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Water availability, water 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 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 in situ WH and supplemental water demands (SWD) in smallholder agriculture in the Thukela River Basin, South Africa. It incorporates process dynamics governing runoff generation and crop water demands, an explicit account of the reliability of in situ WH, and uncertainty considerations.

The agro-hydrological model SWAT (Soil and Water Assessment Tool) was calibrated and evaluated with the SUFI-2 algorithm against observed crop yield and discharge in the basin. 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 the water availability ≥ the SWD. It reflects the risks of failure induced by the temporal variability in these factors.

The results show that the smallholder crop water productivity is 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 km^2 of smallholder lands, 20–28% display a reliability ≥25%, 13–16% a reliability ≥50%, and 4–5% a reliability ≥75% (95PPU). This suggests that the risk of failure of in situ WH is relatively high in many areas of the basin.

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Water availability, water demand, and reliability of in situ water harvesting

J. C. M. Andersson et al.

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 transpirational demands of crop-growth photosynthesis. The strategies to manage water effectively, and achieve food and livelihood security are numerous and of varied success (Yang and Zehnder, 2007).

A family of strategies centre on improving the water productivity in agriculture in order to raise food production on existing agricultural land, avoid aerial expansion of low-productivity agriculture, and not further stress water-limited systems. Of particular interest in this regard is smallholder rain-fed farming in sub-Saharan Africa (SSA) (Rockström et al., 2004). SSA is key due to the high level of undernourishment, rapid population growth, and considerable degree of water stress (FAO, 2009; Schuol et al., 2008). 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). Smallholder farming is central to agricultural water productivity since the productivity is often rather 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 (Gurtner et al., 2006; Rockström et al., 2004). The core aim of WH is to enhance the resilience of the agro-ecosystems 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. Thereby WH seek to raise crop water productivity, yields and yield stability (Rockström and Barron, 2007; Falkenmark and Rockström, 2004).

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; in other words 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). Repartitioning from runoff to infiltration has been the principal mechanism through which WH have enhanced crop yield and water productivity on the field scale. Repartitioning from evaporation to transpiration is difficult in the tropical savannah biome because of its high vapour pressure deficit and low canopy cover (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 of e.g. dry-spell occurrence relative to phenological stage for the amount of demanded water.

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. de Winnaar et al., 2007; Ngigi et al., 2005; Walker et al., 2005). 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 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) an explicit account of the reliability of in situ WH, and (3) consideration of uncertainty. The focus was on the Thukela River 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; Kosgei et al., 2007; de Winnaar 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 km^2 from an altitude of over 3000 m in the Ukhahlamba-Drakensberg World Heritage Site to sea level at the Indian Ocean. Its temperate climate is characterised by dry cool winters, warm summers with intensive precipitation, and a high spatiotemporal variability. 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 (CSIR et al., 2002). 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 (2% of basin area) and rain-fed (6% of basin area) production systems. The smallholder systems (6% of basin area) are predominantly rain-fed, use local cultivars, low amounts 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 (Kosgei et al., 2007; Statistics South Africa, 2006). The commercial irrigated systems principally utilise surface water for irrigation by withdrawals from rivers, blocking small streams or catching hillside runoff 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).

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 source code, and its successful application in a wide range of scales and environmental conditions in previous studies (Gassman et al., 2007; Neitsch et al., 2005).

SWAT is a physical-conceptual, spatially distributed, continuous time 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 land use, soil, and slope classes. In each HRU 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. Crop yield is determined from the biomass at harvest and the harvest index. Plant growth is limited by temperature, water, and nutrient deficiencies; and is influenced by agricultural management (e.g. fertilisation, irrigation, and timing of operations). 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. For more details see 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 (with a ≥2025 ha threshold). The soil data used for hydro-pedological parameter information was the FAO-UNESCO global soil map (FAO, 1995) with two soil layers at 1:5 000,000 scale, supplemented by data from Reynolds et al. (1999) and the ROSETTA model (Kosugi, 1999). Two land cover datasets (the South African National Land Cover 2000 dataset (CSIR et al., 2002) and the South African Crop Field Boundaries dataset (NCSC, 2007)) were combined, homogenised to 10 m resolution and 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)). This to simulate the crop fields at the finest resolution available as well as all the surrounding land use classes. 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.

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 Weather Office (Fig. 1). The simulation period was 1 January 1994 to 31 December 2006 based on the availability of 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, accessed 12 March 2009), and the South African Department of Water Affairs and Forestry (DWAF, www.dwaf.gov.za, accessed 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).

Available quantitative data on water management was incorporated in the model. Daily DWAF data on major reservoirs and water transfers in the basin were used (Fig. 1). The records contained only minor amounts of missing values, which were approximated using LOESS interpolation (Cleveland et al., 1992). The conveyance efficiency of the water transfers was estimated from the transfer scheme near the Thukela mouth (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). 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). 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, accessed 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).

2.3 Calibration, evaluation and uncertainty procedure

The Sequential Uncertainty Fitting algorithm (SUFI-2) was used for calibration and uncertainty analysis (Abbaspour and Johnson, 2004; Abbaspour et al., 2007). 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 ranges were based on physically meaningful limits, within which 500 Latin hypercube parameter set samples were obtained and simulated for each calibration iteration. In SUFI-2, the uncertainty is given as the range, for each time step, within which 95% of the parameter sets fall. This is denoted as the 95% prediction uncertainty band (95PPU) which is evaluated at 2.5% (L95PPU) and 97.5% (U95PPU) of the cumulative frequency distribution of each variable at each point in time.

A dual-objective calibration against ten nested discharge stations on daily temporal resolution, as well as against annual basin-wide maize yield in the smallholder and the commercial production systems was carried out for 1 January 2002 to 31 December 2006. The period 1 January 1997 to 31 December 2001 was not calibrated against, but rather used as an evaluation period in which the predictive power of the model was tested. The observed dataset originated from the DWAF for discharge and from the Crop Estimate Committee of the South African Department of Agriculture for crop yield (CEC, www.nda.agric.za, accessed 12 March 2009). The choice of discharge stations was based on homogeneity of the spatial distribution, range of scales in drainage areas, availability of data, and avoidance of clear upstream reservoir influence.

The selection of parameters to calibrate was based on a sensitivity analysis similar to Faramarzi et al. (2009) on the model response to a broad set of initial parameters 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), and Neitsch et al. (2005). This resulted in three basin-wide, eleven spatially-distributed, and thirteen crop-related parameters to calibrate. The spatially distributed parameters 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).

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

$$\begin{aligned} \Phi &= |b|\,R^2 \quad \text{for} \quad |b| \le 1 \\ \Phi &= |b|^{-1}\,R^2 \quad \text{for} \quad |b| > 1 \end{aligned} \tag{1}$$

where R^2 is the coefficient of determination 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 weighed equally:

$$O = \frac{1}{n}\sum_{i=1}^{n}\Phi_i \tag{2}$$

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):

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

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. Thus, the best simulation was considered as the one with the lowest RMSE. The crop yield was simulated on HRU level and subsequently area-weighed to basin scale for each agricultural system in order to better match the provincial scale of the evaluation data. The two systems were calibrated in parallel rather than weighed and calibrated jointly because of their mutual independence as discrete spatial simulation units with independent parameter sets. However, the crop parameter calibration was carried out conjunctively with the hydrological calibration on a qualitative basis in order to capture inter-linkages affecting all output variables.

The evaluation criteria used to quantify the performance of the entire set of simulations constituting one calibration iteration were 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

For completion, the commercial systems were incorporated in the simulation and calibration process. However, all further analysis centred on the smallholder system in accordance with the objectives.

The crop water productivity (CWP) was derived based on Kijne et al. (2003):

$$\mathrm{CWP}\left(\mathrm{kg\,m^{-3}}\right)=\frac{\mathrm{Yield_{HRU}}\left(\mathrm{kg\,ha^{-1}}\right)}{\mathrm{ET_{HRU}}\left(\mathrm{m^3\,ha^{-1}}\right)} \tag{4}$$

where $\mathrm{Yield_{HRU}}$ is the crop yield in the HRU for the season and $\mathrm{ET_{HRU}}$ is the corresponding seasonal evapotranspiration. 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. In contrast, 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. 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 are 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. Finally, all HRU level analyses were scaled to sub-basin level as an area-weighed 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, despite significantly different yields between the two periods (Fig. 2). The P-factors were ideal while the R-factors were somewhat 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 "over-fitting" of the parameters, considerably reducing the predictive power in the evaluation period (Notarnicola et al., 2008).

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 the box-and-whisker plots (Fig. 2). The size of the annual yield variability was similar to observations for the calibration period, but noticeably larger for the evaluation period (cf. the inter-quartile ranges in Fig. 2). 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 to 10 000s of hectares and 1000s of tons).

3.1.2 Discharge

Table 2 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 capture 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 $m^3 s^{-1}$ observed discharge (46% of the entire simulation period) on which the included 10% measurement error is not effective. In 78% of the cases, the best simulation had flows of $\leq$1 $m^3 s^{-1}$ indicating a close proximity to observations nonetheless. The widths of the 95PPU bands (the R-factor) were generally narrower than the standard deviation of the measured variable.

In certain aspects the simulations 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. 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 2). 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 predictive power was also reduced by the presence of missing data in the flow records, particularly on peak flows (e.g. V5H002 – the Thukela Mouth at Mandini). Nevertheless, given the high temporal resolution and the relatively conservative objective function criterion, the overall model performance was satisfactory.

3.2 Maize yield and crop water productivity

The 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.

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 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). 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.

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). 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).

3.3 Water availability for in situ WH in smallholder systems

The surface runoff is low within most smallholder HRUs (spatiotemporal median: 0–17 mm year^{-1}, 95PPU). The dominant outflow process is E_T as expected in this climatic zone. Averaged over time and space, 70–90% (95PPU) of the precipitation exits the system through E_T.

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 mouth (Fig. 6). The uncertainty of the runoff generation is rather large. Still, a large part of the basin consistently displays low runoff amounts throughout the posterior parameter space. The temporal variability at the L95PPU boundary is relatively small, but considerable and complex at the U95PPU boundary (see supplementary online material). This highlights both the 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).

A comparison was made with Schulze (2007), representing some of the extensive hydrological research carried out in the basin. Schulze (2007) used the ACRU model to simulate daily runoff at Quaternary Catchment (QC) scale over a 50-year time-period for "baseline" land cover conditions (natural vegetation types). The mean annual surface runoff (MAR) was calculated for each sub-basin and area-weighted to the QC scale (from 847 sub-basins to 86 QCs, Fig. 7). The ACRU simulations fell within the 95PPU for the vast majority of QCs, particularly where MAR was 50 to 200 mm $year^{-1}$. Only very few QCs displayed MAR >300 mm $year^{-1}$. For these, the simulations diverged considerably. Beyond fundamental model differences, a possible cause could be significantly altered land use since our study considered the present land use whereas Schulze (2007) simulated natural vegetation. The relatively good agreement in the middle to low range of the MAR is assuring because it is there where in situ WH may be particularly able to meet some of the SWD.

3.4 Supplemental water demand in smallholder systems

The demand for additional water in smallholder systems is relatively high in the central and eastern parts of the basin (Fig. 8). Particularly high peak SWD was obtained around Ladysmith, Newcastle, and Utrecht. The smallholder systems closer to the Drakensberg generally display low peak SWD. The temporal variability is high at the U95PPU boundary but low at the L95PPU boundary (see supplementary online material). 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.

3.5 Reliability of in situ WH in smallholder systems

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 such 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 similarity of the reliability throughout the posterior parameter space (Spearman correlation coefficient=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. This spatial differentiation highlights the importance of spatially explicit reliability estimates. For example, in situ WH investment appears to involve considerably greater risk around Weenen than around Bergville.

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 3 presents the cumulative area and percent 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 demand perspective. At the 75% reliability level, adoption of in situ WH may still be an attractive strategy in approximately 7 000 to 9 000 ha of the smallholder lands.

4 Discussion

4.1 Simulation challenges and opportunities

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, for example, relatively wide, but they represent the uncertainty of the input data rather well (e.g. the coarse resolution of the fertiliser data or the scant availability of information on management practices).

The Mandini flow record (V5H002) contains a disproportionately high level of missing data for high flows because of the inability of the weir to monitor flows above 457 $m^3 s^{-1}$. 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.

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.

4.2 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 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 to reflect the dominant WH types used, and because the water harvesting efficiency varies in space

HESSD
6, 4919–4959, 2009

and time etc.

The reliability was here calculated based on the peak SWD (Fig. 8). 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). Depending on the location, there is a considerable difference in the risk of failure. Which areas to consider suitable for in situ WH depends 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 3. We consider such a risk account to be more useful than the customary assumptions of fixed risk levels.

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 (de Winnaar et al., 2007; Woyessa et al., 2006; 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

HESSD

6, 4919–4959, 2009

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 solid foundation for further research. Here we present one application concerning the reliability of in situ WH. Further applications could 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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HESSD

6, 4919–4959, 2009

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HESSD

6, 4919–4959, 2009

Water availability, water demand, and reliability of in situ water harvesting

J. C. M. Andersson et al.

Title Page | Abstract | Introduction | Conclusions | References | Tables | Figures | Back | Close | Full Screen / Esc | Printer-friendly Version | Interactive Discussion

Table 1. Overview of approaches to identify of 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 (runoff potential)	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 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 gardens	Potshini community, Thukela, South Africa (1.2 km^2)	Static runoff thresholds and AM on ranked soil, slope and land use classes	Indirectly through distance to crop fields and homesteads	Yes, for rainfall	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)	Not estimated directly. Ranking of rainfall, land use and soil classes	Indirectly through static estimate of domestic availability of piped water	No	No
Hensley et al. (2007)	In situ WH	Alleviating field crop water deficits	South Africa (1.2×10^6 km^2)	Not estimated directly. Soil depth and water holding capacity classification	Not estimated	No	No
Senay and Verdin (2004)	Runoff-harvesting and small reservoir storage	Field crop irrigation	Africa (3×10^7 km^2)	Daily simulation with 5-day updating of AM and runoff thresholds	Static and generic African average crop water demand	No	No

Table 2. Performance of the model with respect to daily discharge in the calibration (Cal.) and evaluation (Eval.) periods, respectively. The overall weighed 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	12862	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	28920	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

Table 3. 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	81057	73220	44	40
25	52604	37188	28	20
50	24282	30499	13	16
75	9421	6721	5	4
90	4450	4917	2	3

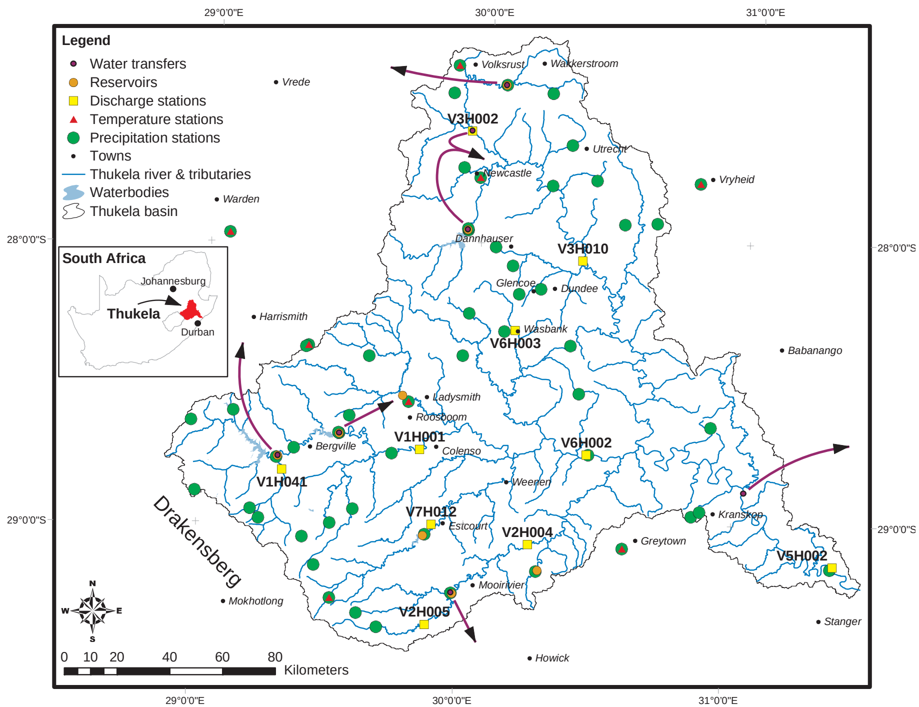


Fig. 1. Overview of the Thukela River Basin study area and the major precipitation, temperature and discharge stations as well as reservoirs and water transfers (purple arrows) included in the model. Projection: Lambert Azimutal Equal Area. Datum: GCS_WGS1984.

HESSD

6, 4919–4959, 2009

Water availability, water demand, and reliability of in situ water harvesting

J. C. M. Andersson et al.

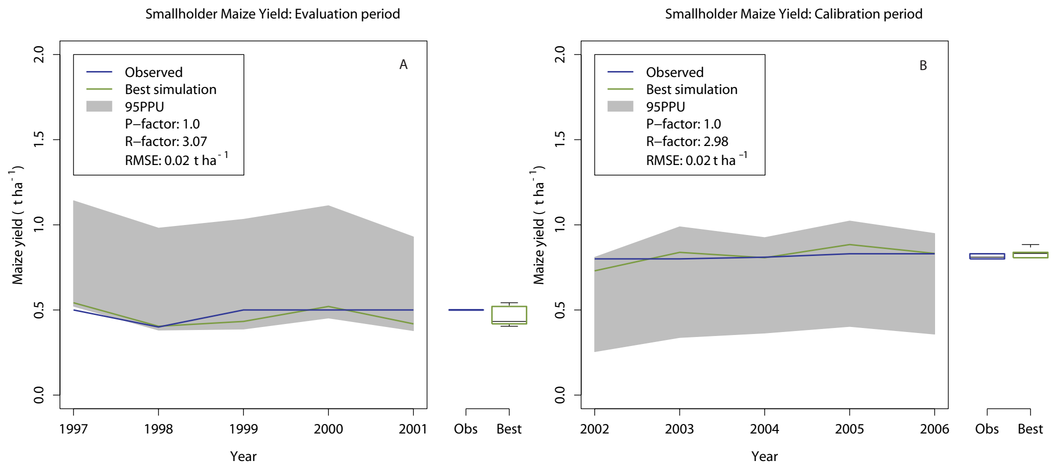


Fig. 2. Observed and simulated annual maize yield in smallholder systems in the evaluation **(a)** and calibration **(b)** periods, respectively. RMSE is Root Mean Squared Error – the objective function used to derive the best simulation – and 95PPU represents the 95% prediction uncertainty band. The time-period summary is shown in the box-and-whisker plots on the right-hand side (Obs is observed and Best is best simulation).

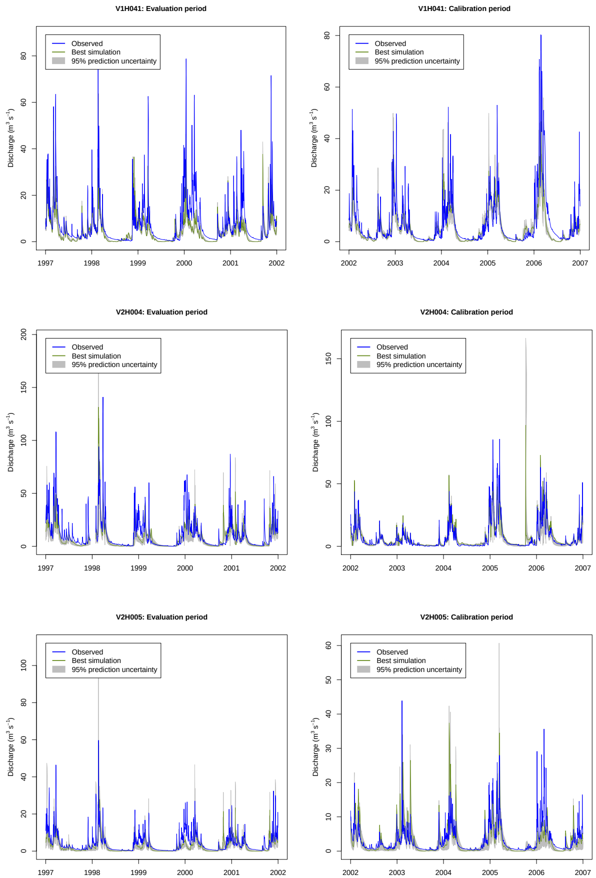


Fig. 3. Observed and simulated daily river discharge for selected stations in the evaluation (left) and calibration (right) periods, respectively. The best simulation is the parameter set with the highest objective function (Φ). Gaps represent missing observations. See Fig. 1 for station locations.

HESSD

6, 4919–4959, 2009

Title Page
Abstract
Introduction
Conclusions
References
Tables
Figures
◂◂
▸▸
◂
▸
Back
Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion

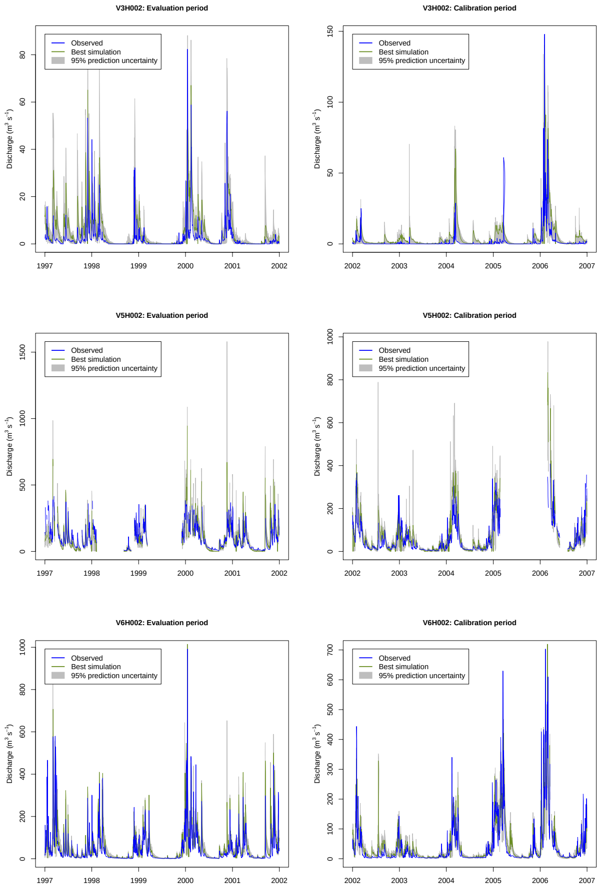


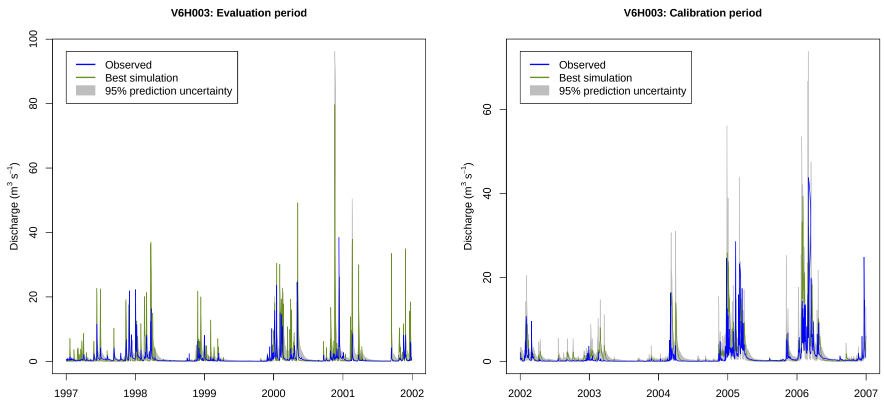
Fig. 3. Continued.

HESSD

6, 4919–4959, 2009

Water availability, water demand, and reliability of in situ water harvesting

J. C. M. Andersson et al.



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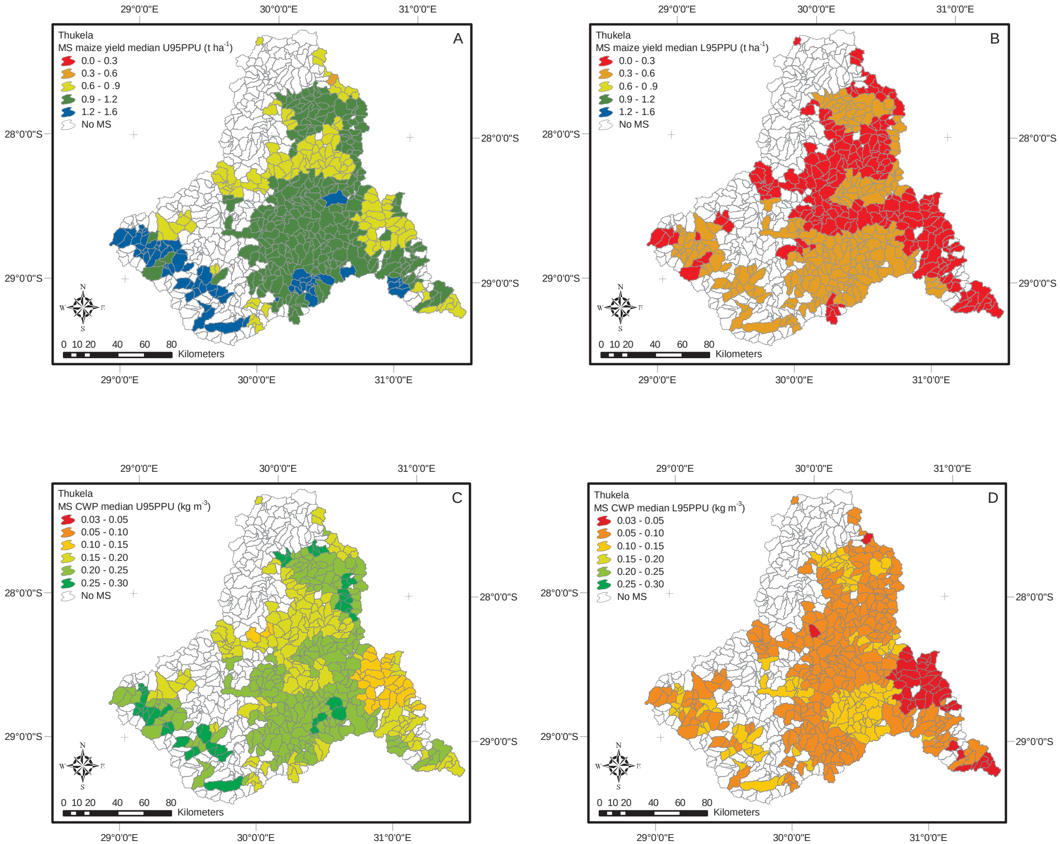

Fig. 4. Median, area-weighted maize yield **(a, b)** and crop water productivity (CWP, **c, d)** in smallholder systems (MS) during the simulation period. U95PPU **(a, c)** is the upper boundary and L95PPU **(b, d)** is the lower boundary of the 95% prediction uncertainty band, respectively. Projection and datum as in Fig. 1.

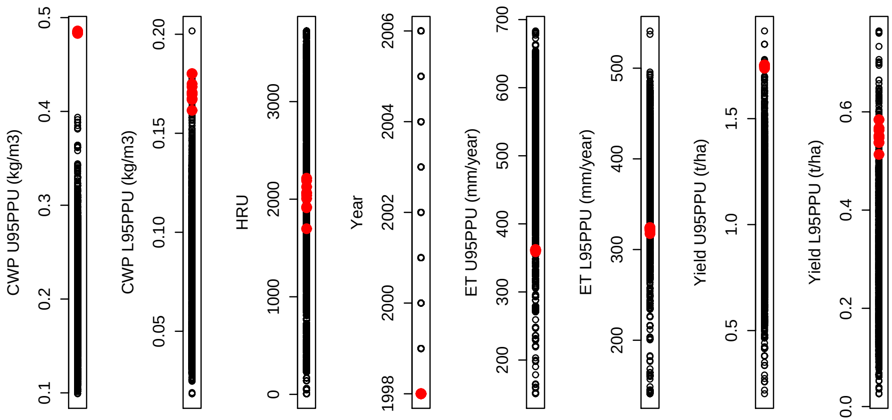

Fig. 5. Parallel coordinate plot of crop water productivity (CWP) in smallholder systems against space (HRU), time (Year), evapotranspiration (E_T) and maize yield (Yield) for the upper (U95PPU) and lower (L95PPU) 95% prediction uncertainty boundaries, respectively. Red items are the space-time combinations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

HESSD

6, 4919–4959, 2009

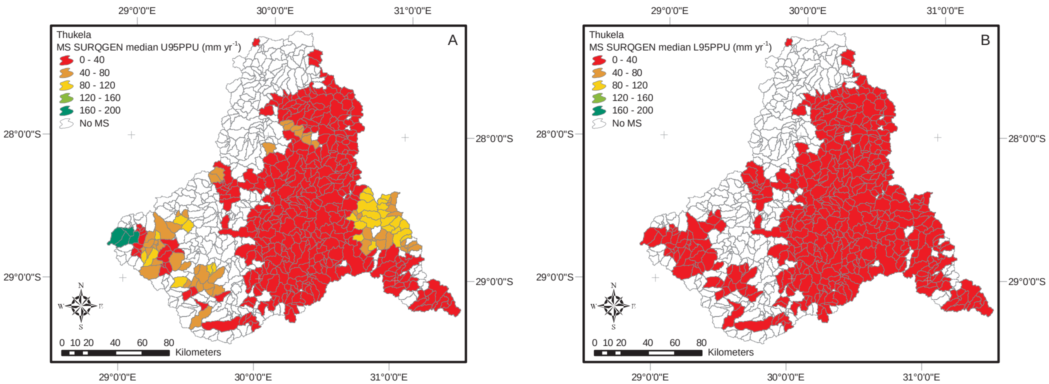

Fig. 6. 1997 to 2006 median annual generated surface runoff (SURQGEN) from the smallholder agricultural production land use class (MS), area-weighted to sub-basin level. U95PPU **(a)** is the upper boundary and L95PPU **(b)** is the lower boundary of the 95% prediction uncertainty band, respectively.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

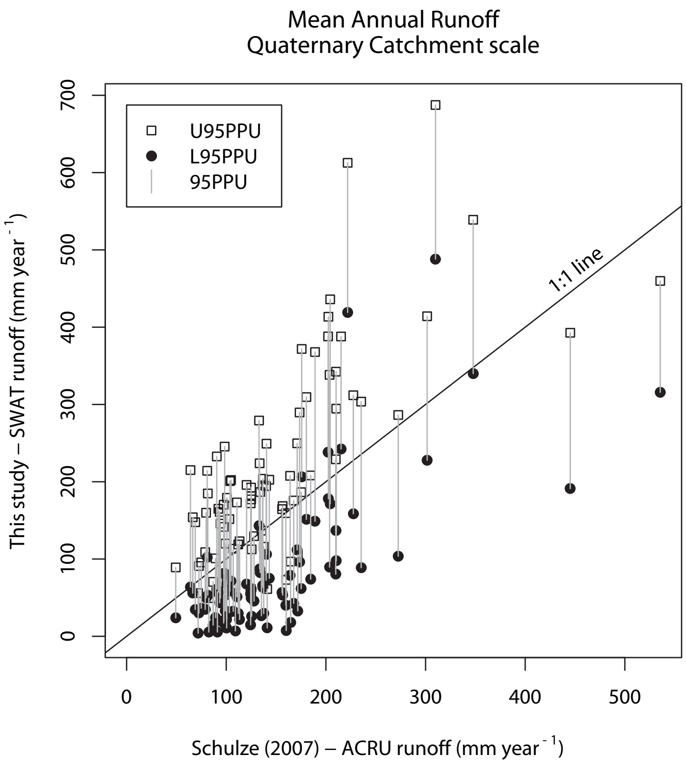

Fig. 7. Comparison of the mean annual runoff at Quaternary Catchment scale from this study (area weighed from the sub-basin scale) with that of Schulze (2007). U95PPU and L95PPU are the upper and lower boundaries of the 95% prediction uncertainty band (95PPU), respectively.

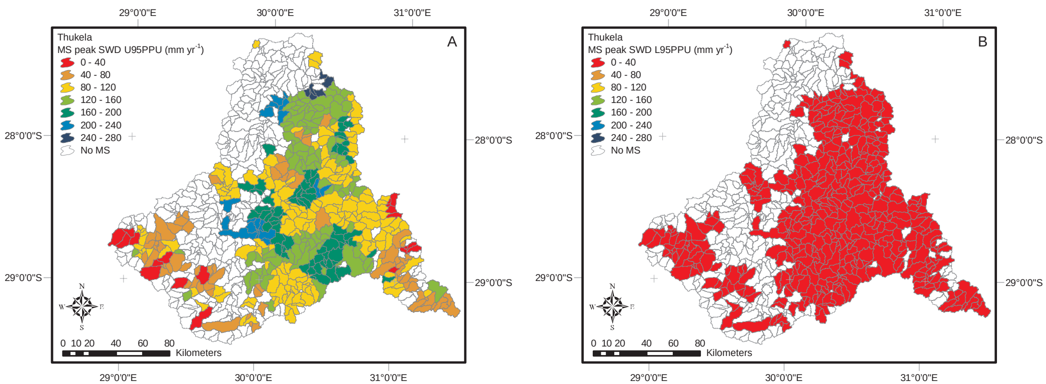

Fig. 8. 1997 to 2006 median annual peak supplemental water demand (SWD) in the small-holder agricultural production land use class (MS), area-weighted to sub-basin level. U95PPU **(a)** is the upper boundary and L95PPU **(b)** is the lower boundary of the 95% prediction uncertainty band, respectively. "No MS" indicates sub-basins without the MS class. Projection and datum as in Fig. 1.

HESSD

6, 4919–4959, 2009

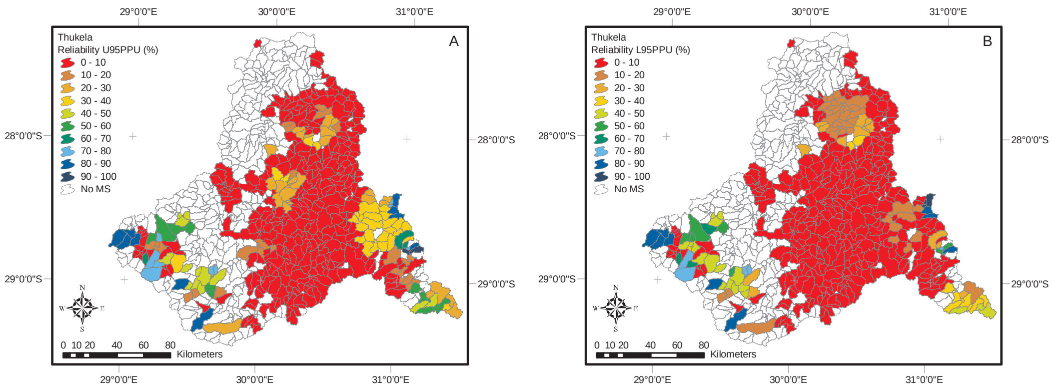

Fig. 9. Reliability of in situ WH in the smallholder agricultural production land use class (MS), area-weighted to sub-basin level. U95PPU **(a)** is the upper boundary and L95PPU **(b)** is the lower boundary of the 95% prediction uncertainty band, respectively. "No MS" indicates sub-basins without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

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6, 4919–4959, 2009