u,m,y,s}$ represents the use of a management option m of land use type u in hydrotape z , in season s of year y . The water model connects to the land use model by setting the sum of the used management options equal to the land use option

$$\sum_m X_{z,u,m,y,s} = XU_{z,u}$$

The use of a land and water management option can involve costs, which are determined by the maximum value of X that is chosen for the modelling period. The runoff and drainage of land use (both agriculture and non-agriculture) are summated for the node that the flow goes to:

$$QRK_{k,t} = \sum_{z|koutz(z)=k} \sum_{u,m} X_{z,u,m,y(t),s(t)} \cdot A_z \cdot (qdrn_{z,u,m,t} + qroff_{z,u,m,t})$$

where $QRK_{k,t}$ is the sum of runoff and drainage connected to node k ($\text{m}^3 \text{s}^{-1}$), $qdrn_{z,u,m,t}$ and $groff_{z,u,m,t}$ are drainage and runoff ($\text{m}^3 \text{s}^{-1} \text{m}^{-2}$). The latter parameters are determined with offline running of the water module in a pre-processing stage.

For modelling water demand the model formulation is more complex, because demand realization depends on water supply decisions that can be flexible, from time step to time step, with water coming from varying sources at specific costs per unit, and with specific constraints (physical or policy driven). The demand realization can come from a local source (groundwater, local surface water) and/or a regional source (the main river). For supply from local groundwater there is not a connection to the network of water bodies. The supply is based on simulations performed offline in the pre-processing phase for the vertical groundwater-soil-crop column, assuming that no groundwater mining is allowed. Whether or not the option is used depends on the decision variable $X_{z,u,m,y,s}$. Supply from regional groundwater and from surface water can be from a node or from an arc of the water network. The chain of equations for water demand satisfaction starts with:

$$\sum_v (QSKV_{v,z,u,t} + QSNV_{v,z,u,t}) = \sum_m X_{z,u,m,y(t),s(t)} \cdot Ac_z \cdot qdem_{z,u,m,t}$$

where $QSKV_{v,z,u,t}$ is the irrigation supply from a node that has been labelled as type of source v (groundwater, local surface water, river water) ($\text{m}^3 \text{s}^{-1}$), $QSNV_{v,z,u,t}$ is the irrigation supply from an arc that has been labelled as source v ($\text{m}^3 \text{s}^{-1}$), Ac_z is cropped area (in ha) and $qdem_{z,u,m,t}$ is the irrigation demand determined with running the offline water module ($\text{m}^3 \text{s}^{-1} \text{m}^{-2}$). The above equation can lead to model infeasibility if there is not enough water. To avoid this, the model application should always include a 'rainfed' option that has no irrigation demand. The model can then selectively use this option in a season with a shortage of water, and in the rest of the seasons use the option with the irrigation enabled. Via the yield coefficients in the objective function the loss of productivity is taken into account.

The irrigation supply from nodes and arcs connect to the water network with:

$$QSK_{k,t} = \sum_{v,z | \text{kinz}_{v,z}=k} QSKV_{v,z,u,t} ; \quad QSN_{j,t} = \sum_{v,z | \text{jinz}_{v,z}=j} QSNV_{v,z,u,t}$$

where $\text{kinz}(v,z)$ links a hydrotope to a water body node, and $\text{jinz}(v,z)$ links a hydrotope to a water body arc. The supply of water can involve costs. The required supply capacity is determined by the maximum supply rate in the modelling period. This can be limited due to physical or cost considerations.

The nodes only act as connection hubs, without any spatial dimension or storage:

$$\sum_{j|koutj=k} QFOUTJ_{j,t} + QRK_{k,t} = \sum_{j|kinj=k} QFINJ_{j,t} + QSK_{k,t}$$

where $QFOUTJ_{j,t}$ is the outflow of arc j ($m^3 s^{-1}$), and $QFINJ_{j,t}$ is the inflow of arc j ($m^3 s^{-1}$).

To model the actual flow through an arc of the network we used the unit hydrograph method (UH). This method provides a means to introduce extra translation time and extra flood wave dispersion. Losses can be modelled schematically by letting the blocks of the UH add up to less than the unit.

RESERVOIR MODEL

For reservoirs we used a variable storage routing method, which includes an area dependent recharge/loss term attached to the arcs:

$$S_{j,t} = S_{j,t-1} + [QFINJ_{j,t} - QFOUTJ_{j,t} - QSJ_{j,t} + A_{j,t} \cdot recha_{j,t}] \Delta t$$

where $S_{j,t}$ is the storage in an arc j (m^3), $A_{j,t}$ is the water area (m^2), $recha_{j,t}$ is the recharge/loss term ($m^3 s^{-1} m^{-2}$), Δt is the length of time interval (s). In order to avoid the non-sustainable use of a reservoir, the model sets the storage at the end of the simulation run equal to that at the beginning, with the model itself determining that storage as part of the optimization. If the latter feature is not desired, a minimum and/or maximum end storage can be specified.

Piece-wise linear functions are used for modelling the relationships between water level, storage and gate outflow capacity of the arc/reservoir itself. The implementation is done with a 'special ordered set of type 2', a so-called SOS2-set of ordered decision variables in the form of weights (Fico, 2014). Such a set ensures that the model is forced to follow a nonlinear table, without 'cutting corners'. The equations that make parallel use of the SOS2-weight variables are given by:

$$H_{j,t} = \sum_{p \in SOS2} h_{sos_{j,p}} \cdot WT_{j,t,p} ; A_{j,t} = \sum_{p \in SOS2} a_{sos_{j,p}} \cdot WT_{j,t,p} ; S_{j,t} = \sum_{p \in SOS2} s_{sos_{j,p}} \cdot WT_{j,t,p}$$

$$QFOUTJ_{j,t} = \sum_{p \in SOS2} q_{sos_{j,p}} \cdot WT_{j,t,p} ; \sum_{p \in SOS2} WT_{j,t,p} = 1$$

where $WT_{j,t,p}$ is a weight variable of the piece-wise linear function, table position p (-), $H_{j,t}$ is the water level (in m) in arc j at time t , $h_{sos_{j,p}}$ is a water level point of piece-wise linear function (m), $a_{sos_{j,p}}$ is a surface water area point of piece-wise linear function (m^2), $s_{sos_{j,p}}$ is a surface water storage point of piece-wise linear function (m^3), and $q_{sos_{j,p}}$ is discharge of piece-wise linear function 1 ($m^3 s^{-1}$).

For simulation of the spillway discharge the table can include an extra discharge term, or the network can include the spillway as a bypass. Lateral losses to groundwater can be modelled with an arc-arc connection. The use of integer variables is computationally demanding and therefore reserved for large reservoirs in the main river system that have a large evapotranspiration that is sensitive for the water area. Apart from restricted use of the option, the used time step is substantially longer than used for the rest of the system description.

For modelling local storage in surface water and groundwater, the so-called V-reservoirs, the used tables have just two entries: one starting at zero, the other for the maximum storage situation. Since the table function of these reservoirs only have two points, there is no need for using the computationally demanding SOS2-set, which makes the implementation of V-reservoirs straightforward LP.

FLOW BOUNDARY CONDITIONS

Outflows of an arc can be set to a maximum, which is especially relevant for canal offtakes from the main river system and for limiting the infiltration capacity to a groundwater body. The defined water network can include arcs that do not actually exist yet. In that case an investment will be required. To describe this, the model has binary variables for activating the arc. If there are multiple parallel options for a new connection, then the user can specify that only one of them can be chosen. Environmental flows can be specified as a minimum flow for each time step, or as a long term average over the full period of the simulation.

CROP PRODUCTION MODEL

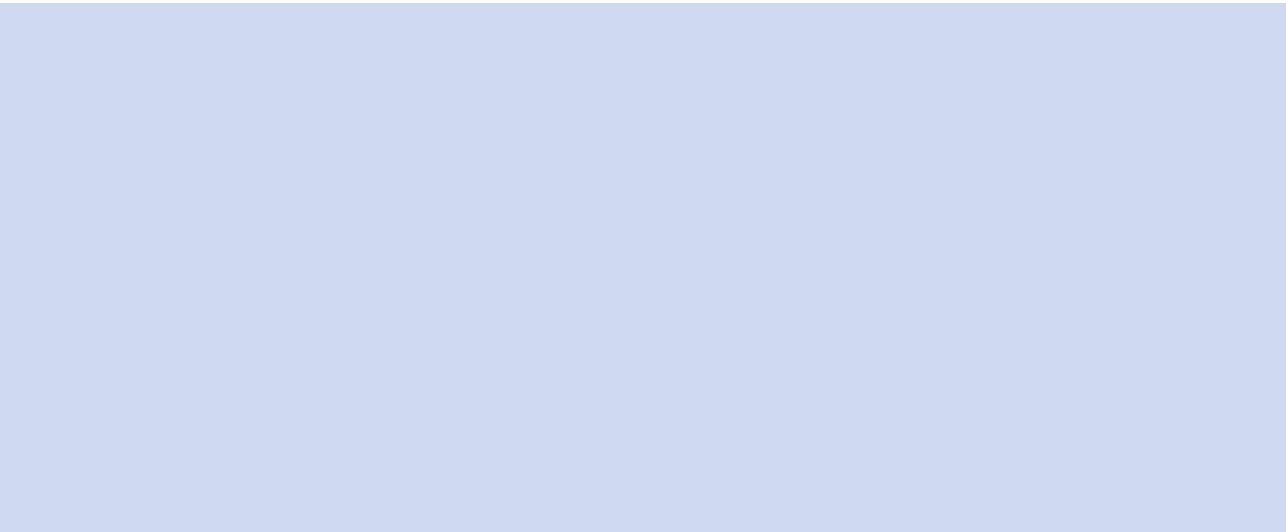
In the integrated code of the optimization model, crop productivity is represented by coefficients that have been determined by running the crop production model in an offline mode (in the case of the Ganges application LPJmL, for the Nile application see ANNEX II). Crop productivity is linked to the decision variable $X_{z,u,m,y,s}$.

HYDROPOWER MODEL

For modelling hydropower there are two options:

- a linear relationship between flow ($QFOUTJ$) and generated power;
- a nonlinear relationship between head (H), flow ($QFOUTJ$) and generated power.

The nonlinear option is implemented with a so-called SOS1 set (FICO, 2014), that makes use of the water level modelled with the SOS2-set of the variable storage routing method. The hydropower model was not used in the Ganges-Meghna-Brahmaputra application.



ANNEX II CROP PRODUCTION AND WATER BALANCE MODULES FOR THE NILE BASIN

II.1 THE WATERWISE-NILE MODEL

WaterWise has external modules on water, food and energy providing the optimization model various land use and reservoir options to choose from (Section S2). These options are interconnected through the WW network of river trajectories (arcs) and nodes, to which hydrotopes are linked, areas of similar soil, meteorology and vegetation characteristics within a subcatchment (Figure S1). This node-arc-area representation is more flexible and generic than the commonly used node-link representations, with “nodes” having multiple meanings, including that of river trajectories (Cai et al., 2003), or nodes also referring to “users”, including the water use by cropped areas (McKinney and Savitsky, 2001). In the latter approach arcs just transfer water and only nodes change water quantity. In our approach water quantity can change in both the nodes and the arcs, and the connecting function of nodes is clearly distinguished from the water use and supply by areas, i.e. hydrotopes, in the vicinity of the nodes.

In the WaterWise-Nile application (WW-Nile), daily water fluxes and seasonal crop productivity are calculated by the external water and food modules at a 1km² pixel scale and then aggregated to the hydrotope units. The pixel level is included for modelling minor climatic variations. In the Nile basin, 1371 hydrotopes were distinguished, clustered in 120 sub-catchments (Figure S1). The water balance and productivity terms at the level of hydrotopes are input into the optimization component of WW-Nile and used as coefficients of the decision variables. The schematization further includes an aggregation to the level of the 10 riparian countries. The sub-catchments were delineated with AVSWAT (Luzio et al., 2004) based on the Digital Elevation Model of the Shuttle Radar Topography Mission (SRTM) (Farr et al., 2007). AVSWAT also generated the main surface water system.

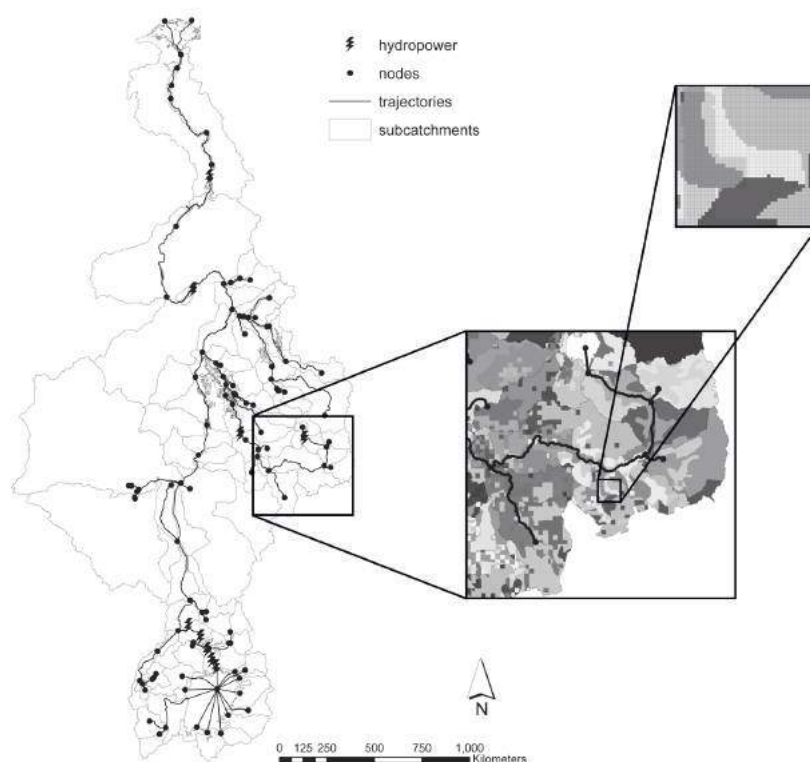


Figure S1 Surface water system with nodes and trajectories (i.e. arcs) and subcatchments of the Nile basin with, in detail, the hydrotopes (shades of grey) and pixels (grid cells)

The model is bounded by investment costs for all major land conversions and new irrigation and hydropower schemes. Depending on the scenario, the model either optimizes total yield-over-cost or yield-over-cost for a certain sector in a specific set of countries (e.g., irrigated agriculture in Sudan and Ethiopia). The allocation of investment capital is not labelled for use in any specific country or sector. The investment strategy thus represents a situation in which a social planner (e.g., a donor agency, investor, or creditor) looks for the highest return on investment (ROI) within the whole basin.

In the next sections, first the individual module concepts for the Nile application will be described. A validation of module results is given with available data on runoff for the various regions and agricultural yield estimates for the basin as a whole. Results in the form of water productivity of different uses are then presented, highlighting the difference between the value of water of the different irrigation systems and various hydropower projects. Finally, results from a limited sensitivity analysis are discussed.

II.2 MODULES

II.2.1 WATER MODULE

The water balance computations are performed by a pre-processor at the basic pixel level, at a daily time step. In the Nile application a soil moisture accounting model of the bucket type is used, very similar to the Aquacrop method of the FAO (Raes et al., 2011), but more advanced in simulating soil storage and drainage, while simplifying the dynamic crop growth. Rainfall in each pixel can contribute to runoff, drainage, or groundwater storage, after correcting for evapotranspiration (Figure S2). The calculation scheme for the evapotranspiration follows the FAO single crop coefficient method (Allen et al., 1998), applied separately to the vegetated and non-vegetated part. The development stage of a crop is assumed to follow a pre-fixed pattern during the season, which is translated to a time-dependent crop coefficient:

$$ET_p = K_c ET_o$$

where ET_p is the potential evapotranspiration, ET_o is the reference crop evapotranspiration, and K_c the time-dependent crop factor. Outside the actual growing season the crop factor is also given a value, to account for the evaporation of developing shrub vegetation and bare soil. The potential transpiration is reduced to the actual value by taking water stresses into account, like is done in the FAO AquaCrop model:

$$ET_a = K_s ET_p$$

where ET_a is the actual evapotranspiration and K_s is the time-dependent soil water stress coefficient. The stress coefficient is set proportional to the soil water content:

$$K_s = S_r / S_{opt} , \quad \text{for } S_r < S_{opt}$$

$$K_s = 1.0 , \quad \text{for } S_r \geq S_{opt}$$

where S_r is the available water root zone content above wilting point, and S_{opt} the lower limit of soil water content for which the transpiration retains the potential value.

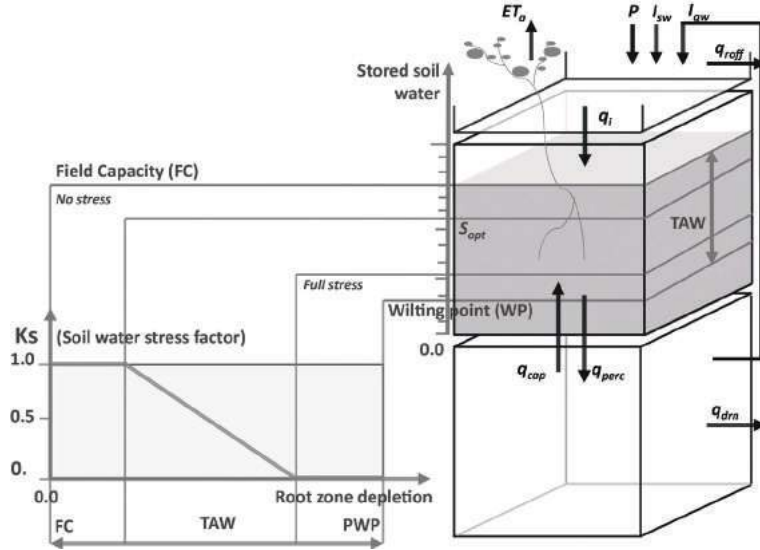


Figure S2 Water module storage components and flow terms (adapted from Raes et al., 2011)

The water storage accounting method uses three storages: one for the soil surface, one for the root zone and one for the subsoil. The accounting method starts with determining the infiltration at the soil surface. After the initial update of the soil surface storage the possible infiltration rate q_i is determined as the limiting value of: i). amount of water on the soil surface; ii). infiltration capacity of the soil, and; iii). available storage deficit of the soil. The soil surface is assumed to have a certain retention capacity in situations with ponding. The moisture accounting for the root zone first does the update for the flows across the upper boundary:

$$S_r^t = S_r^{t-1} + (P + I - ET_a) \Delta t$$

where S_r^t is the amount of water stored in the root zone, and S_{FC} is the water storage at field capacity, P is precipitation and I is irrigation. If the predicted storage is larger than the field capacity, then the excess is simulated as percolation and the storage is set equal to field capacity:

$$q_{perc}^t = (S_r^t - S_{FC}) / \Delta t; \quad S_r^t = S_{FC}$$

The model also has a simple provision for 'capillary rise' from the subsoil storage under extremely wet conditions; that is assumed to be the case when

$$S_g > S_{max} - S_{FC}$$

where S_g is the storage in the subsoil, and S_{max} is the storage capacity of the whole profile, taken with respect to a certain datum plane. A second requirement for simulating capillary rise is that the root zone water content has dropped below S_{opt} , meaning that the actual evapotranspiration is being reduced with respect to the potential value. The drainage flux is simulated with a linear reservoir approach:

$$q_{drn} = \alpha (S_g - S_{g,db})$$

where α is the reservoir coefficient and the subsoil storage for the groundwater level equal to the drainage base.

In WW-Nile, a pixel can draw water from three sources: i) sustainably from its own local groundwater storage component; ii) from the local surface water storage of each sub-catchment; and iii) from the main water courses and reservoirs (Nile, Atbara etc.). Irrigation demand is triggered by the root zone moisture storage, when it has dropped below a specified fraction of S_{FC} . The demand is then computed with:

$$I_{dem} = (S_{FC} - S_r) / f_{app}$$

where I_{dem} is the irrigation demand and f_{app} the assumed application efficiency. The realization of the demand can be from groundwater or from surface water, or from both. In the latter case the model first tries to extract groundwater; if there is not enough available the model supplies the deficit from surface water. The amount of available groundwater is determined from:

$$q_{g,max} = (S_g - S_{g,dead}) / \Delta t$$

where $q_{g,max}$ is the maximum allowed extraction rate and $S_{g,dead}$ is the water in 'dead' storage. By not allowing extraction to draw from dead storage, the model implements the policy of sustainable mining of groundwater. Irrigation from surface water is assumed to involve extra losses. Some of these losses are recoverable, some not. Both types of losses are anticipated by increasing the demand:

$$I_{s,dem} = I_{dem} / (1 - f_{loss,rec} - f_{loss,nonrec})$$

where $f_{loss,rec}$ is the fraction of recoverable losses and $f_{loss,nonrec}$ of non-recoverable losses. The recoverable losses are added to the drainage term. That drainage flows back to the main waterways and becomes available for irrigation from surface water at a downstream location. Irrigation comes at a cost, made up from two components; a fixed cost in USD per ha and a variable costs in USD per m³ of water used. Together these form the costs of local water-management measures for supporting land use (CLWM).

II.2.2 CROP MODULE

Crop production is simulated with a slightly modified form of the K_y approach of FAO (Doorenbos and Kassam, 1979), which most holistic models use for modelling the effect of water availability on crop production. This relatively simple method has the advantage of being robust and requiring a minimum of data. For modelling a specific situation the K_y method requires less parameters than a model like AQUACROP for calibrating a good fit. In the modelling of large basins the robustness and minimum data requirement of the K_y method reduces the risk of model errors due to wrong input data. The method consists of a single modelling equation for the relative yield:

$$(1 - Y_a/Y_p) = K_y(1 - ET_a/ET_p)$$

where Y_a is the actual yield, and Y_p the potential yield, with ET_a/ET_p derived from the water balance module. Values of $K_y > 1$ are for crops sensitive to water stress as assumed here throughout. Making the equation explicit for the relative yield gives:

$$Y_a/Y_p = [ET_a/ET_p - (K_y - 1)/K_y] K_y, \text{ for } ET_a/ET_p \geq (K_y - 1)/K_y$$

$$Y_a/Y_p = 0, \text{ for } ET_a/ET_p < (K_y - 1)/K_y$$

This relationship takes into account that the available water has to exceed a certain threshold for the production of a harvestable product⁷. What it does not take into account is that with increasing degree of water supply there will be diminishing returns for the crop production, meaning that the productivity curve has an S-form. In the WW-Nile model this has been schematically introduced by adding an extra intercept parameter for when the relative productivity reaches 1.0 (Figure S4)⁸:

$$Y_a/Y_p = 1.0, \text{ for } ET_a/ET_p \geq f_y$$

$$Y_a/Y_p = [ET_a/ET_p - (K_y - 1)/K_y] c_y, \text{ for } ET_a/ET_p \geq (K_y - 1)/K_y \text{ and } ET_a/ET_p < f_y$$

$$Y_a/Y_p = 0, \text{ for } ET_a/ET_p < (K_y - 1)/K_y$$

⁷ Formal representation of this threshold introduces a strong nonlinearity in a mathematical programming model, especially if used in combination with land use area as an endogenous decision variable. Therefore the threshold is usually disregarded in the model formulation, e.g. in the Zambezi model of Tilmant et al. (2012). The consequence can be that for $K_y > 1$ their model is forced to supply water to meet the feasibility constraint (non-negative yield), but that the yield is exactly at zero. This we consider an avoidable loss of optimality. In the IBMR model of Yang et al. (2012) the soil-water-plant water balance is directly incorporated in the holistic model. Water shortage is modelled with slack variables that are used in a penalty term of the objective function. In order to avoid a negative yield (implicitly), the crop response must be made completely linear ($K_y = 1$, no threshold).

where f_y is the extra intercept parameter (within $[(K_y - 1)/K_y, 1]$) and c_y is given by:

$$c_y = 1 / [f_y - (K_y - 1)/K_y]$$

In WW-Nile we used two values of the K_y factor. We assumed that on existing rainfed arable land there is scope for an improvement in crops or cropping practices over the period considered. To represent this improved cropping system, an intensive crop variant was introduced; this variant has higher input costs and a steeper production function (higher K_y) and thus a higher threshold value for crop survival (Figure S3). However, its crop production also has a higher price. As a result, the intensive variant was less profitable under conditions of water stress, but gave higher GM when crop water demand could be met.

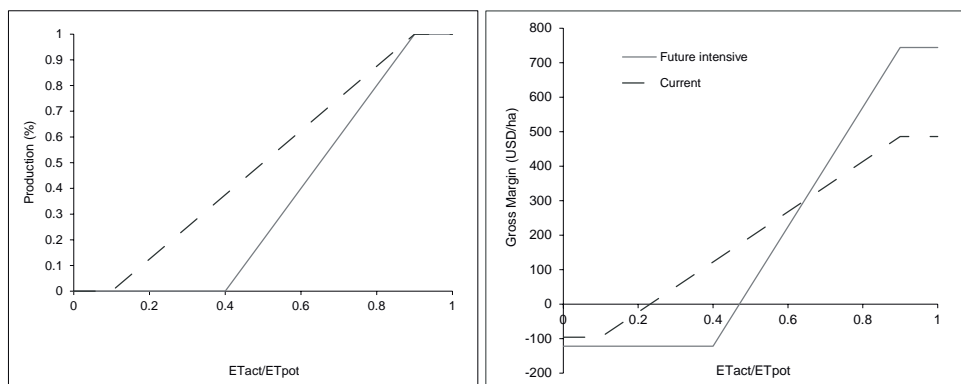


Figure S3 Crop production as a function of water availability (actual evapotranspiration / potential evapotranspiration) and Gross Margin for a 'current' cropping system and the near-future 'intensive' option, using cost and benefits from the Maize-Potato dominated cropping system of Tanzania as an example.

II.2.3 ENERGY MODULE

The WW Hydropower module has two options to calculate the yield of a hydropower scheme; one in which water level in the reservoir (head) influences the energy generated and one where the head is assumed static and flow stationary over the period considered. We choose the latter, more simplified option, as we were mainly interested in the overall yield in relation to basin-wide changes of land use and major changes to the river system,

⁸ This type of nonlinearity is more often included than the zero-production threshold. Marginal returns tend to decrease as the water availability approaches the potential demand. This aspect can be modelled with a piecewise linear function using only linear variables or with a quadratic function as is done in e.g. Cai (2003). We have added an extra parameter to the K_y method, for schematically modelling the reduced rate of return near the production optimum (Figure S4)

rather than focusing on optimizing the management of reservoirs in detail. In WW-Nile the storage dynamics of reservoirs are controlled by optimizing the release for hydropower and/or irrigation on a 3-monthly time step. The energy production according to the static head stationary flow method can be described as:

$$E_{hydropower,\Delta t} = \rho g h_d \beta \frac{\gamma V_{in,\Delta t}}{\Delta t} \frac{\Delta t}{3600} 10^{-3}$$

where $E_{hydropower,\Delta t}$ is total energy produced (kWh), Δt is length of season (s), ρ is the water density (kg/m^3), g is the gravity constant (m/s^2), h_d is static water height at turbine (m), β is the fraction diverted for hydropower (-), γ is the turbine efficiency (-) and $V_{in,\Delta t}$ is the volume of water entering the reservoir (m^3). With ρ , g , h_d , and β constant and $\gamma V_{in,\Delta t}$ equal to $V_{out,\Delta t}$, this can be rewritten as:

$$E_{hydropower,\Delta t} = \frac{E_{\text{maximum capacity}}}{V_{\text{max}}} \frac{V_{out,\Delta t}}{\Delta t} \frac{\Delta t}{3600} 10^{-3}$$

where $E_{\text{maximum capacity}}$ is a function of energy produced at maximum flow (V_{max}) through the turbines. These are a site-specific characteristics depending amongst others on the height difference and the turbine size and efficiency and are generally reported for hydropower schemes. Based on this maximum capacity, maximum flow through the turbines, and a generally accepted average world market price for hydropower-generated electricity of 0.08 USD/kWh (Whittington et al., 2005), a revenue per m^3 of flow through the turbines was determined for each of the hydropower stations. Actual revenue was then calculated by the model as actual simulated flow times this revenue per m^3 . No costs were included. Aggregating all hydropower revenues leads to the total GM of hydropower (YHP , in USD/yr).

Table S1 shows the existing large reservoirs and hydropower generation facilities, as well as all major proposed new dams. Figure S3 shows the location of the major hydropower dams in the main rivers within the Nile Basin. Data was collected from various sources, most of them grey literature. Cost of large scale hydropower investments are described in table S1 and range from 450 million USD to 4700 million USD for individual schemes. It is very likely that these figures do not include all costs involved, like a possible reallocation of the local population.

Table S1 Characteristics of existing and potential hydropower stations in the Nile basin (Deekker, 1972; Murakami, 1995; Shahin, 1985; Sutcliffe and Parks, 1999; www.small-hydro.com, 2012)

Country	Hydropower station	Investment (million USD)	Capacity (MW)	Maximum discharge (m ³ /s)
Uganda	Owen Falls	Existing	300	1800
Ethiopia	Tis Abbay & II, Tana - Beles	Existing	544	180
Sudan	Roseires	Existing	210	1689
Egypt	Aswan Old Dam and High Dam	Existing	2600	4152
Uganda	Bujugali	730	250	1316
Uganda	Kalagala	680	315	1344
Uganda	Karuma Falls	450	200	577
Uganda	Ayago, Murchison	1000	800	400
Ethiopia	Grand Ethiopian Renaissance Dam	4700	5250	1750
Sudan	Merowe	1700	1250	3600

II.3 VALIDATION OF MODULE OUTPUT

The hydrological modelling was validated with averaged yearly water balance data for the main subcatchments (MWRI, 2005; Sutcliffe and Parks, 1999). WW-Nile runoff from the main contributing catchments corresponds well to the figures of these two studies. The impact of marshes on water losses in the White Nile, the Bahr El Gazal, and Sobat catchments was well represented. Releases at Lake Nasser were determined by irrigation demands in downstream Egypt. Water losses in Lake Nasser were calculated at 15 km³/yr; this is higher than the often reported long-term average losses of approximately 10 km³/yr, but corresponds to the estimated maximum evaporation loss. Overall water losses in the main surface water system (seepage and evapotranspiration, including marshes in the Bahr El Ghazal) accounted for 84 km³/yr in the whole basin. Total average annual water abstraction for irrigation was estimated to be 86 km³, with 2 km³ in the Atbara basin, 14 km³ in the Blue Nile sub-basin in Sudan downstream of the Roseires Reservoir and 70 km³ in the valley and delta of Egypt. With 16 km³, including return flows, Sudan currently abstracts several km³ less than the 18.5 km³ it has been allocated under the 1959 treaty. The water abstractions of 70 km³ to Egypt support unofficial estimates, suggesting that actual releases at Aswan are higher for the period evaluated than the, often reported, officially allocated 55.5 km³ (Nicol and Cascão, 2011). These figures include canal losses and return flows.

The food module was validated with the single available FAO estimate for the basin (Appelgren et al., 2000). The annual agricultural GM calculated for the baseline situation was

15.3 billion USD per year, which is about 35% lower than the FAO estimate. The inclusion of livestock in the latter figure, estimated at 18-35% of African agricultural GDP (Ehui et al., 2002; Sansoucy, 1995), can explain a large part of the difference. Livestock was not included in our analysis, as we focused on arable farming, which has a far larger claim on land and water resources. We assumed livestock raising to be integrated with arable farming in mixed agricultural systems, without explicit additional land and water demands. An exception to this in the Nile basin could be the large grazing areas in Sudan and South Sudan. Conversion of these existing pastoral lands to arable lands was not restricted in the model. However, in general, the model did not select these areas for arable expansion. The mere existence of pastoral lands can, in itself, be an indication that biophysical circumstances make such lands less suitable for arable farming, for example because of erratic or strong seasonality in rainfall. The potential yield of 4 kg/ha for rainfed agriculture that we imposed, based on the maximum country-specific yield, corresponds well with earlier estimates for maximum crop yields in East Africa for the near future (Penning de Vries et al., 1997). By using a region-specific potential, region-specific limiting factors other than water, for example, phosphate shortages, pests, or restrictions in the agro-food chain infrastructure, are implicitly taken into account.

Figures on actual hydropower production for the various hydropower schemes or the region as a whole are not easily obtained. Our estimates of total energy production were thus not validated. However, the used yield value of 0.08 USD per kWh is widely accepted to as a global estimate of hydropower yields and our results will therefore mainly differ from previous model estimates (Block and Strzepek, 2010; Whittington et al., 2005), because of a different optimization of water flows.

II.4 OPTIMIZATION MECHANISM: THE VALUE OF WATER IN THE NILE BASIN

In Figure S4, water productivity of irrigation and hydropower in different countries, as derived from WW-Nile, is compared. The range of values in WW-Nile for existing irrigation schemes in Egypt and Sudan is consistent with the low (0.02 USD/m³) and high estimates (0.08 USD/m³) that are generally used (Whittington et al., 2005) or reported (Hellegers and Perry, 2006). New irrigation schemes in Ethiopia have a much higher productivity per m³ applied (0.18 USD/m³). This is a result of the relatively high effective rainfall in combination with a lower potential evapotranspiration and thus a smaller threshold deficit to be covered by irrigation for getting the revenue from the steep part of the production curve. The low productivity of Sudan's existing schemes (0.025 USD/m³) can be explained by lower agricultural productivity due to waterlogging and siltation of canals; its maximum attainable yield is assumed to be only half of Egypt's maximum. When the existing schemes

are rehabilitated, irrigation water demand in this part of Sudan becomes similar to that of Egypt, resulting in similar water productivity (0.08 USD/m³). New irrigation schemes in Sudan are envisaged near the new Merowe reservoir in the north of the country. High evapotranspirative demand and very low rainfall result in a very high irrigation demand per hectare and a comparatively low water productivity (0.05 USD/m³) in these schemes. Hydropower stations with the highest water productivity (Figure S4) are mainly situated upstream in Ethiopia and Uganda, where hills and mountains provide possibilities for high dams (Ethiopian Renaissance Dam) or create natural elevation differences (Tana and Ayago-Murchison). The resulting large drop in water level delivers more MW at a lower discharge. There is no competition between hydropower and irrigated agriculture as the latter is situated mainly downstream of these high water-productive hydropower plants. In cases where there is competition, the water productivity of agriculture is higher than that of hydropower, even when adding up hydropower yields of stations in series (like Merowe and Aswan on the main Nile). As a result, irrigated agriculture will receive priority in the allocation of water. On the other hand, the existence of hydropower strengthens the prioritization of downstream irrigation. This is in line with hydro-economic principles described in previous studies focusing specifically on the interaction between hydropower and irrigation in the basin (Block et al., 2007; Whittington et al., 2005).

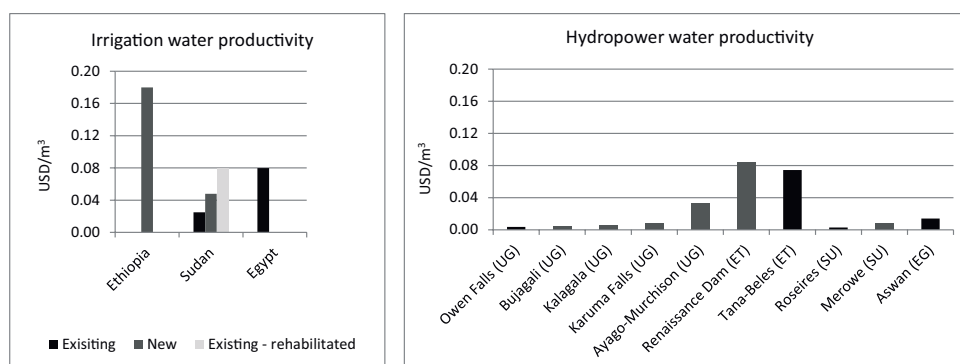
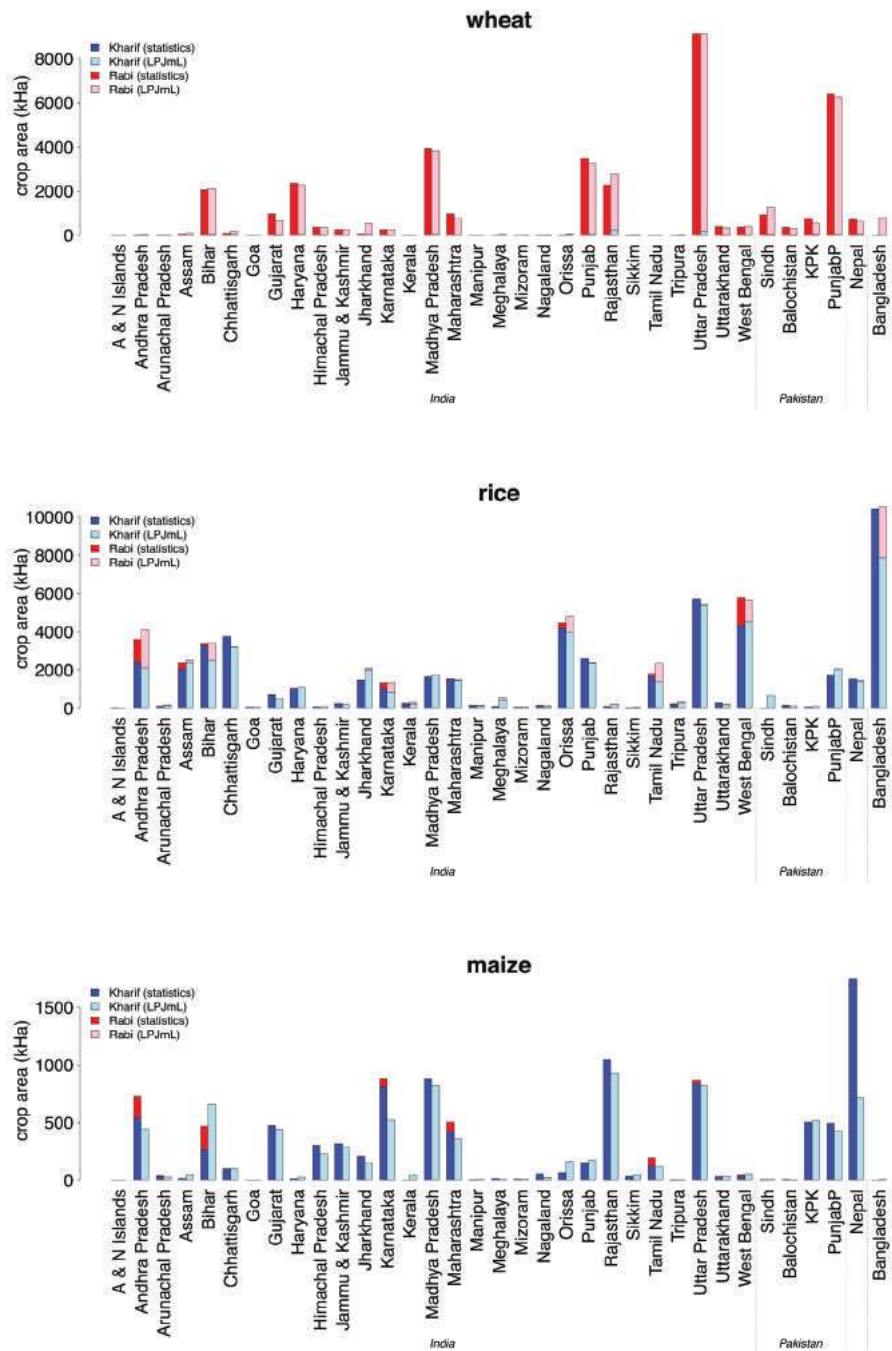


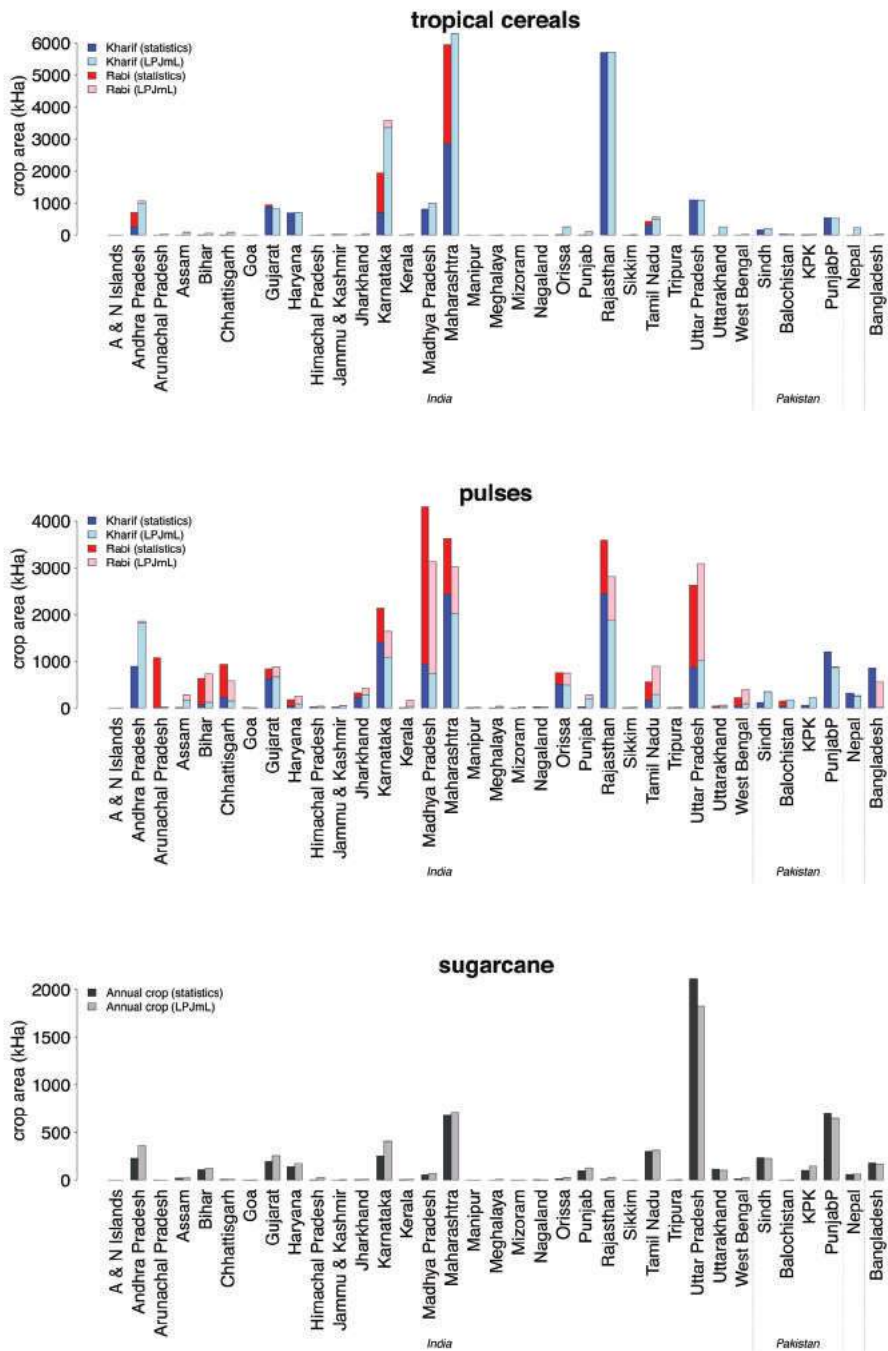
Figure S4 Water productivity for existing, new, and rehabilitated irrigation schemes. Country averages are based on irrigation water demand, which is a result of: potential evapotranspiration minus effective precipitation multiplied by irrigation efficiency; a maximum gross margin of approximately 1800 USD/ha for new/rehabilitated schemes (and 600 USD/ha for degraded schemes in Sudan) and for existing and (potential) new hydropower stations (based on a kWh price of 0.08 USD, with UG = Uganda, ET = Ethiopia, SU = Sudan and EG = Egypt).

II.5 SENSITIVITY ANALYSIS OF ECONOMIC PARAMETERS

A partial sensitivity analysis was performed on three parameters: the yield of hydropower, the yields of the current irrigation system in Sudan schemes (which are lower than Egypt's and difficult to estimate with precision), and the investment cost of land cover change. Together, these three parameters determine the balance in prioritizing hydropower, irrigation agriculture, or rainfed agriculture. Values were increased and decreased by 25%, at a 125 billion USD investment level. Varying the price of hydropower (0.08 USD/kWh +/- 0.02 USD/kWh) has a direct impact on the revenues from hydropower itself, but does not tip the balance between the ROI of hydropower and land use investments. Varying the yields of Sudan's current irrigation also does not change the outcome much in terms of total basin food production. Under both an increase and decrease, Sudan actually increases its food production slightly. With 25% lower yields under the current irrigation schemes, there is more incentive to invest in their rehabilitation at the cost of some conversion to rainfed agriculture in Ethiopia, as this leads to a higher ROI, buffering overall basin loss in GM. With 25% higher yields, the part not rehabilitated keeps providing slightly higher GM for Sudan, leading to overall higher total basin GM as well. Varying the investment costs of land use conversion has an effect on food production and total basin GMs, but does not alter the main outcomes. With 25% lower investment costs, more land can be converted, leading to a 2 billion USD increase in agricultural and total GM. With 25% higher costs, agricultural GM decreases by only 1.3 billion USD; that is because Sudan partly compensates for the higher costs of land use conversion by rehabilitating more irrigated area and converting less rainfed area.

ANNEX III VALIDATION OF SOUTH ASIAN LAND USE





Figures S1 to S6 comparison of land use according to state and country statistics and LPJmL input adapted from MIRCA2000 (Portmann et al., 2010)

ANNEX IV CHANGES IN VARIABILITY OF CROP PRODUCTION, YIELD AND AREA IN INDIA



Overall, at all-India level, fluctuations in crop production have increased in absolute terms, but decreased in relative terms, as a result of large increases in area, yield and production over the past decades (Table S1). We split the data in three parts: 1950-1965, representing the pre-Green revolution period, 1965-1990 the era of cropland expansion and increases in yield and production and 1991-2013 as the liberalization period in which India opened its markets and liberalized its economy. For both rice and wheat absolute variability in production has increased over the periods considered. But, as total production has increased faster, relative variability in production has decreased from 11.4% (for rice) and 15.6% (for wheat) in the first period cropped to 6.4% (for rice) and 6.3% (for wheat) in the most recent period. Yield variability shows a similar pattern. Only the change in variability in area differs between rice and wheat; fluctuations in cropped area of rice have become larger while those in cropped area of wheat seem to have become smaller in both absolute and relative terms.

Table S1 Changes in absolute and relative cropped area, yield and production variability for rice and wheat in India (expressed as standard deviation and relative standard deviation)

	Absolute variability (SD)			Relative variability (% RSD)		
	Area (in million ha)	Yield (in kg/ha)	Production (in tons)	Area	Yield	Production
Rice						
1950-1965	0.59	83.9	3.32	1.8%	9.6%	11.4%
1966-1989	0.89	93.0	4.60	2.2%	7.1%	8.7%
1990-2012	1.18	97.7	5.37	2.7%	4.9%	6.4%
Wheat						
1950-1965	1.13	71.5	1.77	8.3%	8.8%	15.6%
1966-1989	1.19	88.6	2.45	6.4%	6.5%	9.1%
1990-2012	0.88	124.7	5.14	3.2%	4.6%	6.3%

* P < 0.1 (double-sided F-test)

** means P < 0.05 (double-sided F-test)

ANNEX V CORRELATION BETWEEN INTER-ANNUAL RAINFALL ANOMALIES AND CROP PRODUCTION ANOMALIES



To get an indication how much of the observed variability in production is associated with rainfall, we estimated the correlation between rainfall anomalies (for the monsoon, i.e. the total of JJAS months) and anomalies in de-trended annual production data. R-squared of such a correlation represents the explained variance, in this case by rainfall, divided by the total variance. From this it follows that Pearson's r represents the explained standard deviation (σ_{prod}). We multiplied the Pearson's r value with observed σ_{prod} for the shorter time series for our model domain at different spatial aggregation levels (district, state, basin), to get an estimate of rainfall-induced variability at each level. This allowed us to compare results of the model with observations. We thereby assume that the influence of rainfall variability on rice and wheat production in the Ganges basin is similar to that for the whole of India, an assumption that seems reasonable as approximately 50% of rice and 70% of wheat production occurs in states within in the basin. We used a Fisher's z' transformation to calculate the upper and lower bound (90% confidence interval, $n = 57$) around the Pearson's r value.

We found the correlation between monsoon rainfall and de-trended production anomalies to be of medium strength, with a Pearson's r of 0.61 for rice and Pearson's r of 0.50 for wheat for the whole of India over the period 1951-2007, indicating that 61% and 50% of standard deviation in production (σ_{prod}) can be explained by rainfall variation. Applying a 90% confidence interval, using the Fisher's z transformation, gave an indicative range for the influence of rainfall variations on rice σ_{prod} from 46% to 74%. For wheat, the indicative range is from 31% to 65% (as reflected by the uncertainty ranges, "Observed rain-induced", in Figure 4 and 6 in the main text). In an extensive earlier study on the relation between climate and food production in India, Krishna Kumar et al (2004) found $r = 0.77$ for the correlation between rice production anomalies and rainfall anomalies and $r = 0.47$ for wheat. Mainly the difference in de-trending method – Krishna Kumar et al. took the relative difference between the value in one year compared to the value of the previous year – explains the lower correlation for rice in our analysis.

⁹ *Agricultural Statistics at a glance 2012, Government of India, Ministry of Agriculture, New Delhi.*



SUMMARY

A major global challenge is to produce enough food in a changing climate. One of the main manifestations of a changing climate will be increased rainfall variability. This thesis explores flexibility in land use through deliberate seasonal adjustments in cropped area as a specific strategy for coping with inter-annual rainfall variability. Together with diversification, flexibility forms an evolutionary potential to adapt to changing circumstances. Whereas diversification has been given ample attention as an approach to adapt to climate change in agriculture and water management, flexibility, with its focus on temporal and intentional, pro-active aspects of adaptation, has received less attention.

The main aim of this thesis is to further enhance our understanding of flexible strategies for coping with rainfall variability in two important food producing regions, South Asia and east Africa, and to explore the future of food production under these variable conditions. Two major basins, the Ganges and the Nile basin, provided relevant case-study examples. The study design follows a classic approach of empirical studies combined with exploration by modelling: two retrospective studies determine the extent of current rainfall variability and flexibility in land use from the local to the regional scale. At the regional scale, for the Ganges basin, an existing hydro-economic model called 'WaterWise' was further developed to explore the concept of flexibility. The same model was applied to the Nile basin to find the best allocation of land and water resources to meet future food requirements, shifting focus to permanent land use changes rather than seasonal adjustments in cropped area.

In the first part of this thesis (chapters 2,3 and the first part of chapter 5), the sensitivity of the agro-ecosystem to rainfall variability is determined and cropped area-related coping strategies are identified. A longitudinal study of land and water use in a tank irrigation site, using six years of water use and crop production data, shows that high rainfall variability leads to considerable inter-annual fluctuations in cropping intensity, income and water productivity. Farmers demonstrate great flexibility in dealing with this rainfall variability. Results suggest that improved conjunctive use of water lead to a more stable cropping intensity, increased economic water productivity and a higher net agricultural income. Remote sensing was then applied as a tool to observe sensitivity of the cropping system to rainfall variability at the catchment scale, and to identify deliberate, flexible response in the form of a seasonal adjustment in cropped area. Such a coping strategy of leaving more land fallow during dry years is observed primarily in the drier western part of the Ganges basin.

An analysis of time-series data derived from Indian government statistics on crop yield, area and production shows that seasonal adjustments in cropped area can explain up to 50% of the existing variability in food production. This makes these adjustments almost as important as variability in yield.

In the second part (Chapters 4 and 5), it is shown that variability in crop production can be simulated well if cropped area is allowed to vary, and is made dependent on the costs of cultivation and the amount of groundwater available. For this, cropped area was introduced as an endogenous decision variable in a hydro-economic optimization model, WaterWise. Using crop yields and water demand from an existing crop-vegetation model (LPJmL) - updated with a region specific seasonal cropping pattern and monsoon dependent planting dates (Chapter 4) - as inputs, WaterWise was validated against observed variability in crop production. With the validated model, the value of flexibility was quantified, i.e. the foregone costs of choosing not to crop in years when rainfall is scarce. The value of flexibility in the Ganges basin appears to be higher for wheat than for rice. In the drought prone state of Rajasthan the value of flexibility for wheat is estimated as high as a 34% increase in gross margin.

In the third part of this thesis (Chapter 6), the WaterWise model was used to explore future food production in the Nile basin under various cooperation scenarios. It is shown that the future of food production lies not in the disputed reallocation of irrigation water, but in utilizing the vast and forgotten potential of rainfed agriculture in the upstream interior, with supplemental irrigation where needed. Expansion of rainfed agriculture is suggested primarily in unstable regions of South Sudan and northern Uganda.

The study demonstrates that flexibility in land and water use is a relevant strategy for coping with increased rainfall variability in regions where there is a strong seasonality in rainfall, where a second crop is cultivated using water stored in reservoirs, soil or shallow aquifers, and/or where seasonal rainfall is highly predictable. Such conditions occur in much of the monsoon-dominated (sub)tropics. Agricultural production in these regions will have to increase to feed a growing population. This thesis supports pleas for a transition towards a climate-smart sustainable agriculture, with information exchange, infrastructure development and strengthened institutional capacity essential to deal with current and future rainfall variability in both basins.

ACKNOWLEDGEMENTS

Writing this thesis would not have been such an interesting and exciting exercise had I not been supported by so many colleagues, friends and family.

First of all I would like to thank you, my promotors, Ekko van Ierland and Pavel Kabat, and co-promotor, Petra Hellegers, for guiding me all these years. We did not really know each other before and I am happy that you were willing to take the risk of engaging with me, while I kept on working for Alterra. There were always projects to be finished, trips to be made or proposals to be written, but you remained patient and managed to lure me away more and more from day-to-day project work. Ekko, you taught me – amongst others - how to build up a storyline and you pushed me to dig deeper and think a step further than the obvious. Pavel, you would grasp the content within a couple of minutes, making suggestions for a better introduction or title in the next. Petra, you were honest, sharp and critical - I enjoyed our discussions a lot.

This PhD period is intrinsically linked to my time at Alterra. I would like to thank my successive team leaders at Alterra, Frank, Jochen and Eddy, for supporting me, by shielding me from all the institute's regular tasks and chores. Frank, you planted the seed in my head and gave me the freedom to let it grow. Jochen, you created the projects to keep me working in India, teaching me the art of acquisition on the go. Eddy, you showed me how to finish a PhD while leading challenging projects with international partners. Our climb to the source of the Ganges was one of the highlights for me. Paul, thank you for introducing me into your masterpiece; the WaterWise model. I admire your skill of putting thoughts and concepts in code - and making it work. I hope our cooperation will continue.

I very much enjoyed the company of my colleagues; Hester, Annemarie, Koen, Robert, Wouter, and all with whom I shared work trips to India and Nepal, writing weeks, spontaneous Tour de France rooftop afternoons, rare nights out, the occasional wedding or just simple coffee moments. Thanks to all in the ESS group that joined the tasty international dinners, movie nights and fun dance evenings.

Ype and Arnaut, the trilogy is completed. It was an honour to be your paranymp and I am glad I can finally return the favour. Bert, being the reserve paranymp is never an easy role, but it is one you bear well.

Outside of work I was lucky to have many friends around; the 'Oosterhout group' who were always interested and understanding, in the typical down-to-earth style of the Brabanders

('when is that little essay of yours finally finished?'); the study friends from CP, my old student house (being the seventh Dr out of eleven is not a bad score!); and the many new friends abroad (Stuti, I will make it to Hyderabad someday). If there has been any neglect, I will try to make up for it –you are all welcome in London.

Then, almost last but not least, I want to thank my family for always providing a welcome home during these years. Mom, while I tried to advance my knowledge in science you and dad taught me a lot about life - about cherishing all the good moments, dealing with the challenges and setbacks of illness and gracefully accepting the inevitable. I am deeply impressed.

Finally, Tanya, you make life so much more beautiful and interesting. The past years have been amazing and I'm looking much forward to the next phase, celebrating life together. One can never celebrate enough!

SHORT BIOGRAPHY

Christian Siderius was born in Ede, Gelderland, The Netherlands on March 10, 1978. He grew up in Weert and Oosterhout, where he attended the St Oelbert Gymnasium, graduating in 1996. He then went to Thailand for a year to work for a gibbon rehabilitation project.

Christian studied 'Soil, Water and Atmosphere' at Wageningen University from 1997 until 2004, specialising in hydrology. He completed his minor MSc thesis with the Soil Erosion group determining the water use of olive trees and the effect of water harvesting near Aleppo, Syria, working for four months at ICARDA. He completed his major MSc thesis with the Integrated Water Management group in cooperation with the 'Rijksinstituut voor Kust en Zee' (RIKZ) in Middelburg focusing on a scenario analysis of the south-western delta in the Netherlands. For his internship he went to Jambi, Sumatra, Indonesia, to measure and model the subsidence of peat swamps due to logging and forest fires – a topic still very relevant today. This was done at Alterra, part of Wageningen University and Research Centre, in partnership with IAC Wageningen, Jambi University and Wetlands International Indonesia.

Upon completion of his internship in 2004 Christian was asked by Alterra to further improve his peat swamp model and to train Indonesian and Malaysian scientist in applying it. He then joined Alterra permanently. Between 2005 until 2012 he worked on various Dutch and European research projects in the field of water quality, focussing mostly on sources and pathways of eutrophication and salinization. From 2008 onwards his research focus slowly shifted towards climate change adaptation and water allocation issues, with research projects increasingly situated in South Asia. Christian worked on research projects like APWAM, HighNoon, Water4Crops and HI-AWARE, visiting India, Nepal and Pakistan often.

For the last five years Christian combined his research position at Alterra with an external PhD at the Environmental Economics and Natural Resources Group and the Earth System Sciences Group, both part of Wageningen University. In this PhD research he explored flexibility in land use as a specific strategy for coping with inter-annual rainfall variability. The Ganges and the Nile basins provided two relevant case-study areas. He applied remote sensing techniques, a hydrological model and further developed a hydro-economic model during this period.

Christian will be continuing his career as a researcher with the Grantham Research Institute at the London School of Economics. In this new position he will study decision making under climate uncertainty in Southern Africa. He will also remain connected to Alterra for one day a week, continuing to work on similar issues in South Asia.

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*Netherlands Research School for the
Socio-Economic and Natural Sciences of the Environment*

D I P L O M A

For specialised PhD training

The Netherlands Research School for the
Socio-Economic and Natural Sciences of the Environment
(SENSE) declares that

Christian Siderius

born on 10 March 1978 in Ede, The Netherlands

has successfully fulfilled all requirements of the
Educational Programme of SENSE.

Wageningen, 18 December 2015

the Chairman of the SENSE board

Prof. dr. Huub Rijnaarts

the SENSE Director of Education

Dr. Ad van Dommelen

The SENSE Research School has been accredited by the Royal Netherlands Academy of Arts and Sciences (KNAW)



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The SENSE Research School declares that **Mr Christian Siderius** has successfully fulfilled all requirements of the Educational PhD Programme of SENSE with a work load of 49.5 EC, including the following activities:

SENSE PhD Courses

- o Research in Context Activity: 'Co-organising writing week for the Earth System Science chair (ESS) group and Climate change and adaptive land and water management (CALM) team' (2011)
- o Sense Summer Academy: 'Emerging Issues in Sustainable Energy and Water Systems' (2013)
- o Environmental Research in Context (2015)

Other PhD and Advanced MSc Courses

- o Writing for academic publication, Linda McPhee Consulting (2010)
- o Environmental Economics for Environmental Sciences, Wageningen University (2012)
- o Economics and Management of Natural Resources, Wageningen University (2013)

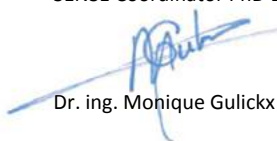
Management and Didactic Skills Training

- o Supervising three MSc students with theses entitled 'The value of short term weather forecasts in a rice-wheat cropping system in North-East India' (2011), 'Impact of snow and glacier melt on the water security of users in the Ganges, India' (2011), and 'Temporal variability of crop production in the Indian Ganges basin' (2013)
- o Teaching in the Spring school 'Uncertainty in water resources modelling', Highnoon project, New Delhi (2012-2013)
- o Co-convenor EGU session 'Socio-hydrology and river basin development: scaling and sustainability issues' (2014)
- o Guest lecturing in the BSc courses 'Environmental Economics in practice' and 'Climate Adaptation' (2014-2015)

Oral Presentations

- o *Future water and food security in the Nile Basin*. OECD Workshop 'Water Allocation and Green Growth', 22 November 2012, Wageningen, The Netherlands
- o *Can we model climate change impacts on India's river basins?: experiences from the Ganges*. Delhi Sustainable Development Summit, 1 February 2013, Delhi, India
- o *The impact of inter-annual rainfall variability on food production in the Ganges basin*. European Geosciences Union – EGU2014, 27 April-2 May 2014, Vienna, Austria
- o *Future directions for adaptation research in the glacier and snowpack dependent river basins of the Himalaya*. 3rd International Climate Change Adaptation Conference, 12-16 May 2014, Fortaleza, Brazil

SENSE Coordinator PhD Education



Dr. ing. Monique Gulickx

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