

Water availability, demand and reliability of in situ water harvesting in smallholder rain-fed agriculture in the Thukela River Basin, South Africa

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Abstract. Water productivity in smallholder rain-fed agriculture is of key interest for improved food and livelihood security. A frequently advocated approach to enhance water productivity is to adopt water harvesting and conservation technologies (WH). This study estimates water availability for potential in situ WH, and supplemental water demand (SWD) in smallholder agriculture in South Africa's Thukela River Basin (29 000 km², mean annual precipitation 550–2000 mm yr⁻¹). The study includes process dynamics governing runoff generation and crop water demands, quantification of prediction uncertainty, and an analysis of the reliability of in situ WH.

The agro-hydrological model SWAT (Soil and Water Assessment Tool) was calibrated and evaluated with the Sequential Uncertainty Fitting algorithm against observed discharge (at ten stations) and maize yield (the dominant crop type) for the period 1997–2006. The water availability was based on the generated surface runoff in smallholder areas. The SWD was derived from a scenario where crop water deficits were met from an unlimited external water source. The reliability was calculated as the percentage of years in which water availability \geq SWD. This reflects the risks of failure induced by the temporal variability in the water availability and the SWD.

The calibration reduced the predictive uncertainty and resulted in a satisfactory model performance. For smallholder maize yield, the Root Mean Squared Error was 0.02 t ha⁻¹

during both the calibration and the evaluation periods. The width of the uncertainty band was reduced by 23% due to the calibration. For discharge during the calibration (evaluation) period, the ten-station range in the weighted coefficient of determination (Φ) was 0.16–0.85 (0.18–0.73), and in the coefficient of determination (R^2) 0.42–0.83 (0.28–0.72). The calibration reduced the width of the uncertainty band by 25% on average.

The results show that the smallholder crop water productivity is currently low in the basin (spatiotemporal median: 0.08–0.22 kg m⁻³, 95% prediction uncertainty band (95PPU)). Water is available for in situ WH (spatiotemporal median: 0–17 mm year⁻¹, 95PPU) which may aid in enhancing the crop water productivity by meeting some of the SWD (spatiotemporal median: 0–113 mm year⁻¹, 95PPU). However, the reliability of in situ WH is highly location specific and overall rather low. Of the 1850 km² of smallholder lands, 20–28% display a reliability \geq 25%, 13–16% a reliability \geq 50%, and 4–5% a reliability \geq 75% (95PPU). This suggests that the risk of failure of in situ WH is relatively high in many areas of the basin.

1 Introduction

Approximately 850 million people currently live in food insecurity, often linked with water scarcity, poverty and stressed ecosystems (FAO, 2009). An expected additional 1–2 billion people will need to be fed by 2025 (UN, 2009). This translates to a veritable water resources challenge in water-limited areas because of the large amounts of water required



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for food production. The strategies to manage water efficiently, and achieve food and livelihood security are numerous and of varied success (Yang and Zehnder, 2007).

A family of strategies focuses on increasing food production on existing agricultural land, avoiding horizontal expansion of low-productivity agriculture, and not further stressing water-limited systems by improving the crop water productivity. Of particular interest in this regard is smallholder rain-fed farming in sub-Saharan Africa (SSA) (Rockström et al., 2004). SSA is significant due to high levels of undernourishment, rapid population growth, and a considerable degree of water stress (Schuol et al., 2008; FAO, 2009). Rain-fed systems are essential for improved food security because of the high degree of reliance of the food insecure population on these systems (Liu et al., 2008). Increasing the crop water productivity in smallholder farming is key since the productivity is often low but has the largest potential to be enhanced (Molden, 2007).

A frequently advocated approach to enhance water productivity in smallholder rain-fed agriculture is to adopt water harvesting and conservation technologies (WH) such as tied ridges and contour bunds, micro-basins, mulching, runoff harvesting, and other conservation farming technologies (Rockström et al., 2004; Gurtner et al., 2006). The core aim of WH is to enhance the resilience of the agroecosystems to some of the biophysical challenges in the tropical savannah biome such as the high spatiotemporal variability in precipitation, and the low soil fertility. The high variability in precipitation causes frequent dry spells and sometimes high water stress during critical crop-growth stages. This often results in low yields and high yield variability (Rockström, 2003). The key function of WH is to alter the partitioning of precipitation into less surface runoff and more soil moisture; and partition more of the soil moisture into crop transpiration and less to soil evaporation. Thus, WH seeks to raise crop water productivity, yields and yield stability (Falkenmark and Rockström, 2004; Rockström and Barron, 2007). In situ WH refer to all technologies which alter the rainfall partitioning of the agricultural fields themselves, while external WH systems concentrate runoff from uncultivated areas onto the agricultural fields (sometimes via storage and supplemental irrigation systems).

The capacity of the WH strategy to fulfil its aim is influenced by a number of spatially varying factors (e.g. rainfall and soil type (FAO, 2003; Ali et al., 2007)). For effective policy-making, it is of key interest to identify the set of potential locations where such factors converge and implementation of WH may be appropriate; i.e. the suitability of a given WH technology. Previous contributions to WH suitability have focussed on various types and purposes of WH, and various aspects influencing the suitability across a range of spatial scales (Table 1).

The surface runoff generation potential constitutes a key component of most suitability studies because it is the principal water source for WH (Makurira et al., 2009). Repar-

tioning from runoff to infiltration has been the principal mechanism through which WH has enhanced crop yield and water productivity on the field scale. Repartitioning from evaporation to transpiration is difficult in the tropical savannah biome because of the high atmospheric evaporative demand, low canopy cover and high opportunity cost of crop residues (Rockström, 2003). The runoff generation potential is primarily estimated either as a ranked runoff level by combining soil, slope, and land use datasets; or as a quantified runoff amount using climatic datasets together with static antecedent soil moisture conditions (AM) and static runoff thresholds (Table 1). The advantage of these estimation methods is their ease of application with readily available datasets. However, they run the risk of over-generalisation by not accounting for the critical temporal variability in e.g. AM and consequential runoff generation potential from a given rainfall event.

Agricultural water use is the most frequent intended purpose of WH in suitability assessments (Table 1). Potential crop water demands are, however, seldom estimated. If included, they are generally estimated as static in time and generic in space. That is despite equally significant spatiotemporal variability in e.g. dry-spell occurrence. This affects the amount of demanded water because of the variability in water demand over the crop growth cycle.

The high variability in climatic conditions in the savannah biome implies that water is not available or demanded everywhere or all the time. Therefore, implementation of WH at any given location involves a degree of risk acceptance that the system may fail to raise crop yields or water productivity. Inclusion of explicit risk accounts may render WH suitability characterisations more transparent and more appropriate for effective and flexible decision-making. Some attempts have been made to assess this risk on the local scale (e.g. Ngigi et al., 2005; Walker et al., 2005; de Winnaar et al., 2007). However, most large-scale integrated suitability assessments implicitly assume a fixed risk level (e.g. considering average annual conditions, Table 1). The reliability of a given WH system, expressed as the percentage of time that the water availability equals or exceeds the crop water demand, is here taken as an indicator of the degree of this risk. A high reliability represents a low risk of failure.

The uncertainty of component datasets and process simulations constituting the foundation of suitability estimates is often rather large (Jewitt, 2006). However, suitability estimates generally lack an uncertainty account without which an unreasonably high level of confidence may be attributed to their predictions (Table 1).

Against this background, the objective of this study was to estimate the water availability for potential in situ WH, and water demands in smallholder agricultural systems by incorporating: (1) spatiotemporal process dynamics governing (i) runoff generation and (ii) crop water demands, (2) quantification of prediction uncertainty, and (3) an analysis of the reliability of in situ WH. The focus was on the Thukela River

Table 1. Overview of approaches to identify potentially suitable locations of WH. AM is antecedent soil moisture conditions.

Study	Type of WH	Purpose of WH	Spatial scale	Method of water availability estimation	Method of water demand estimation	System reliability consideration	Uncertainty consideration
This study	in situ WH	Alleviating field crop water deficits	Thukela River Basin, South Africa (2.9×10^4 km ²)	Daily simulation with dynamic adjustment of AM and runoff thresholds.	Daily simulation of and crop water deficits with dynamic phenological development	Yes, for runoff and crop water deficits	Yes
de Winnaar et al. (2007)	Runoff-harvesting and small reservoir storage	Supplemental irrigation for homestead	Potshini community, Thukela, South Africa (1.2 km ²)	Static runoff thresholds and AM on ranked soil, slope and land use classes.	Indirect: distance to crop fields and homesteads	Yes, for rainfall	No
Mbilinyi et al. (2007)	in situ WH and small reservoir storage	Alleviating field crop water deficits and water stress	Makanya catchment, Tanzania (200 km ²)	Indirect: Weighted overlay of ranked rainfall, land use soil, slope, and drainage.	Not estimated	No	No
Ramakrishnan et al. (2008)	Check dams, percolation ponds	Multiple	Kali catchment, India (200 km ²)	Mean monthly water balance simulation.	Not estimated.	No	No
Kahinda et al. (2008)	in situ WH and ex situ WH	Alleviating field crop water deficits	South Africa (1.2×10^6 km ²)	Indirect: weighted overlay of ranked rainfall, land use and soil.	Indirect: domestic availability of piped water (static)	No	No
Hensley et al. (2007)	in situ WH	Alleviating field crop water deficits	South Africa (1.2×10^6 km ²)	Indirect: soil depth and water holding capacity classification.	Not estimated.	No	No
Mati et al. (2006)	Roof tanks, runoff-harvesting, sand dams, in situ WH	Multiple	Africa (3×10^7 km ²) datasets with static runoff threshold.	Overlay of rainfall, slope, land use, drainage network	Population density.	No	No
Senay and Verdin (2004)	Runoff-harvesting and small reservoir storage	Field crop irrigation	Africa (3×10^7 km ²) thresholds.	Daily simulation with 5-day updating of AM and runoff water demand	Static and generic African average crop	No	No

Basin in South Africa because the WH strategy has been suggested to hold some degree of potential in the basin, given its erratic and predominantly semi-arid climate and extensive smallholder farming communities with a history of low crop yields. In addition, field-scale measurements and local suitability assessments of WH have been conducted in the basin (Kongo and Jewitt, 2006; de Winnaar et al., 2007; Kosgei et al., 2007). This provides the opportunity to compare basin-scale simulation outputs with local data in specific areas.

2 Methodology

2.1 Study area

The Thukela River Basin in South Africa (Fig. 1) is a diverse basin stretching over approximately 29 000 km² from an altitude of over 3000 m in the Ukhahlamba-Drakensberg World Heritage Site to sea level at the Indian Ocean. Its climate is characterised by dry cool winters, warm summers with intensive precipitation, and a high spatiotemporal variability. The mean annual precipitation ranges from 550 mm yr⁻¹ in the central regions to 2000 mm yr⁻¹ in the mountainous west of the basin. In the upper catchment, rainfall is highly seasonal with over 90% falling between October and March, and commonly zero precipitation in the dry winter months. The mean annual potential evapotranspiration ranges between 1600 and 2000 mm yr⁻¹. The mean daily maximum temperature in

January ranges from 20 to 32°C, and the mean daily minimum temperature in July ranges from 0 to 10°C (Taylor et al., 2001). The basin is relatively water rich, with multiple reservoirs and transfer schemes supplying water as far away as Johannesburg. In contrast, many rural communities in the basin lack piped water supply and rely on local groundwater or river discharge for their water needs.

The dominant land use in the basin is unimproved grassland, whereas the major anthropogenic land uses are agriculture, livestock grazing and forestry (Table 2, CSIR et al., 2002). Chromic Vertisols and Orthic Luvisols dominate the basin (Table 3). There is a duality of agricultural systems with both large-scale (>700 ha) commercial farmers and small-scale (ca. 1.5 ha) smallholder farmers (Taylor et al., 2001; Kosgei et al., 2007). The commercial systems are characterised by a high level of mechanisation, utilisation of fertilisers, commercial cultivars, and other inputs in both irrigated and rain-fed production systems. The smallholder systems are predominantly rain-fed, use local cultivars, and low amounts of fertilisers and other inputs. The main cultivated crop types in the commercial systems are maize, soybean, sorghum, and winter wheat. Maize dominates the smallholder systems (Statistics South Africa, 2006; Kosgei et al., 2007). The commercial irrigated systems principally utilise surface water for irrigation through sophisticated irrigation systems consisting of linked storage and transfer schemes, off-channel storage, withdrawals from rivers, blocking small streams or catching hillside runoff

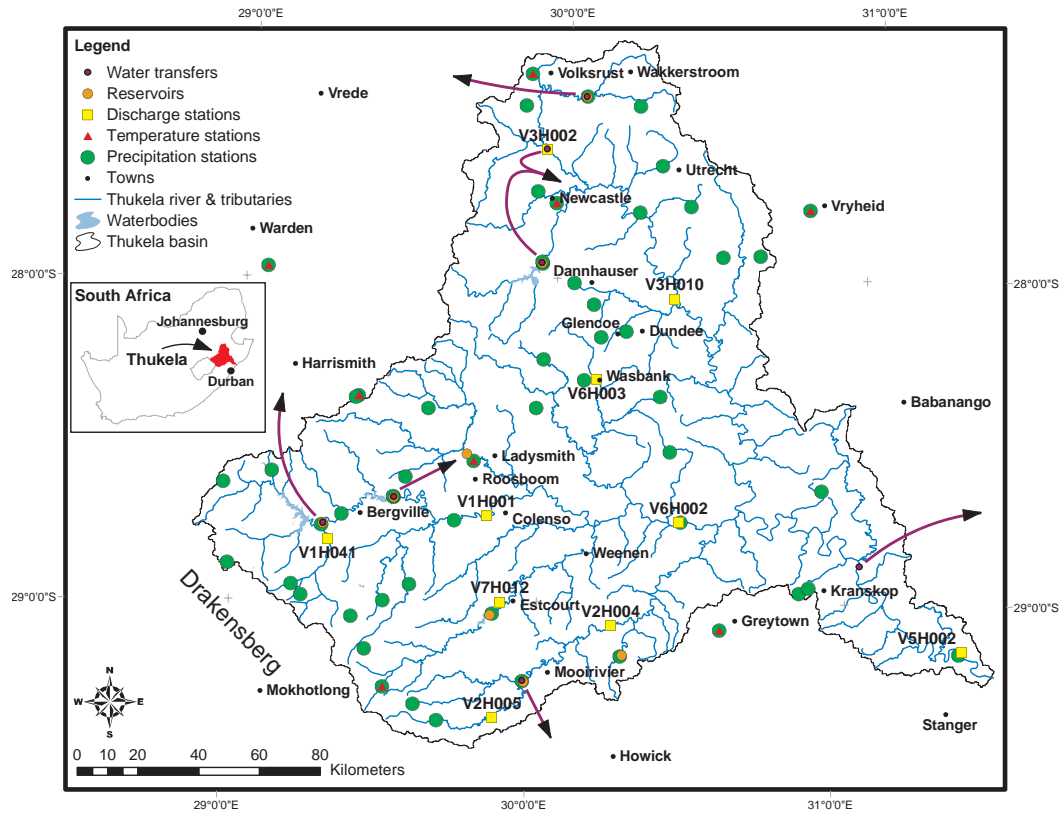


Fig. 1. Overview of the Thukela River Basin and the major precipitation, temperature and discharge stations as well as reservoirs and water transfers (purple arrows) included in the model. Projection: Lambert Azimutal Equal Area. Datum: GCS_WGS1984.

with small dams. Although smallholder systems are mainly rain-fed, some small-scale irrigation schemes have been instigated with varied success. There are ongoing efforts to promote WH in the basin through e.g. the LandCare project (Smith, 2006) and the Smallholder Systems Initiative (Rockström et al., 2004). Both projects targeted rural community adoption of a set of WH techniques including conservation tillage, cover cropping, mulching as well as small surface and subsurface storage schemes in the Bergville area. Aside from the adoption stemming from these projects, the present adoption of WH techniques intended for smallholder agriculture is negligible in the basin. By contrast, many of the commercial farmers have adopted conservation tillage practices already.

2.2 Model, data and setup

2.2.1 The SWAT model

The Soil and Water Assessment Tool (SWAT, Arnold et al., 1998) was used to simulate hydrological and vegetation-growth processes in the Thukela basin. SWAT was chosen because of the close linkage between its development purpose and the objectives of this project, open access to the

Table 2. Dominant land cover classes in the basin derived from the South African National Land Cover dataset (CSIR et al., 2002).

Class	Area (% of basin)
Unimproved (natural) grassland	54.4
Thicket, bushland, bush clumps, high fynbos	16.1
Degraded unimproved (natural) grassland	7.9
Cultivated, smallholder, rain-fed	6.4
Cultivated, commercial, rain-fed	6.1
Degraded thicket, bushland, bush clumps, high fynbos	3.1
Cultivated, commercial, irrigated	2.2
Other	3.8

source code, and its successful application in a wide range of scales and environmental conditions, including humid, temperate and semi-arid climates (Van Liew and Garbrecht, 2003; Bouraoui et al., 2005; Neitsch et al., 2005; Gassman et al., 2007).

SWAT is a physical-conceptual, spatially distributed model operating on a daily time step. The spatial characterisation of a river basin is carried out by topographically dividing the basin into multiple sub-basins. Each sub-basin is divided into hydrological response units (HRU) based on

Table 3. Major soil types of the basin. Moist bulk density, organic carbon content, hydraulic conductivity and available water capacity are presented for the top layer of the soil profile (0–30 cm depth).

FAO soil unit	Area (% of basin)	Texture	Maximum rooting depth (cm)	Moist bulk density (g cm^{-3})	Organic carbon content (% soil weight)	Saturated hydraulic conductivity (mm hr^{-1})	Available water capacity ($\text{mm H}_2\text{O per}$ mm soil)
Chromic Vertisol	41.97	Clay-loam	81	1.3	1.2	7.43	0.12
Orthic Luvisol	31.83	Loam	91	1.4	0.6	6.87	0.16
Rhodic Ferralsol	14.41	Clay	96	1.2	1.5	16.07	0.16
Lithosol	5.53	Clay-loam	69	1.2	2.2	13.14	0.12
Eutric Cambisol	4.90	Clay-loam	91	1.2	1.0	12.35	0.16
Eutric Cambisol	0.79	Sandy-loam	91	1.4	0.8	20.18	0.13
Chromic Vertisol	0.39	Clay	100	1.5	0.8	2.84	0.14

land use, soil, and slope classes. In each HRU and on each day the hydrological and vegetation-growth processes are simulated based on the Curve Number rainfall-runoff partitioning method (accounting for AM) and the heat unit phenological development method (Neitsch et al., 2005). Discharge-sustaining processes are aggregated to sub-basin level and routed to the basin outlet.

Energy availability governs vegetation phenology. At each point in the growth cycle, biomass production is derived from the interception of solar radiation by leaves, plant-specific radiation-use-efficiency and leaf area index (LAI). A set of parameters characterise leaf area development for each vegetation type, from which LAI is derived. Crop yield is calculated at harvest by multiplying the above-ground biomass with the harvest index. The harvest index is the fraction of the above-ground plant dry biomass removed as dry economic yield. The biomass remaining after harvest is converted to residue on the soil surface, modifying the soil cover and the soil water balance. Plant growth is limited by temperature, water, and nutrient availability in the soil; and is influenced by agricultural management (e.g. fertilisation, irrigation, and timing of operations). For more details the interested reader should refer to Neitsch et al. (2005).

2.2.2 Model setup and input data

The ArcSWAT interface (Olivera et al., 2006) as well as the R statistical computing environment (R Development Core Team, 2008) were utilised in project setup and analysis. The HydroSHEDS hydrologically conditioned digital elevation model at 3 arc-second spatial resolution (Lehner et al., 2006) was employed to derive slope and drainage network, and to delineate the sub-basins. The sub-basins were delineated with a ≥ 2025 ha threshold based on verification against field-validated drainage-network data yielding 847 sub-basins in total. The soil data used for hydro-pedological parameter information was the FAO-UNESCO global soil map (FAO, 1995) with two soil layers at 1:5000,000 scale, supplemented by data from Reynolds et al. (1999) and the ROSETTA

model (Kosugi, 1999). Two land cover datasets were utilised: the South African National Land Cover 2000 (NLC) dataset (CSIR et al., 2002) and the South African Crop Field Boundaries (CFB) dataset (NCSC, 2007). The CFB (native resolution 10 m) was used to simulate the crop fields, and the NLC (native resolution 30 m) for all other land use classes. The NLC was resampled to CFB resolution in order not to lose crop field resolution. The combined dataset was parameterised for SWAT based on Schuol et al. (2008) supplemented by local information (e.g. the South Africa Curve Number method, Schulze et al., 2004). Each sub-basin was split into unique combinations of land use classes and soil types to individually capture the different land use systems' agro-hydrological characteristics, resulting in 3754 HRUs in total.

The climatic inputs consisted of daily data on precipitation, maximum and minimum temperatures from a set of stations in the basin; and hourly solar radiation from the Durban Airport Weather Office (Fig. 1). The simulation period was 1 January 1994 to 31 December 2006 based on the availability of land use, crop yield, discharge, and climatic data. The first three years were used for model initialisation and were not included in subsequent analyses. The climatic data originated from Lynch (2003), the South African Weather Service (www.weathersa.co.za, access: 12 March 2009), and the South African Department of Water Affairs and Forestry (DWAF, www.dwaf.gov.za, access: 12 March 2009). Only stations with $<20\%$ missing data were included and the weather generator of SWAT was used to fill remaining gaps. Hourly precipitation data from a station near Bergville was used to improve the parameterisation of peak rainfall intensity (driving sub-daily peak runoff rate) in the weather generator (Kongo et al., 2007). Potential evapotranspiration was estimated by the Hargreaves method, while actual evapotranspiration (E_T) was simulated based on Ritchie (1972). The daily value of leaf area index was used to partition between evaporation and transpiration.

Available quantitative data on water management was incorporated in the model. This was daily DWAF data on major reservoir outflows and water transfers in the basin (Fig. 1). The records contained only minor amounts of missing values (on average 3%), which were approximated using LOESS interpolation (Cleveland et al., 1992). Reservoirs were simulated as impoundments on the main river channels, each with its respective water balance. The measured reservoir outflow fed the downstream river network, and the reservoir balance was calculated by accounting for this outflow. Reported withdrawal data fed the water transfer simulations. The conveyance efficiency between withdrawal and discharge was estimated from the transfer scheme near the Thukela river mouth to ca. 53% (Fig. 1).

The two major agricultural systems were simulated on each relevant land cover class. The management of the smallholder systems was modelled as rain-fed maize without added inorganic fertilisers. Timing of planting, harvest, and mouldboard plough tillage was based on field-scale research and assumed uniformity in space and time (Kosgei et al., 2007). The parameterisation of the cultivar type was derived from climatic data and local expertise (J. Kosgei, personal communication, 2008). The commercial systems were simulated as rain-fed or irrigated according to their respective land cover class. Irrigation was based on plant-water-stressed automatic scheduling, and withdrawn from local reaches. The four major crop types were simulated on both rain-fed and irrigated lands in proportions derived from provincial-level data (Statistics South Africa, 2006). Single cropping was assumed based on reported cropping intensity (FAO, 2005). Cultivar parameterisation and timing of operations originated from Schulze (2007), ARC (2008), du Toit (1999) and Ma'ali (2007). All irrigated and most rain-fed commercial system HRUs were fertilised with inorganic fertilisers based on crop-type specific proportions and compositions given by the Fertiliser Society of South Africa (www.fssa.org.za, access: 13 March 2009). Plant-nutrient deficit automatic fertilisation scheduling was employed, and the annual maximum application amount was derived from ARC (2008). The locations of crop type and fertiliser usage were randomly distributed among the commercial system HRUs according to their respective proportions because no additional information on their spatial distribution was available. Tillage effects of commercial farmers were assumed to be captured in the calibration process. Remaining crop parameters, and parameters for non-crop land covers, originated from the SWAT default database (Neitsch et al., 2005). Parameters sensitive to model outputs were subsequently calibrated to the local conditions.

2.3 Calibration, evaluation and uncertainty procedure

The model was calibrated against local observations of discharge, maize yield in smallholder systems, and maize yield in commercial systems. The calibration period was 1 January 2002 to 31 December 2006. The period 1 January 1997 to 31 December 2001 was used as an independent evaluation period in which the predictive power of the model was tested. DWAF datasets from ten nested discharge stations on daily temporal resolution were used (Fig. 1). The choice of discharge stations was based on homogeneity of spatial distribution, range of scales in drainage areas, availability of data, and avoidance of clear upstream reservoir influence. The maize yields were calibrated on annual and basin-wide resolution, and the data originated from the Crop Estimate Committee of the South African Department of Agriculture (CEC, www.nda.agric.za, access: 12 March 2009).

The Sequential Uncertainty Fitting algorithm (SUFI-2) was used for calibration and uncertainty analysis (Abbaspour and Johnson, 2004; Abbaspour et al., 2007). SUFI-2 was chosen because of its ability to analyse multiple parameters and output variables simultaneously, and because of the computational efficiency of the algorithm relative to other calibration and uncertainty estimation techniques (Yang et al., 2008). In SUFI-2 all sources of uncertainty are mapped to a set of parameter ranges. They are calibrated with the dual aim of bracketing most of the observed data with an as narrow as possible uncertainty band in a Bayesian approach. Initial parameter ranges were based on physically meaningful limits. Within the ranges, 500 Latin hypercube parameter set samples were drawn for each calibration iteration. In each iteration 500 simulations were run, where each simulation corresponded to one parameter set sample.

The selection of parameters to calibrate was based on a sensitivity analysis similar to Muleta and Nicklow (2005). A broad set of initial parameters were derived from Lenhart et al. (2002); van Griensven et al. (2006); Holvoet et al. (2005); Abbaspour et al. (2007); Ruget et al. (2002); Wang et al. (2005); Liu (2009); Faramarzi et al. (2009), and Neitsch et al. (2005). A set of Latin hypercube samples were drawn from the parameter ranges and the objective functions were calculated for each of these. A step-wise regression analysis was carried out between parameter values and objective functions. Parameters significantly influencing the objective functions were chosen for calibration. Some parameters were also included because they influenced the hydrograph patterns relative to observed data (Table 4). Spatially distributed parameters affecting discharge were grouped into ten calibration regions according to the nearest downstream discharge station and calibrated in parallel in order to better capture the region-specific and scale-specific difference between them (Faramarzi et al., 2009). For the crop related parameters, one parameter group was used for all smallholder HRUs and another for all commercial maize-growing HRUs (Table 4).

Table 4. Parameter sensitivity of calibrated parameters in relation to the objective function values for discharge (d), smallholder maize yield (s), and commercial maize yield (c), respectively. The *t*-value indicates parameter sensitivity: the larger the absolute *t*-value, the more sensitive the parameter. The *p*-value indicates the significance of the *t*-value: the smaller the *p*-value, the less chance of a parameter being accidentally assigned as sensitive.

Parameter	Definition	Target objective function	<i>t</i> -value	<i>p</i> -value
RCHRG_DP	Deep aquifer percolation fraction	d	-16.23	6.3×10 ⁻⁴⁶
ESCO	Soil evaporation compensation factor	d	8.89	2.1×10 ⁻¹⁷
GW_DELAY	Groundwater delay time (days)	d	-7.27	1.9×10 ⁻¹²
SOL_BD	Moist bulk density of soil (g cm ⁻³)	d	6.30	7.9×10 ⁻¹²
SOL_K	Saturated hydraulic conductivity of soil (mm h ⁻¹)	d	6.04	3.5×10 ⁻⁹
CN2	Initial SCS curve number for moisture condition 2	d	-5.56	4.9×10 ⁻⁸
SOL_AWC	Available water storage capacity in soil (mm H ₂ O/mm soil)	d	-4.39	1.5×10 ⁻⁵
CH_K2	Effective hydraulic conductivity of the main channel alluvium (mm h ⁻¹)	d	-2.17	0.030
REVAPMN	Threshold depth of water in the shallow aquifer for revap to occur (mm)	d	-2.15	0.032
ALPHA_BF	Baseflow alpha factor (days)	d	2.96	0.0033
GW_REVAP	Groundwater revap coefficient	d	2.78	0.0057
SMFMX	Minimum snow melt rate (mm °C ⁻¹ day ⁻¹)	d	1.57	0.12
TIMP	Snow pack temperature lag factor	d	-0.77	0.44
SURLAG	Surface runoff lag time (days)	d	-0.25	0.79
HVSTI	Harvest index for optimal growing conditions	s	-28.83	6.1×10 ⁻¹⁰⁸
HEAT_UNITS	Total heat units for plant to reach maturity (cumulative °C)	s	-3.94	9.4×10 ⁻⁵
WSYF	Harvest index for water-stressed growing conditions	s	-0.84	0.40
BIO_E	Radiation use efficiency (g J×10 ⁻⁷)	s	0.36	0.72
HVSTI	Harvest index for optimal growing conditions	c	-45.57	1.7×10 ⁻¹⁷⁸
HEAT_UNITS	Total heat units for plant to reach maturity (cumulative °C)	c	-21.35	5.2×10 ⁻⁷²
AUTO_NYR	Maximum amount of mineral N application in any one year (kg N ha ⁻¹ yr ⁻¹)	c	-9.03	3.8×10 ⁻¹⁸
BIO_E	Radiation use efficiency (g J×10 ⁻⁷)	c	-2.99	0.0030
WSYF	Harvest index for water-stressed growing conditions	c	-0.56	0.58
AUTO_NSTRS	Plant nitrogen stress threshold triggering automatic fertilisation	c	-0.47	0.64
AUTO_WSTRS	Plant water stress threshold triggering automatic irrigation	c	-0.09	0.93

The objective function Φ was used to evaluate the performance of each simulation at each discharge station (Krause et al., 2005):

$$\begin{aligned} \Phi &= |b|R^2 && \text{for } |b| \leq 1 \\ \Phi &= |b|^{-1}R^2 && \text{for } |b| > 1 \end{aligned} \quad (1)$$

where R^2 is the coefficient of determination (sensu Dalgaard, 2008) and b the slope of the regression line between the simulated and measured data. All discharge stations were conjunctively calibrated with an overall objective function O where each station was weighted equally:

$$O = \frac{1}{n} \sum_{i=1}^n \Phi_i \quad (2)$$

where n is the number of stations. The range of Φ and O is 0 to 1 where 1 indicates a perfect match. The best simulation was considered as the one with the highest O value. It

constituted the basis of the input parameter ranges for each subsequent iteration.

The objective function used to evaluate the performance of each simulation with respect to crop yield was the Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (M_i - S_i)^2} \quad (3)$$

where n is the number of observations, M is the measured data and S is the simulated data. The range of RMSE is 0 to ∞ where 0 is optimal. The best simulation was considered as the one with the lowest RMSE. The crop yield was simulated on each HRU in each season. From this the area-weighted average basin yield was calculated and compared with the CEC provincial-scale data for each agricultural system.

Discharge, smallholder maize yield and commercial maize yield were simultaneously calibrated. No combined objective function between these was defined because of the

incommensurable nature of maize yield and discharge, and because the two agricultural systems were simulated on independent HRUs with independent parameter groups. For the parameters affecting all output variables, range refinement between iterations considered all objective functions.

In SUFI-2 the entire set of simulations constituting one calibration iteration form the basis of the uncertainty quantification. The range within which 95% of the output variable values of all simulations fall represents the uncertainty. This is denoted as the 95% prediction uncertainty band (95PPU). The 95PPU is calculated from the cumulative frequency distribution of all simulation output values for each variable at each point in time. The lower boundary of the 95PPU (L95PPU) reflects the 2.5 percentile, while the upper boundary (U95PPU) reflects the 97.5 percentile of the distribution. The performance of each iteration is evaluated with the *P*- and *R*-factors. The *P*-factor is the fraction of the measured data bracketed by the 95PPU band. It ranges from 0 to 1 where 1 is ideal. The *R*-factor is the average width of the 95PPU band divided by the standard deviation of the measured variable. It ranges from ∞ to 0 where 0 is ideal and <1 is desirable (Abbaspour et al., 2007). A 10% measurement error for all observed variables was included in the *P*- and *R*-factor calculations (Butts et al., 2004). A number of calibration iterations were carried out seeking to reach more optimal *P*- and *R*-factors until a further improvement in one factor was not possible without a deterioration in the other. The last iteration was then taken as the posterior set of parameter ranges on which the subsequent analyses were based.

2.4 Analysis of smallholder systems and in situ water harvesting

In this paper we focussed the analysis on the smallholder systems in accordance with the objectives. The crop water productivity (CWP, kg m^{-3}) was derived based on Kijne et al. (2003):

$$\text{CWP} = \frac{Y}{E_T} \quad (4)$$

where *Y* is the crop yield in the HRU for the season (kg ha^{-1}) and *E_T* is the corresponding seasonal evapotranspiration ($\text{m}^3 \text{ha}^{-1}$). A higher CWP thus constitutes a more water productive agricultural system. Some analysts further separate *E_T* into soil and open water evaporation, evaporation of intercepted water in the canopy foliage as well as transpiration through vegetation (Savenije, 2004). However, we chose to treat them as an aggregated flux in this study for ease of comparison with previous research.

Given that the principal source of water for in situ WH is locally generated surface runoff, the availability of water for in situ WH in smallholder systems was considered to be the annual cumulative generated surface runoff from these HRUs under current management conditions. This can be seen as the upper boundary of water availability for in situ WH tech-

niques capturing runoff (see discussion). The supplemental water demand (SWD) was estimated in a separate simulation by allowing automatic irrigation from an unlimited external source onto the smallholder HRUs in response to crop water deficits while holding all other variables constant. The SWD (the applied amount) is the amount of water required – in addition to rainfall – to meet the crop water deficit, and the additional amount of soil evaporation accumulated over the crop-growing season. It thus represents the intended function (soil moisture addition) of the surface runoff captured through in situ WH. The peak SWD is defined as the amount applied when irrigation is induced as soon as there is crop water deficit (i.e. >0 water stress). In the SWD simulations, some stresses still remain on the crop (e.g. from plant nutrient deficiencies). Further water demand may therefore arise if these stresses were to be alleviated as well. However, because in situ WH is primarily aimed at addressing the crop water deficits, no further stresses were assumed to be conjunctively alleviated.

The reliability of in situ WH in smallholder systems was estimated as the percentage of years during the simulation period in which the availability of water for in situ WH equalled or exceeded the peak SWD. The correlation between the reliability at the U95PPU boundary and the L95PPU boundary was assessed with Spearman's rank correlation coefficient (ρ , Spearman, 1904). Finally, all HRU level analyses were scaled to sub-basin level as an area-weighted mean for presentation purposes.

3 Results

3.1 Calibration and evaluation

3.1.1 Maize yield

A set of simulations throughout the posterior parameter space were capable of reproducing reported yields in both the calibration and the evaluation periods, respectively (Fig. 2). The *P*-factors were ideal while the *R*-factors were large, indicating that the set of simulations cover the observations well but that they were somewhat blunt in doing so. It is certainly possible to refine the prediction bands further. However, it may result in “overfitting” of the parameters, potentially reducing the predictive power in the evaluation period considerably (Notarnicola et al., 2008). The calibration reduced the width of the predictive uncertainty band (the *R*-factor) for maize yield by 23%. The aggregated smallholder maize yields over the two time-periods were well captured by the best parameterisation. This is demonstrated by the low RMSE and close proximity of the medians in both the calibration period (observed: 0.81 t ha^{-1} , simulated: 0.83 t ha^{-1}), and the evaluation period (observed: 0.50 t ha^{-1} , simulated: 0.43 t ha^{-1}).

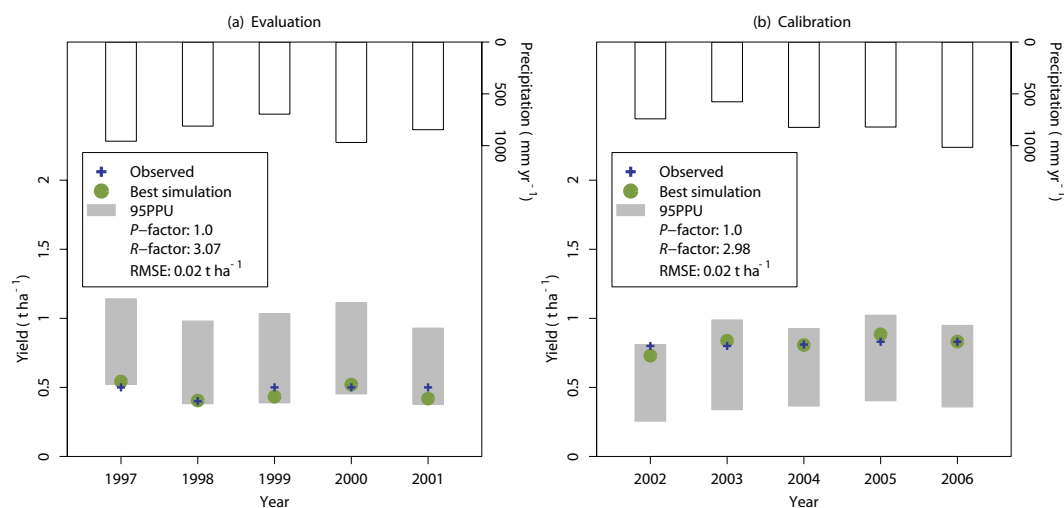


Fig. 2. Observed and simulated annual maize yield in smallholder systems during (a) the evaluation period and (b) the calibration period. RMSE is Root Mean Squared Error – the objective function used to derive the best simulation – and 95PPU represents the 95% prediction uncertainty band. The basin-average precipitation for each year is presented at the top of the figure.

Table 5. Performance of the model with respect to daily discharge in the calibration (Cal.) and evaluation (Eval.) periods, respectively. The overall weighted objective function (O) was 0.47 for the calibration period and 0.36 for the evaluation period.

Discharge station	Drainage Area (km ²)	P -factor		R -factor		Φ		R^2	
		Cal.	Eval.	Cal.	Eval.	Cal.	Eval.	Cal.	Eval.
V3H002	1518	0.34	0.47	0.89	1.37	0.85	0.42	0.63	0.43
V3H010	5887	0.77	0.63	0.40	0.55	0.36	0.23	0.69	0.53
V6H003	312	0.78	0.84	0.96	1.06	0.42	0.35	0.42	0.28
V1H001	4176	0.64	0.64	0.28	0.38	0.67	0.61	0.83	0.71
V6H002	12 862	0.62	0.57	0.48	0.61	0.68	0.73	0.77	0.72
V1H041	434	0.46	0.32	0.32	0.32	0.32	0.23	0.65	0.53
V7H012	196	0.70	0.59	0.65	0.60	0.16	0.18	0.45	0.32
V2H004	1546	0.61	0.56	0.49	0.49	0.65	0.34	0.79	0.56
V5H002	28 920	0.70	0.58	0.84	0.92	0.73	0.38	0.65	0.46
V2H005	260	0.66	0.54	0.79	0.72	0.41	0.27	0.48	0.49

3.1.2 Discharge

Tables 5 and 6, and Fig. 3 summarise and exemplify the results of the calibration and evaluation of river discharge. The model performance varies in space and time and certain aspects of the regimes are captured better than others. Φ is lower in the evaluation period than in the calibration period. However, the overall reduction is only about 20% suggesting no “overfitting” of the parameters. The coverage of the observed data by the 95PPU band (the P -factor) was on the whole satisfactory, although rather low for V3H002 and V1H041. A probable cause in the case of V3H002 is the prevalence of $0 \text{ m}^3 \text{ s}^{-1}$ observed discharge (46% of the entire simula-

tion period) on which the included 10% measurement error is not effective. In 78% of the cases, the best simulation had flows of $\leq 1 \text{ m}^3 \text{ s}^{-1}$ indicating a close proximity to observations nonetheless. Another reason may be erroneous observations, given the difficulty of accurately measuring low discharge fluxes. Inadequate simulation of discharge peaks is less likely to have been the main cause of the low V3H002 P -factor (83% of flows \geq the 95% percentile of observations were within the 95PPU). The widths of the 95PPU bands (the R -factor) were generally narrower than the standard deviation of the measured variable. The calibration reduced the R -factor by 25% on average. Overall there is no indication of bias in the cumulative discharge for either the calibration

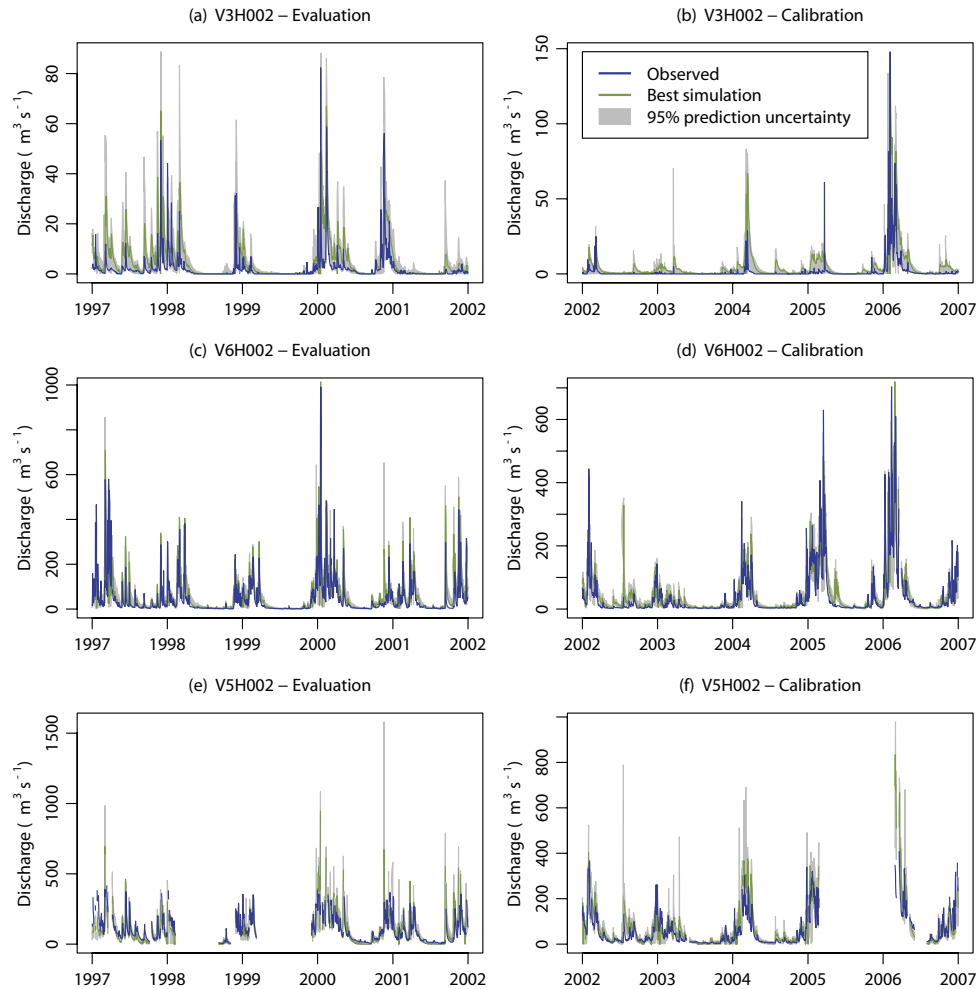


Fig. 3. Observed and simulated daily river discharge for V3H002 (**a, b**), V6H002 (**c, d**) and V5H002 (**e, f**) in the evaluation (**a, c, e**) and calibration (**b, d, f**) periods, respectively. The best simulation is the parameter set with the highest objective function (Φ). Gaps represent missing observations. See Fig. 1 for station locations.

Table 6. Cumulative discharge for all days with observed flow records during the calibration and evaluation periods, respectively (km^3 per period). U95PPU is the upper boundary and L95PPU is the lower boundary of the 95% prediction uncertainty band, respectively.

Discharge station	Calibration period			Evaluation period		
	Observed	L95PPU	U95PPU	Observed	L95PPU	U95PPU
V3H002	0.25	0.11	1.08	0.33	0.22	1.38
V3H010	2.19	0.41	2.77	3.02	0.69	3.51
V6H003	0.14	0.07	0.46	0.14	0.05	0.42
V1H001	3.86	2.26	4.68	3.92	2.46	5.46
V6H002	5.85	4.09	9.69	6.85	5.23	12.72
V1H041	1.10	0.55	1.06	1.17	0.48	0.96
V7H012	0.13	0.04	0.19	0.16	0.05	0.23
V2H004	1.03	0.57	1.39	1.71	0.57	1.70
V5H002	6.47	4.58	11.19	9.91	6.54	14.53
V2H005	0.49	0.13	0.63	0.63	0.16	0.73

or the evaluation period (Table 6). Given the high temporal resolution and the relatively conservative objective function criterion, the overall model performance was adequate for further analysis.

3.2 Maize yield and crop water productivity

The smallholder maize yields are rather low in the basin (Fig. 4). Still, there is some degree of spatial differentiation. Areas in the Southwest and South have relatively high yields while areas in the North central and East have lower yields. The connection between parameter values and yields is non-uniform in space. This is exemplified by a set of sub-basins in the far West which fell in the same yield category at the U95PPU boundary but in different yield categories at the L95PPU boundary. Of the simulated yield constraints, the soil nitrogen content is the primary regulator of the yield level and spatial variability (median N-stress: 38–77 days yr⁻¹, 95PPU). Soil acidity is also known to limit the crop growth in the region (Narambuye et al., 2008). The results further suggest the temporal yield variability is significantly (p -value: $<2 \times 10^{-16}$) related to the variability of soil moisture in the root zone (particularly in 2004), and to temperature stress (especially at high latitudes in combination with high heat unit parameterisations).

The CWP in the smallholder systems is rather low (spatiotemporal median: 0.08–0.22 kg m⁻³, 95PPU). Even at the U95PPU boundary, some sub-basins in the East display a CWP value <0.15 kg m⁻³ (Fig. 4). The spatial pattern varies in concert with the spatial variability in yield and E_T . In a broad sense there is a meandering belt of sub-basins with low CWP in the central North, East and toward the river mouth; and areas of higher CWP at the higher elevations in the West and North. The temporal variability is often rather small (see supplementary online material: <http://www.hydrol-earth-syst-sci.net/13/2329/2009/hess-13-2329-2009-supplement.zip>). However, a distinct set of HRUs display relatively high CWP values in 1998. This was principally caused by particularly high yields rather than exceptional E_T values (Fig. 5), suggesting that increasing yields through WH adoption may also raise CWP.

3.3 Water availability, demand and reliability of in situ WH in smallholder systems

3.3.1 Water availability for in situ WH

The surface runoff is low within most smallholder HRUs (spatiotemporal median: 0–17 mm year⁻¹, 95PPU). The dominant outflow process is E_T , both in the smallholder HRUs and in the basin at large, as expected in this climatic zone (Table 7).

The principal areas of relatively high runoff generation are in the headwaters in the West close to the Drakensberg and to some extent in the East toward the river mouth (Fig. 6). The

Table 7. Average annual water balance for the basin. The range indicates the 95% prediction uncertainty band.

Water balance component	Amount (mm yr ⁻¹)	Percentage
Precipitation	826	100
Evapotranspiration	620–687	75–83
Surface runoff	5–16	1–2
Lateral flow	50–93	6–11
Shallow aquifer return flow	39–76	5–9
Deep aquifer recharge	23–69	3–8

uncertainty of the runoff generation is rather large, though a large part of the basin consistently displays low runoff amounts throughout the posterior parameter space. The low runoff amounts are particularly related to the high atmospheric evaporative demand and soil moisture deficits in large parts of the basin. At higher altitudes, the precipitation is higher and the temperature lower, leading to lower evaporative demand and higher surface runoff.

The temporal variability at the L95PPU boundary is relatively small, but considerable and complex at the U95PPU boundary (see supplementary online material). At U95PPU, the parameter values render the model sensitive to the temporal dynamics of climate and soil moisture. Such variability is reduced at L95PPU by the parameterisation of the most sensitive parameters affecting surface runoff (Table 4). This highlights both the temporal variability itself but also the large uncertainty with which it is associated. Consequently, the water availability is hard to predict; and relying on it as a base for food production involves considerable risk, a fact also reported for the local scale (de Winnaar et al., 2007).

3.3.2 Supplemental water demand

The demand for additional water in smallholder systems is relatively high in the central and eastern parts of the basin (Fig. 7). The high SWD is mainly related to the radiation-induced biomass production potential and the high evaporative demand. Particularly high peak SWD was obtained around Ladysmith, Newcastle, and Utrecht, with a relatively dry climate. The smallholder systems closer to the Drakensberg generally display low peak SWD. The SWD simulations significantly (p -value: $<2 \times 10^{-16}$) reduced the water stress on crop growth (range of water stress: 0–134 days yr⁻¹ for current conditions and 0–9 days yr⁻¹ for the peak SWD scenario at U95PPU). Although the water stress is relieved to a large extent, the results suggest crop growth is still inhibited by e.g. low soil nitrogen content (median N stress for the SWD scenario: 39–77 days yr⁻¹, 95PPU).

The temporal variability in SWD is high at the U95PPU boundary but low at the L95PPU boundary (see supplementary online material). It is largely driven by the climate

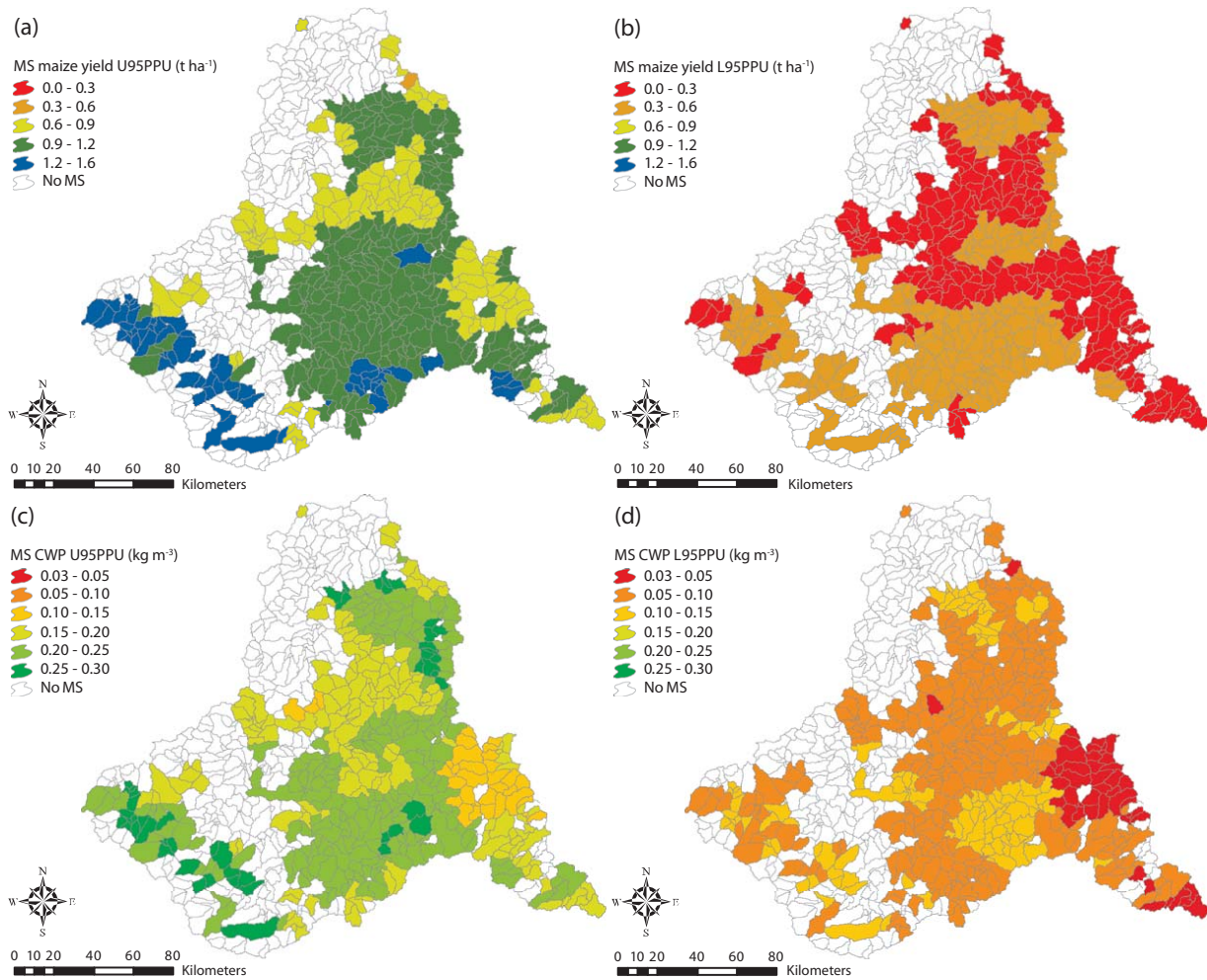


Fig. 4. Median, area-weighted maize yield (**a, b**) and crop water productivity (CWP), (**c, d**) in smallholder systems (MS) during the simulation period. U95PPU (**a, c**) is the upper boundary and L95PPU (**b, d**) is the lower boundary of the 95% prediction uncertainty band, respectively. “No MS” indicates sub-basins without the MS class. Projection and Datum as Fig. 1.

dynamics (e.g. variability in evaporative demand and dry-spell occurrences) and variable water demands at different stages of the crop growth cycle. The uncertainty is again considerable (spatiotemporal median: 0–113 mm year⁻¹, 95PPU). Nevertheless, the spatial patterns of water availability and demand are relatively consistent and on the whole inversely related – areas of low SWD coincide with the areas of high availability. At the extremes, water is not available where demanded or not demanded where available. It is in the interface between the extremes that WH may fill a gap by bridging some of the crop water deficits. This is illustrated by the intra-seasonal patterns of water availability and SWD at two locations near Weenen and Bergville (Fig. 8). Near Weenen the majority of the seasonal SWD precede the surface runoff, rendering surface runoff capture only marginally efficient. In contrast, near Bergville the runoff generally precede the SWD, enabling timely soil moisture enhancement.

3.3.3 Reliability of in situ WH

Given the risks associated with the inter-annual variability in both the water availability for in situ WH and the SWD in smallholder systems, it is pertinent with an analysis of the reliability of in situ WH technologies (Fig. 9). The reliability of in situ WH is particularly high in the Southwest toward the Drakensberg, and to some extent in the Southeast and toward the river mouth. The reliability is low in the majority of sub-basins along a North-South transect through the basin. The reliability patterns are closely related to the spatial variations in precipitation, temperature, and atmospheric evaporative demand. This spatial differentiation highlights the importance of geographically explicit reliability estimates. For example, in situ WH investment appears to involve considerably greater risk around Weenen than around Bergville.

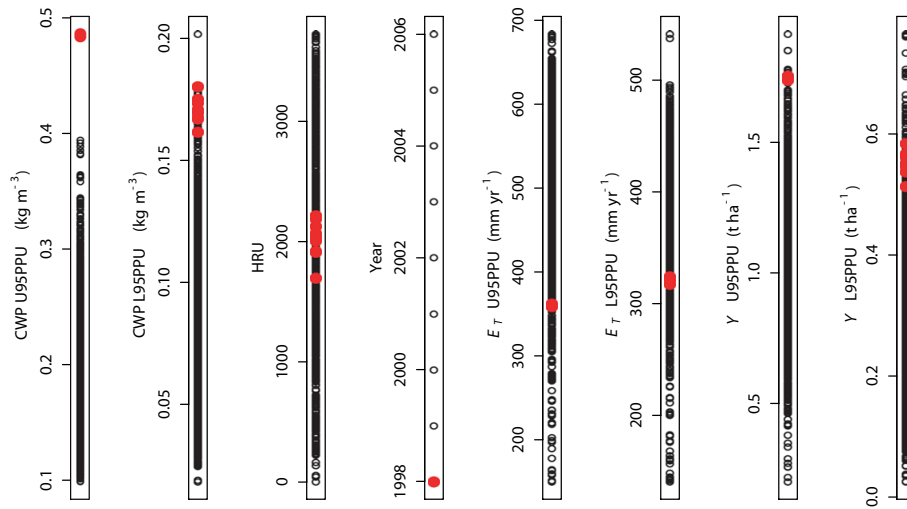


Fig. 5. Parallel coordinate plot of crop water productivity (CWP) in smallholder systems against space (HRU), time (Year), evapotranspiration (E_T) and maize yield (Y) for the upper (U95PPU) and lower (L95PPU) 95% prediction uncertainty boundaries, respectively. Red items are the space-time combinations with relatively high CWP ($>0.4 \text{ kg m}^{-3}$, U95PPU).

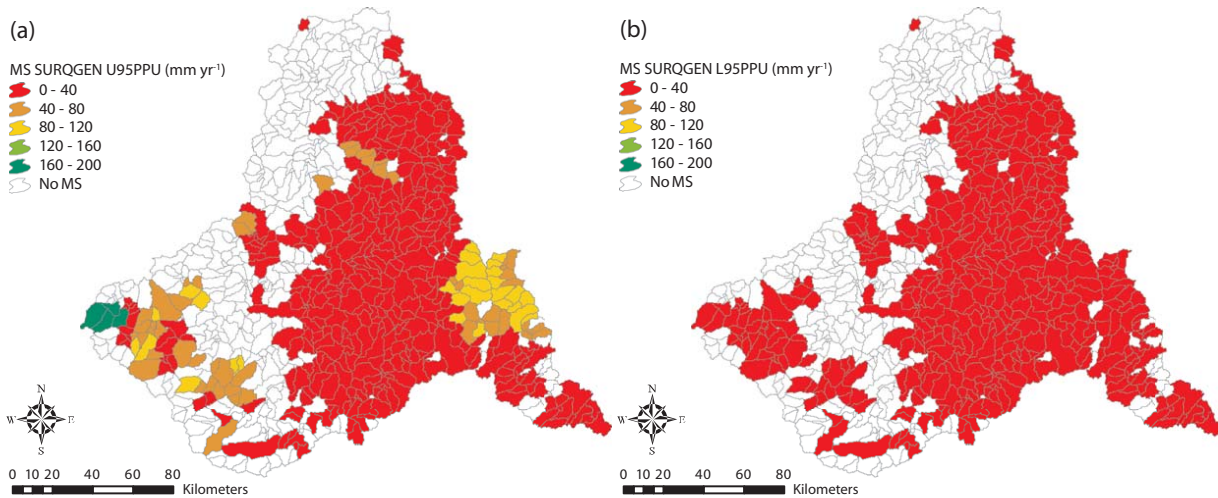


Fig. 6. 1997 to 2006 median annual generated surface runoff (SURQGEN) from the smallholder agricultural production land use class (MS), area-weighted to sub-basin level. U95PPU (a) is the upper boundary and L95PPU (b) is the lower boundary of the 95% prediction uncertainty band, respectively. “No MS” indicates sub-basins without the MS class. Projection and Datum as Fig. 1.

The similarity of the reliability throughout the posterior parameter space ($\rho=0.78$) indicates a relatively high confidence in the reliability estimate. In certain areas the reliability is somewhat higher at the L95PPU boundary relative to the U95PPU boundary (e.g. between Newcastle and Utrecht). However, in the majority of sub-basins an indifferent or reverse relationship was found. Although parameter uncertainty affects the magnitude of the water availability and SWD, the effect on the temporal patterns is relatively small such that the climatic variability signal dominates the reliability results.

The reliability represents the convergence of water availability for in situ WH and SWD in smallholder systems in space and time. Along with a set of other factors, these influence the suitability of in situ WH. If the reliability alone is taken as an indicator of the suitability of in situ WH, then the potentially suitable areas for in situ WH at any given risk level can be derived. Based on that premise, Table 8 presents the cumulative area and percentage of smallholder HRUs potentially suitable for in situ WH relative to a set of system reliability levels. At an inconceivably high risk level of 10% reliability, less than 50% of the smallholder HRUs appear to be suitable for in situ WH from a water availability and

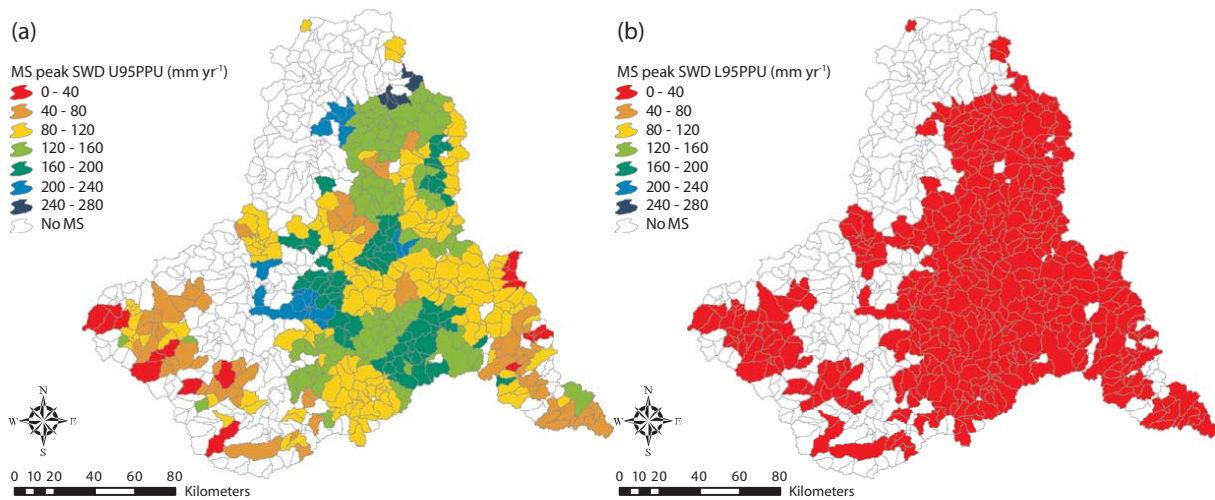


Fig. 7. 1997 to 2006 median annual peak supplemental water demand (SWD) in the smallholder agricultural production land use class (MS), area-weighted to sub-basin level. U95PPU (a) is the upper boundary and L95PPU (b) is the lower boundary of the 95% prediction uncertainty band, respectively. “No MS” indicates sub-basins without the MS class. Projection and Datum as Fig. 1.

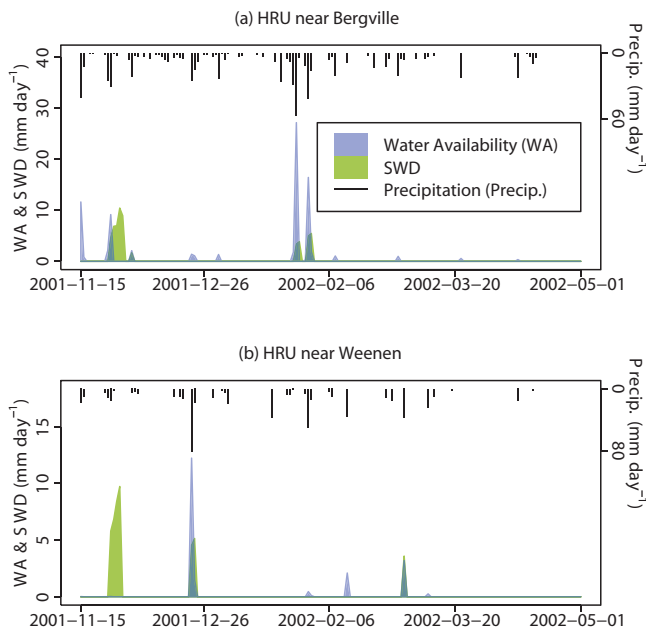


Fig. 8. Daily water availability (WA), peak supplemental water demand (SWD) and precipitation (Precip.) during the 2001–2002 smallholder cropping season for a smallholder HRU near (a) Bergville (reliability=50–60%, 95PPU) and (b) Weenen (reliability=10–20%, 95PPU). The daily range represents the 95% prediction uncertainty band (95PPU) for WA and SWD.

demand perspective. At the 75% reliability level, adoption of in situ WH may still be an attractive strategy in approximately 7000 to 9000 ha (4–5%) of the smallholder lands.

4 Discussion

4.1 Simulation performance

Simulations of agro-hydrological systems are challenging. The challenges include: data quality and resolution; uncertainty in the process understanding, model structure and parameterisation; and conditionality of the results on the type of uncertainty evaluation procedure utilised (Beven, 1993; Abbaspour and Johnson, 2004). Uncertainties were explicitly accounted for here to improve the transparency of the results to such challenges.

The uncertainty bands of the maize yield simulations are relatively wide, reflecting the uncertainty of the model structure and the input data. Structural simplifications include lack of biodiversity, competition, and soil acidity considerations. Input data uncertainty originate from e.g. the coarse resolution of the fertiliser and soil data, the scant availability of information on management practices, and the scale difference between the CEC yield estimate (KwaZulu-Natal province, 92 100 km²) and the simulated area (Thukela basin, 29 000 km²). However, the best parameterisation is satisfactorily able to capture the reported maize yields (RMSE 0.02 t ha⁻¹, i.e. 2% and 4% of mean reported maize yield for the calibration and evaluation periods, respectively). The reduced performance of the model in the evaluation period may be explained by the roughness of the CEC estimate of smallholder maize yields (based on information averaged

Table 8. Cumulative area and percent of smallholder HRUs potentially suitable for in situ WH at different reliability levels (i.e. smallholder HRUs with reliability equal to or above the given reliability level). U95PPU is the upper boundary and L95PPU is the lower boundary of the 95% prediction uncertainty band, respectively.

Reliability level (%)	Area (ha)		Percent	
	U95PPU	L95PPU	U95PPU	L95PPU
10	81 057	73 220	44	40
25	52 604	37 188	28	20
50	24 282	30 499	13	16
75	9421	6721	5	4
90	4450	4917	2	3

to 10 000 s of hectares and 1000 s of tons). Krysanova et al. (1998), Krysanova et al. (1999), and Wechsung et al. (2000) have evaluated the model's performance against observed maize, wheat, barley, and potato yields on district level in Germany. Similarly to our best parameterisation, they found a good agreement between observed and simulated yields on average-annual resolution (6% lower than observed for maize).

The large uncertainty of our maize yield results provides impetus for further model refinement and improved evaluation. Given the sensitivity of the crop yield to harvest index alterations (Table 4), refinement of the harvest index equations are likely to reduce the uncertainty. Luo et al. (2008) suggested that sensitising the harvest index to varying water and nutrient stress during different phenological stages may aid in this pursuit. Including additional plant growth constraints (e.g. soil acidity, weed infestation, and plant diseases), and a dynamically joined constraint module may help to differentiate between various sources of uncertainty. Aside from model conceptual improvements, it is critical to improve the input and evaluation databases to further reduce the uncertainty. Key here is better knowledge of local cultivar types (e.g. biomass development profiles, harvest indices) and management practices (e.g. spatiotemporal cultivar distributions and timing of operations), as well as more precise yield observations, systematically collected and representative of a given area.

Certain aspects of the discharge results also leave room for further improvement. In some cases the recession of the peak flow was not as fast as in the observations, possibly caused by inadequate simulation of soil processes (e.g. soil-groundwater interactions, cf. V3H002). Occasionally the reverse was observed (e.g. V1H041). In some instances discharge peaks were present in the simulations but not in the observed data (e.g. V2H004). Performance generally appeared to decrease proportionally with drainage area (Table 5). Possible causes include the coarser scale of the input data relative to the drainage area for small catchments,

or simplification of hydrological processes that may be more important on the local scale.

The model performance criteria may be elevated at observation stations just downstream of reservoirs with included outflow records. This does not indicate a real performance improvement because the proximity renders the stations essentially indifferent to varying process parameterisations in the rest of the basin. To minimise this effect, stations close to, or with clear flow-record impacts from reservoirs were here excluded.

The predictive power was reduced by the presence of missing data in the flow records, particularly on peak flows (e.g. V5H002 – the Thukela Mouth at Mandini). The Mandini flow record contains a disproportionately high level of missing data for high flows because of the inability of the weir to monitor flows above $457 \text{ m}^3 \text{ s}^{-1}$. This may bias the calibration toward lower flows. The bias was here counterbalanced by conjunctively calibrating all discharge stations. Occasional over-prediction of the peaks at this station may hence be nearer to the historical reality than the flow record suggests. This hypothesis could only be tested if discharge data above $457 \text{ m}^3 \text{ s}^{-1}$ were available.

4.2 Crop water productivity

Field-scale studies in the region substantiate the CWP results obtained in this study. In a field trial in the headwaters of the Thukela basin, Kosgei et al. (2007) measured seasonal E_T and maize yield in a conventional tillage smallholder system resulting in a CWP of ca 0.4 kg m^{-3} during 2005–2006. The median CWP values obtained here are somewhat lower (probably related to seasonal fluctuations and the temporal averaging). However, around 2% of the smallholder HRUs did have similar CWP values in 2005–2006 (0.3 – 0.4 kg m^{-3}); of which some correspond to the area of their field trial near Bergville (Fig. 1). Kosgei et al. (2007) measured E_T to be 92% of the rainfall input during the crop-growing season. The equivalent simulated values during the particular season of their trial correspond satisfactorily (76–98%, 95PPU). Rockström and Barron (2007) reviewed a set of field-scale studies of water productivity in the savannah biome in Eastern and Southern Africa with low CWP values at low yields (0.05 – 0.6 kg m^{-3} for yields <0.3 – 2 t ha^{-1}). These data agree rather well with the results obtained here (Fig. 4).

A number of factors contribute to the low CWP. The E_T is closely coupled with the climatic setting of the basin, and also influenced by residue management (Prihar et al., 1996; Klocke et al., 2009). The maize yield is limited primarily by low soil fertility but also by low soil moisture availability, which is in line with field-scale research in other areas of SSA (e.g. Burkina Faso, Fox and Rockström, 2003). This provides impetus for efforts aimed at raising the soil fertility and the soil water availability.

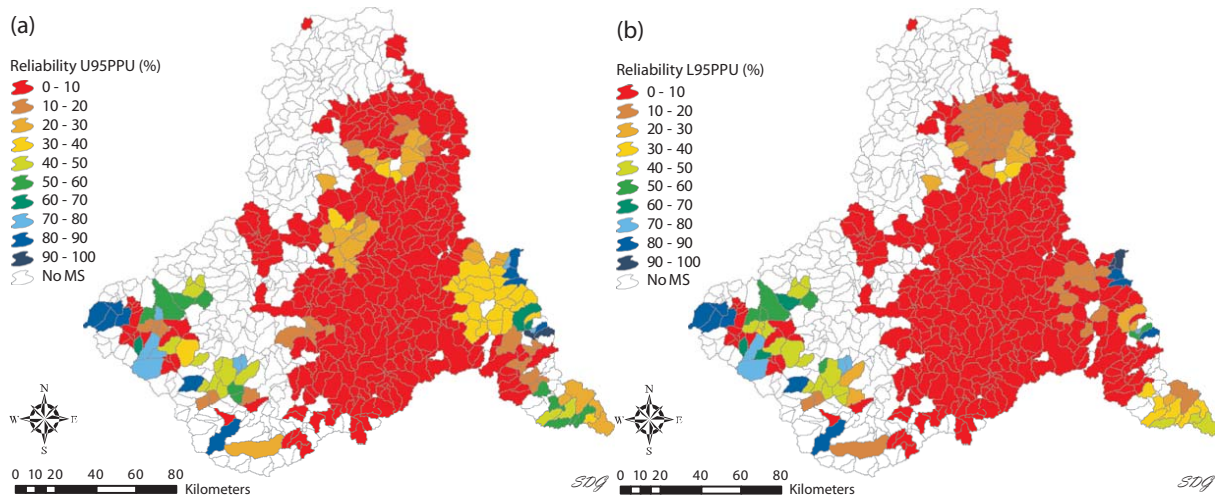


Fig. 9. Reliability of in situ WH in the smallholder agricultural production land use class (MS), area-weighted to sub-basin level. U95PPU (a) is the upper boundary and L95PPU (b) is the lower boundary of the 95% prediction uncertainty band, respectively. “No MS” indicates sub-basins without the MS class. Projection and Datum as Fig. 1.

4.3 Reliability and suitability of in situ WH

In this study we considered the entire amount of generated surface runoff within the smallholder lands as the water available for in situ WH (Fig. 6). In practice, the entire runoff depth will not be available for use since the efficiency in runoff capture, storage, and application is often less than 100%. Kosgei et al. (2007) noted a seasonal runoff reduction of ca. 30% at a field trial of conservation tillage vs. conventional tillage cultivation. Hence, the water availability component of the reliability may be an overestimate of the practicably available water. It could, however, be enhanced if measures to reduce soil evaporation and increase transpiration (e.g. mulching) can be made practicably available, tapping into the considerably larger E_T flows. In this study it was considered more appropriate to regard the entire runoff amount as the available resource in order to reflect the dominant WH types used, and the reliability at the upper boundary of their water availability potential.

The reliability was here calculated based on the peak SWD (Fig. 7). It reflects a condition where crop water deficits are met to their full extent (holding other variables constant). This may not necessarily be required for improved yields or CWP, particularly if relatively short dry spells limit the crop growth. Significantly higher yields may potentially be obtained from lower amounts than peak SWD. Therefore, the reliability estimate is rather conservative from the water demand perspective. In future studies we aim to explore how much of the available water in situ WH may utilise, and to what extent this meets the crop water deficits, which may potentially translate to higher yields and CWP.

The reliability of in situ WH is generally low in the basin, but considerable differences exist between different areas (Fig. 9). Which areas to consider suitable for in situ WH depend on the willingness of risk acceptance of the decision-makers. The implications of explicitly accounting for the level of risk can be seen in Table 8. We consider such a risk account to be more useful than the customary assumptions of fixed risk levels. Research in East Africa has highlighted the sensitivity of farmers to such risks (Hatibu et al., 2000). Hence, promotion of WH in the basin and in similar environments elsewhere may more effectively influence the adoption mechanisms if risk accounts – and strategies to estimate and reduce them – are explicitly included.

In this study, the reliability was taken as an indicator of the suitability of in situ WH. In reality, suitability is much more complex than merely a question of water availability and water demand. Factors such as legal rights to water, economic ability to invest in new technologies and safety mechanisms (e.g. reservoirs and fences), financial viability of the production systems, cultural preferences and social norms, complementary livelihood strategies etc., are of prime importance for actual implementation (Woyessa et al., 2006; de Winnaar et al., 2007; Kahinda et al., 2008). However, the mechanistic understanding of the interactions between the various factors is not yet clear, and the associated databases are not available so far. Therefore, these factors were not included in the present analysis. Future suitability assessments may be further refined when the necessary information at various scales becomes available.

Just as Kumar et al. (2006) found, it is the smallholder areas in the headwaters and close to the river mouth that display the highest reliability. Potential hydrological impacts of in situ WH adoption in either of these areas may differ.

Adoption in the headwaters may affect water availability for downstream reservoirs or aquatic ecosystems if WH alters river discharge. Adoption close to the river mouth may have less impact if beneficiaries are upstream of the implementation areas. Clearly, the potential effects of in situ WH depend on the location and sensitivity of the beneficiaries, and on the spatial reach of these effects.

Given the capacity of the model to simulate hydrological and crop-growth processes, this study provides a foundation for further research. Here we present one application concerning the reliability of in situ WH. Further work could aim at reducing the prediction uncertainty or explore potential effects of WH on crop yield, CWP, and discharge. Such knowledge can be used to inform management strategies aimed at enhancing food and livelihood security.

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