Journal of the Indian Institute of Science
A Multidisciplinary Reviews Journal
ISSN: 0970-4140 Coden-JIISAD

REVIEWS

Improved Modeling of Groundwater Recharge in Agricultural Watersheds Using a Combination of Crop Model and Remote Sensing

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Abstract | For improved water management and efficiency of use in agriculture, studies dealing with coupled crop-surface water-groundwater models are needed. Such integrated models of crop and hydrology can provide accurate quantification of spatio-temporal variations of water balance parameters such as soil moisture store, evapotranspiration and recharge in a catchment. Performance of a coupled crop-hydrology model would depend on the availability of a calibrated crop model for various irrigated/rainfed crops and also on an accurate knowledge of soil hydraulic parameters in the catchment at relevant scale. Moreover, such a coupled model should be designed so as to enable the use/assimilation of recent satellite remote sensing products (optical and microwave) in order to model the processes at catchment scales. In this study we present a framework to couple a crop model with a groundwater model for applications to irrigated groundwater agricultural systems. We discuss the calibration of the STICS crop model and present a methodology to estimate the soil hydraulic parameters by inversion of crop model using both ground and satellite based data. Using this methodology we demonstrate the feasibility of estimation of potential recharge due to spatially varying soil/crop matrix.

Keywords: *agro-hydrology, crop model, recharge, soil hydraulic parameters.*

1 Introduction

Modeling and quantifying the spatio-temporal variability of water resources is an essential component of integrated and comprehensive water resources management. Such processes involve the complex interplay of hydrology, ecology, meteorology, pedology, agronomy and climatology. The approach of integrated modeling is increasingly becoming an important tool in studies on water quality and quantity management. Interaction between vegetation soil and atmosphere determine the dynamic equilibrium of a soil vegetation atmosphere system. In most land surface and SVAT models (e.g., WAVES, MOSAIC, SWAP), vegetation does not respond to any change in the soil water status.[1] The effect of stresses on the vegetation and the feedback between the vegetation and hydrological variables are often not considered, and vegetation is often considered as a specified boundary condition rather than as an interactive interface between the soil and atmosphere. This results in improper representation of the model and thus lead to inaccurate simulation of hydrological fluxes (e.g., recharge, evapotranspiration, runoff). However, the type of crop and its growth dynamics play a major role in the hydrological fluxes. Precise simulation of these variables requires that the vegetation should be considered as a dynamic component in the models. Several studies have been made in the past decade to develop and apply transient–dynamic coupled vegetation models.[2–6]

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Traditional land surface models do not consider the bottom boundary conditions as an interactive process. Such models, even though are mass conservative, ignore processes that can alter surface fluxes, runoff, vegetation dynamics and soil moisture reserve. Hence studies have been made for coupling land surface models with groundwater models. Levine and Salvucci[7] observed that simulated recharge was closer to the observation when a coupled groundwater model was used, instead of an uncoupled land surface model with specified lower boundary condition. Yeh and Eltahir[8] developed a lumped unconfined groundwater model dynamically coupled to a land surface model to simulate the fluxes between the water table and lower soil layer of the land surface model. Further advancements were made to land surface models by including detailed ecological and biogeochemical processes.[9–11] Maxwell and Miller[12] coupled a land surface model (Common Land Model) and a variably saturated groundwater model (ParFlow) to study the effect of the coupling scheme on the simulation of soil water fluxes, and demonstrated the need for improved groundwater representation in land surface schemes.

On the contrary, groundwater models have a simplified upper boundary condition that is externally specified and represents fluxes of water related to processes such as infiltration and evapotranspiration. These fluxes are often simplified and uncoupled, may be averaged in space and time, and sometimes miss the key dynamics of the important processes, which takes place in the rooting zone of the vegetation. To understand the effects of vegetation on soil water fluxes and groundwater recharge, a modeling scheme, which allows one to simulate the dynamics of interaction between a vegetation and groundwater system is essential. Coupled groundwater models such as the MODFLOW-HYDRUS[13] and ParFlow,[14] simulate the water balance and the soil water movement in saturated and unsaturated zones, but they simplify the evapotranspiration process as these models consider vegetation as a static component. Ledoux et al.[15] added a new dimension to this coupling strategy by bringing in a dynamic crop model (STICS) to an already coupled surface-groundwater model (MODCOU) to predict the fate of nitrogen fertilizers and the transport of nitrate from the rooting zone of agricultural areas to surface and groundwater of Seine basin. An integrated hydrological (TOPMODEL) and nitrogen model (STICS), called TNT2 (Topography-based Nitrogen Transfer and Transformation) was developed by Beaujouan et al.[16] to study the nitrogen fluxes in a Kervidy catchment in France.

In all these coupling schemes even though the coupling between the models are well achieved, the feedback between the two models is not considered. Moreover, the agriculture in tropical arid and semi-arid regions mainly depends upon the irrigation, especially in the non-rainy season and in some regions even in the rainy season, to supplement crop water requirements not met by precipitation. If the irrigation is from groundwater, and also if the level of irrigation is higher than the recharge then groundwater levels would decline, which in turn would affect the crop production. Thus there is a need for optimal irrigation, which maximizes crop production but with sustained groundwater levels. To simulate such optimal water management scenarios, an integrated model of crop and groundwater system is required. The dynamics of interaction between the two models could give deeper insight into the interaction between the two processes. Performance of such a coupled crop model would depend on the availability of a calibrated crop model for various irrigated crops, and also on accurate representation of soil parameters in the model. In addition, such a coupled model should be able to use satellite remote sensing products so as to model at catchment scales.

In this study we present the calibration of STICS model, which is used in the coupled crop-groundwater model developed under the AICHA project. Then we discuss the methodology of estimating soil hydraulic properties by crop model inversion using ground and satellite based data. We also discuss the application of the crop model in estimating the potential recharge, root zone soil moisture and crop variables such as leaf area index, biomass and yield. Finally we demonstrate the performance of calibrated crop model using remote sensed weather products (rainfall and potential evapotranspiration). The above studies are conducted in an experimental catchment in the tropical semi-arid region of South India.

2 Materials and Methods

2.1 *Study area and field experiments*

The study area pertains to the AMBHAS research observatory (www.ambhas.com) located in the Kabini river basin in South India, (Fig. 1), which is an experimental watershed for carrying out agro-hydrological, remote sensing and hydrological investigations.[46] It belongs to the long term environmental observatory BVET (http://bvet.ore.

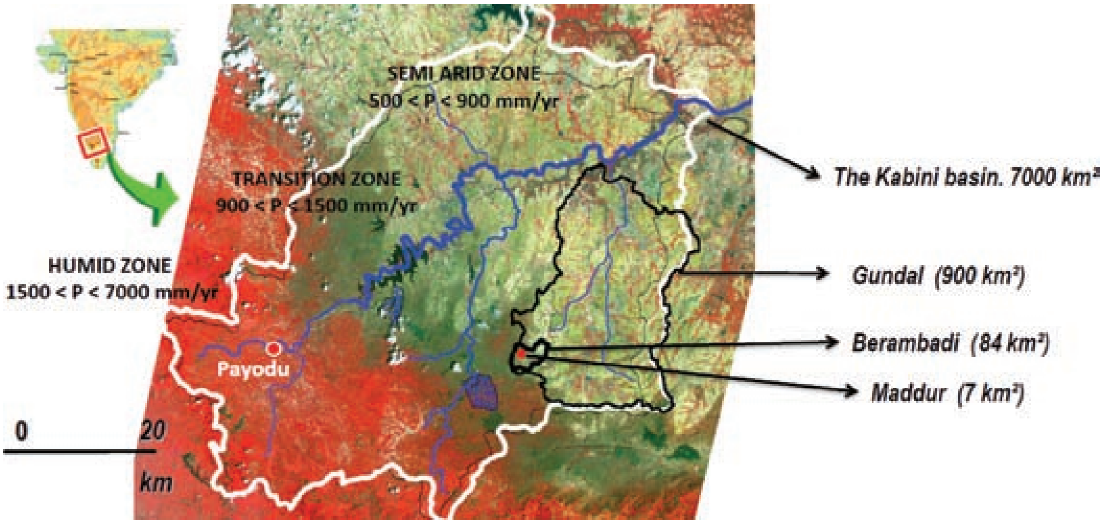


Figure 1: Study area.

fr/).[47-49] Climate is tropical semi arid, with an average rainfall of 800 mm/year and PET of 1100 mm. There are mainly two types of soils in the watershed comprising black soils (Calcic Vertisols) and red soils (Ferralsols and Calcic Luvisols),[50] underlain by granitic/gneissic rocks. The land is used for agriculture and the main crops are sunflower, maize, marigold, sugarcane, finger millet, groundnut etc.

Field experiments were carried out on several crops in the agricultural plots of the Ambhas Research Observatory during the year 2010–2012. Soil and crop related measurements were performed during the cropping period from October-2010 to Dec-2012. Leaf Area Index (LAI) was measured by laser leaf area meter (CI-202, CID, Bio science Inc, USA) on a ten day frequency from the germination stage to harvest stage. Above-ground biomass and yield were measured at harvest date.

Daily records of air humidity, wind velocity, maximum and minimum temperature, precipitation and global radiation were obtained from an automatic weather station (CIMEL, type ENERCO 407 AVKP). Surface soil moisture and root zone soil moisture profiles were measured using theta probe (**Delta-T devices,** ThetaProbe Soil Moisture Sensor—ML2x) and AquaPro soil moisture sensors respectively. Soil depth was measured by soil augering. Leaf area Index and surface soil moisture were retrieved from microwave remote sensing images (RADARSAT-2, 10 m resolution, 24 day revisit interval) collected during the satellite passes and the field measurements were done on the corresponding days.

2.2 *Theory and methodology*

2.2.1 Calibration of STICS crop model: Crop growth models have been indispensable tools of agro-meteorological and plant production research for several years now. There are many crop models in the literature. Some are designed for particular crops, *e.g.,* for wheat, ARCWHEAT[17] and CERES-Wheat,[18] while others are generic models, *e.g.,* EPIC,[19] DAISY[20] and STICS.[21] One of the important preconditions of the application of dynamic models is the evaluation of the model reliability in reproducing the real world processes at the given place and time.[22–23] The processes of evaluation of any crop model are relatively long and difficult because they require the collection of large data sets including weather, soil, crop and crop management data over extensive time periods. Crop growth models are great tools for studying and anticipating the future impacts of rising demands for agricultural production while satisfying constraints with respect to product safety, the landscape, water resources and the environment. Before crop growth models can be applied, however, they need to be calibrated and evaluated for cultivars representative of a study area. Calibration of crop models, which is a crop parameter estimation process, is an integral part of the modeling exercise, because together with the form of the model equations, the crop parameter values determine the quality of variable predicted by the model. Often crop specific parameters are obtained from literature, however, not all parameters are available in the literature and these parameters vary within cultivars of the same crop. Using approximate values for all parameters result in the accumulation of errors in the parameter values and this leads to the model giving poor agreement with field data.

STICS[21] is a dynamic, daily time-step model which simulates the functioning of a soil-crop system over a single or several successive crop cycles. Among the large variety of available crop models, the main strong points of STICS is its adaptability to many crop types, its robustness in a large range of soil and climate conditions and its modularity.[24] It has been successfully used for spatial applications and coupled with hydrological models at the catchment scale.[16] The upper boundary conditions are governed by standard climatic variables (radiation, minimal and maximal temperatures, rainfall, reference Evapo-transpiration or alternatively wind speed and humidity) and the lower boundary condition is the soil/sub-soil interface. Crops are described by their above-ground biomass and nitrogen content, leaf area index, and the number and biomass of harvested organs. Daily root front depth and distribution of root density is also simulated. The soil is defined as a succession of up to five horizons of variable thickness with homogenous properties. Each horizon is divided into horizontal layers of 1 cm thickness, for which mineral nitrogen and organic nitrogen contents are computed. Soil and crop interact via the roots, which are defined by the root density distribution in the soil profile.[25]

STICS simulates the daily carbon balance, the water balance (evaporation and transpiration) and the nitrogen balance in the system, which makes it possible to calculate both agricultural and environmental variables in a variety of agricultural situations. In the STICS crop model, the total number of parameters is large. They are specific for each crop, soil, cropping techniques and on-field management practices.

2.2.2 Inversion for estimation of soil hydraulic properties: Good estimates of soil hydraulic parameters and their distribution in a catchment is essential for crop-hydrology models. Measurements of soil properties by experimental methods are expensive and often time consuming, and in order to account for spatial variability of these parameters in the catchment, it becomes necessary to conduct large number of measurements. Although extensive soil data is becoming more and more available at various scales in the form of digital soil maps,[42] there is still a large gap between this available information and the input parameters needed for hydrological models.[43] Inverse modeling has been extensively used but the spatial variability of the parameters and insufficient data sets restrict its applicability at the catchment scale. Montzka[44] demonstrated the possibility of estimating the soil hydraulic parameters using remotely-sensed surface soil moisture measurements by applying a sequential filtering technique to the mechanistic soil-water model HYDRUS 1-D. Sreelash[45] showed that the multilayered soil hydraulic properties can be estimated using observations of surface soil moisture and crop canopies by inversion of a crop model. Use of remote sensed soil moisture data to estimate soil properties using the inverse modeling approach received attention in recent years but yielded only an estimate of the surface soil properties. However, in multilayered and heterogeneous soil systems the estimation of soil properties of different layers yielded poor results due to uncertainties in simulating root zone soil moisture from remote sensed surface soil moisture. Crop biophysical parameters such as Leaf Area Index (LAI) and above ground biomass, on the other hand, are sensitive to the properties of the root zone soil, and hence these observations can be useful for estimating the properties of deeper soil layers. Leaf area index and biomass can be estimated from optical/microwave remote sensing data.

Surface soil properties can be estimated by inverse approach using surface soil moisture data retrieved from remote sensing data. Since soil moisture retrieved from remote sensing is representative of the top 5 cm only, inversion of models using surface soil moisture cannot give good estimates of soil properties of deeper layers. Crop variables like biomass and leaf area index are sensitive to the deeper layer soil properties. Here we discuss the methodology of estimating the properties of deeper layers by inversion of a crop model STICS using crop canopy variables and surface soil moisture retrieved from microwave remote sensing. Parameter estimation by inversion of a dynamic crop model like STICS is a complex process, since such models involve parameter interactions and hence obtaining a single optimum soil parameter set is not realistic. Generalized Likelihood Uncertainty Estimation[27] (GLUE), an informal Bayesian method using prior information about parameter values for estimating model parameters can be used for the parameter estimation process. Here we estimate the soil water related parameters like field capacity, wilting point and depth of soil water reserve/rooting depth/depth of soil layer. A combined likelihood function based on sum of absolute errors, which represents the goodness of fit when output variables possess different magnitudes. Thus in this study we propose to use crop biophysical parameters to estimate the multilayered soil properties by inversion of a crop model using the Generalized Likelihood Uncertainty Estimation (GLUE) approach. With the availability crop type information from remote sensing this approach can be used to estimate the soil properties at watershed scale.

Here we demonstrate an approach of soil parameter estimation using crop model STICS and the GLUE approach. The STICS model contains about 60 soil parameters. Varella et al.[28] reduced this number by selecting the simplest options for simulating the soil system, and by considering only two soil horizons; they performed sensitivity analyses and selected seven soil parameters characterizing both water and nitrogen processes. In the present study, we restricted the analysis to the five soil-water related parameters (Table 1). These parameters are the water content at field capacity and wilting point of both the horizons, HCC1, HCC2, HMINF1 and HMINF2 respectively and the thickness of the second horizon, EPC2. Figure 2 shows the methodology that is adopted in this study for soil parameter estimation from ground and satellite based data.

For model inversion, the initial ranges of soil parameters comprised between the maximum and minimum values corresponding to a broad variety of soils. This broad range was used in order to assess whether the parameter estimation approach is efficient even when prior information on the soil properties is poor. As results of estimated parameters vary greatly according to the type of observation set,[29] we used seven combinations L1 to L7 (Table 2), using either individual (L5 to L7) or combined observation sets of SSM, BM and LAI, (L1 to L4).

2.3 *Recharge modeling*

In semi-arid agricultural areas, the question is that under what conditions groundwater recharge occurs, and its magnitude, are fundamental to the management of water resources.[30] Understanding the spatial and temporal variability of potential recharge in semi-arid regions gains importance as the potential recharge varies as a function soil, vegetation and climate types. The re-distribution of the rainfall in the soil horizon, and its interaction with the vegetation such as root water

Table 1: Soil parameters of model STICS selected for estimation along with their initial ranges used as prior information for model inversion in the field experiments.

Parameter	Definition	Unit	Range
HCC(1)	Water Content at Field Capacity of 1st horizon	gg^{-1}	10–40
HCC(2)	Water Content at Field Capacity of 2nd horizon	gg^{-1}	10–40
HMINF(1)	Water Content at Wilting Pont of 1st horizon	gg^{-1}	5–30
HMINF(1)	Water Content at Wilting Pont of 2nd horizon	gg^{-1}	5–30
EPC(2)	Thickness of 2nd horizon	cm	10–200

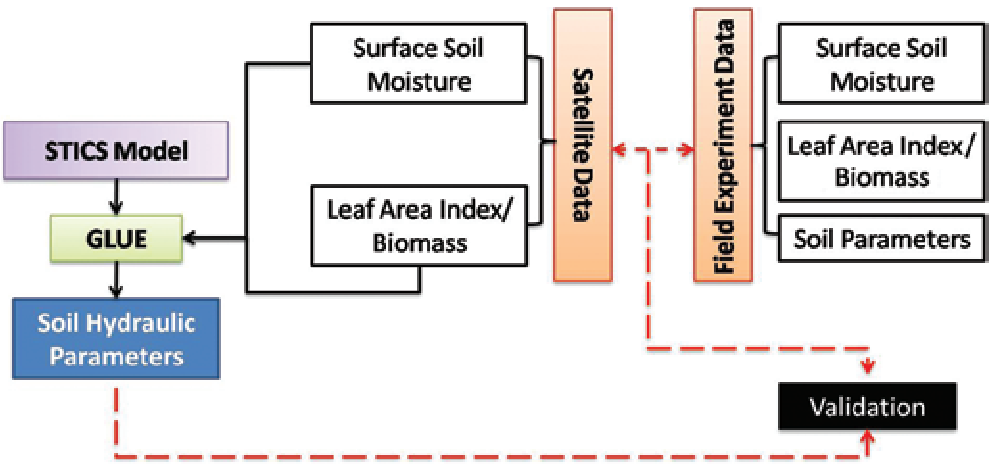


Figure 2: Methodology for soil parameter estimation from ground/satellite data.

Table 2: Cases with combinations of Surface Soil Moisture (SSM), above-ground biomass (BM) and Leaf Area Index (LAI).

Likelihood combination	Combination of observation set
L1	SSM + LAI + BM
L2	LAI + BM
L3	SSM + LAI
L4	SSM + BM
L5	LAI
L6	BM
L7	SSM

uptake needs to be adequately represented in models intended in providing reliable estimates of groundwater recharge. Several methods have been developed in the past for estimating the groundwater recharge,[31–34] each method being suitable for the choice of intended application of the recharge estimate and the spatial and temporal scales being considered.

Estimates of potential recharge by soil moisture budgeting models are prone to large error in recharge rates.[35] Estimation of groundwater recharge through simple water balance models or through soil moisture balance approaches often do not consider the effect of soil and crop type which critically affect the recharge process. This becomes particularly important in semi-arid agricultural catchments where the agriculture also depends on groundwater irrigation. Groundwater recharge in a semi-arid region, while generally low can be highly variable depending on the soil type and plant cover even under same climatic conditions. Soil hydraulic properties such as field capacity, permanent wilting point and depth of soil water reserve plays a major role in the potential recharge that may eventually reach the water table. In soil moisture balance approach the potential recharge is found to be sensitive to water holding capacity and rooting depth.[36] Moreover, Martinez et al.,[37] using a root zone modeling approach to estimate groundwater recharge, stressed that future studies should focus on quantifying the uncertainty in recharge estimates due to uncertainty in soil water parameters such as field capacity, rooting depth etc. Hence, a good estimate of soil water related parameters and depth of soil layers along with their uncertainty is essential for a reliable estimate of the potential recharge.

Different crops have varying quantities of crop water requirement and depending on the rooting depth of the crops; the water from the soil water reserve is taken up the crop and is added to the actual Evapo-transpiration. This process largely affects the recharge process. Hence, a crop model based approach is better suited to assess sensitivity of recharge for various crop-soil combinations in agricultural catchments. In this study we focus on using the soil parameters estimated from inversions to quantify the potential recharge. The potential recharge obtained from the crop model is used as an input to the groundwater model and the dynamics of feedback between crop and a groundwater system is simulated using a coupled model. Figure 3 shows the scheme in which a crop model can be used as a potential tool for estimating the potential recharge into the groundwater system.

In this section we demonstrate how a crop model such as STICS can be used to simulate the potential recharge and its uncertainty for an irrigated turmeric crop. The mechanism of soil water transfer in the STICS model is shown in Fig. 4. In the STICS model, water transfer in the soil microporosity is calculated per elementary 1 cm layer using reservoir-type analogy. Water fills the layers by downward flow, assuming that the upper limit of each basic reservoir corresponds to the layer's field capacity. The soil layers affected by evaporation can dry until they reach the residual soil water content. In deeper layers, the water is only extracted by the plant, and therefore always remains above the wilting point.

The flowchart (Fig. 5) shows the methodology adopted in this study for estimating the spatial variability of potential recharge using STICS crop model.

2.4 *Crop modeling using satellite weather products*

Management of water resources in semi-arid regions is particularly important due to the high temporal and spatial climatic variability. The fusion of remote sensing data in crop growth model provides a powerful tool for estimating the biomass and yield and for predicting/monitoring the impacts of drought and other management activities. The integration of remote sensing information of crop variables such as leaf area index, biomass, nitrogen level estimates into a crop model has been made in several studies.[39–41,56–61] These studies aim at improving the model prediction by assimilating these variables in the crop model. Large scale monitoring and estimation of crop yield is essential for food security related issues. The high spatial and temporal variability of weather variables make it difficult for a crop model

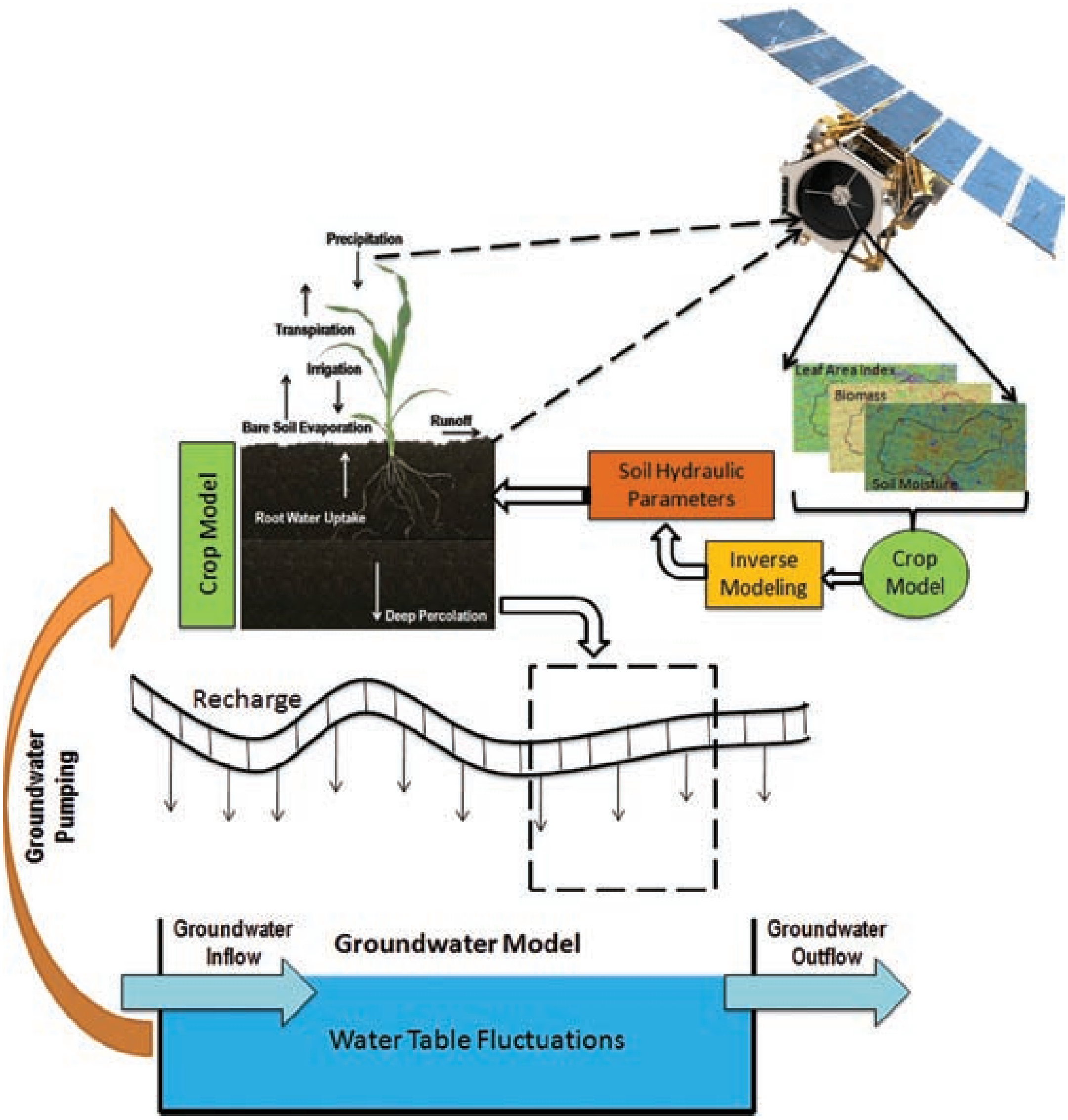


Figure 3: Scheme of using crop models for estimating potential recharge (modified from Portoghese et al.[38]).

to predict the variability crop yield at large scale. Remote sensing information of climate variables such as rainfall can provide the additional information necessary to capture the effect of the spatial variability of rainfall on the estimated yield.

With the increasing availability of climate forcing and soil related information from satellite products, hydrological and crop models can be used to estimate variables such as soil moisture or groundwater resources at large scales. In recent years, better satellite based products are being made available, which have a good spatial resolution. On the other hand, management of ground network of rain gauges is a costly and difficult task. Several studies attempted to estimate and evaluate different satellite rainfall products and demonstrated their suitability in modeling various hydrological processes. Satellite-based precipitation products are prone to a variety of error sources and require a thorough evaluation. One way to evaluate is the direct comparison of the satellite rainfall estimates to the rain gauge networks. The bias and the uncertainty in the retrieved rainfall products needs to be quantified before a satellite product can be applied to a hydrological model. The error in the satellite rainfall estimates propagates into the simulated variables and quantifying this is important. With the availability of climate forcing and soil related information from satellite products, crop and hydrological models can be used to estimate the variables at a larger scale.

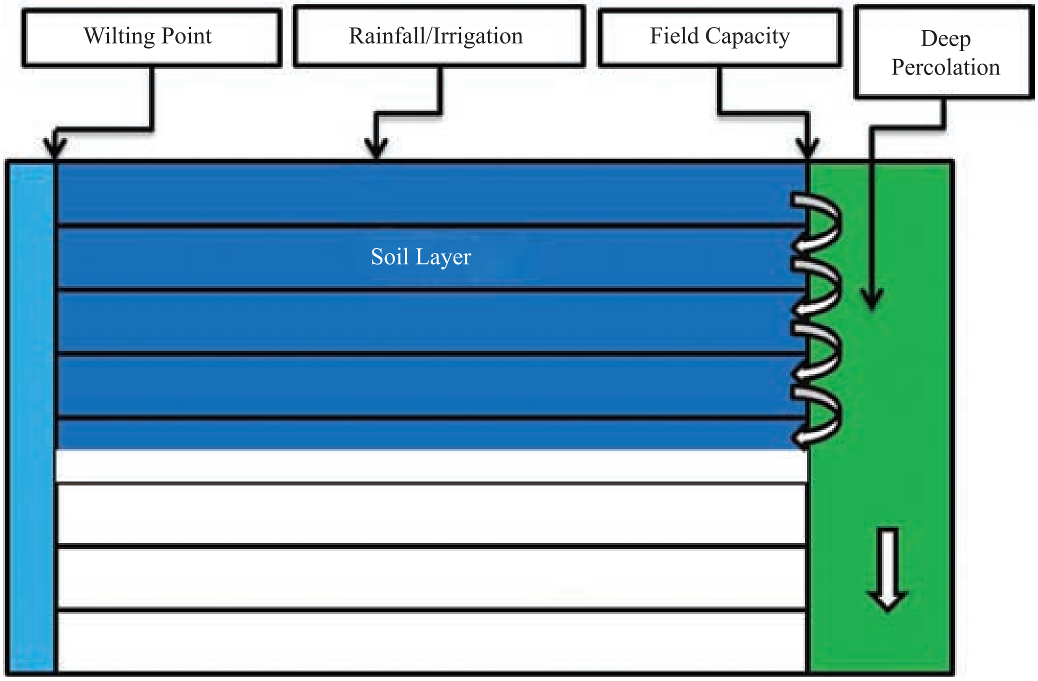


Figure 4: Mechanism of soil water transfer in STICS.

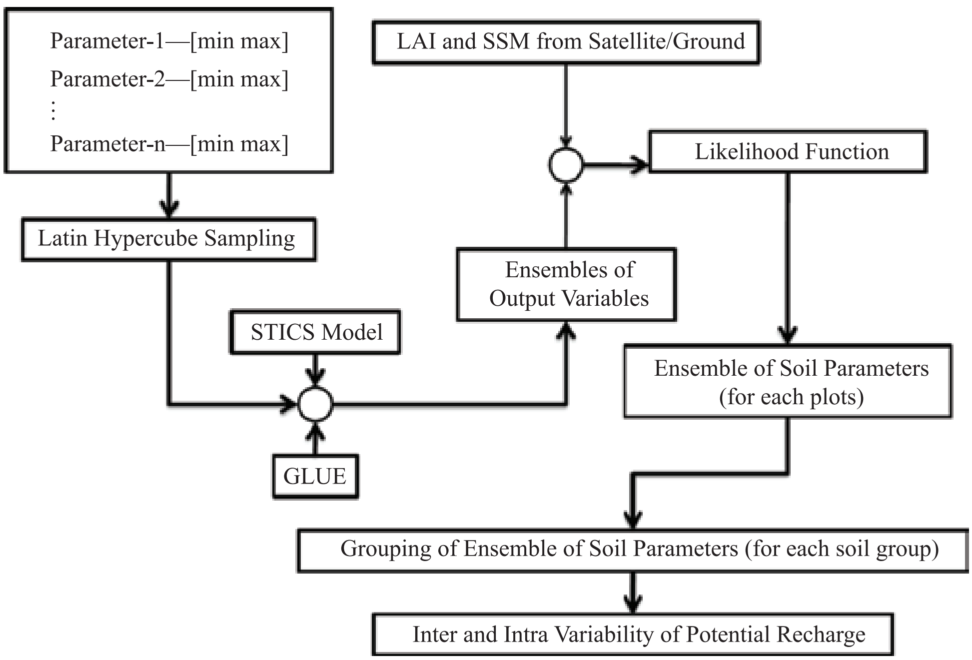


Figure 5: Methodology for using STICS model for estimating spatial variability of potential recharge.

In this study we demonstrate the application of satellite rainfall and potential evapotranspiration for estimating the crop variables and potential recharge used the rainfall estimates from two satellites (Kalpana and TRMM) and the potential evapotranspiration (PET) from Kalpana Satellite to estimate the crop variables. We compared rainfall estimated from Kalpana and TRMM satellite data with ground measurements at different time scales and evaluated the relevance of satellite data for agro-hydrological processes simulation. We quantified the errors in the estimates of agro-hydrological variables induced by the uncertainty in the rainfall estimates from the satellite data. We use the calibrated crop model STICS to simulate the agro-hydrological variables such as potential recharge, leaf area index and yield for a wet growing season in 2011 using gauge and satellite data.

3 Results and Discussion

3.1 *Calibration of STICS crop model*

An example of the calibration of turmeric crop using OptimiSTICS is shown in Fig. 6. We used GLUE approach to estimate the crop parameters which are related to leaf area index, biomass and yield formation. Additionally, a crop parameter estimation tool called OptimiSTICS,[26] which was specifically available with STICS model was used to calibrate some of the corps. The simulated LAI, biomass, yield at harvest and root zone soil moisture agree closely with the measured values indicating that the calibrated model is able to simulate the crop variables and root zone soil moisture with fairly good accuracy.

3.2 *Estimation of soil hydraulic properties using crop model inversion*

Relative Error (RE) in parameter estimation for each combination case (Table 3) shows that combinations of observed variables of soil moisture and crop canopy (L1, L3 and L4) gave better parameter estimates and lower uncertainty. L4 (SSM + BM)

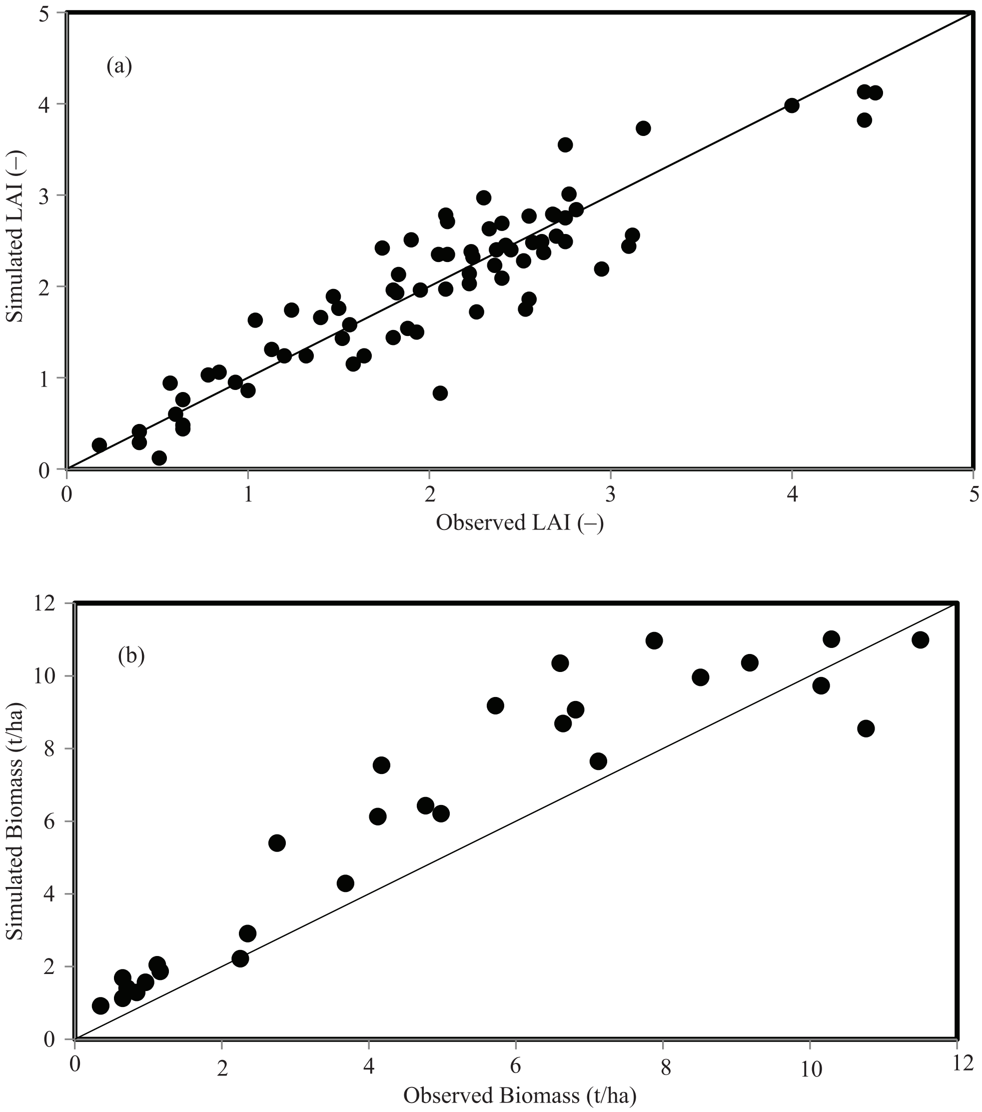
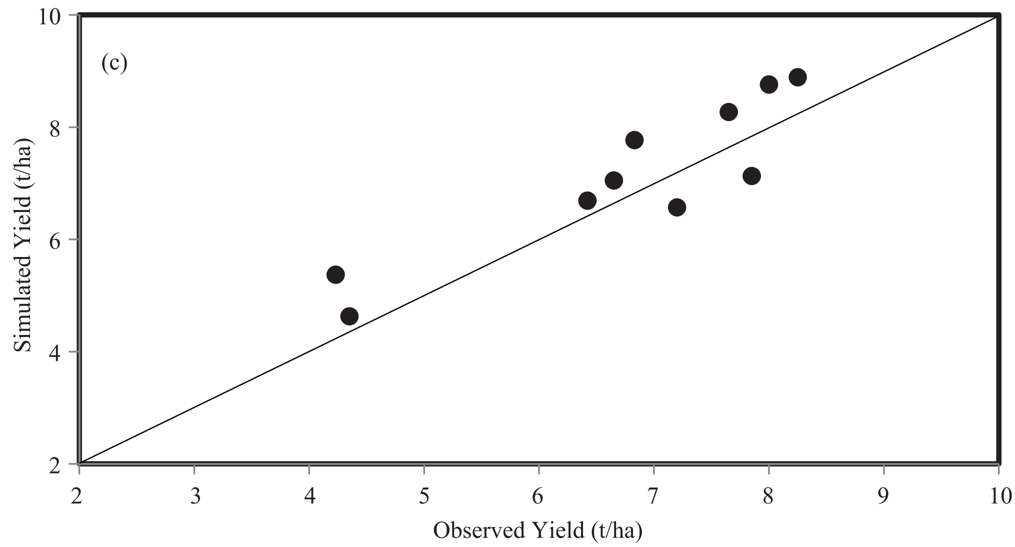


Figure 6: Results of calibration of STICS model for turmeric crop using OptimiSTICS (a) Simulates versus observed LAI, (b) Simulated versus observed biomass in t/ha, (c) Simulated versus observed yield in t/ha and (d) Simulated versus observed root zone soil moisture (HR3) in g/g.



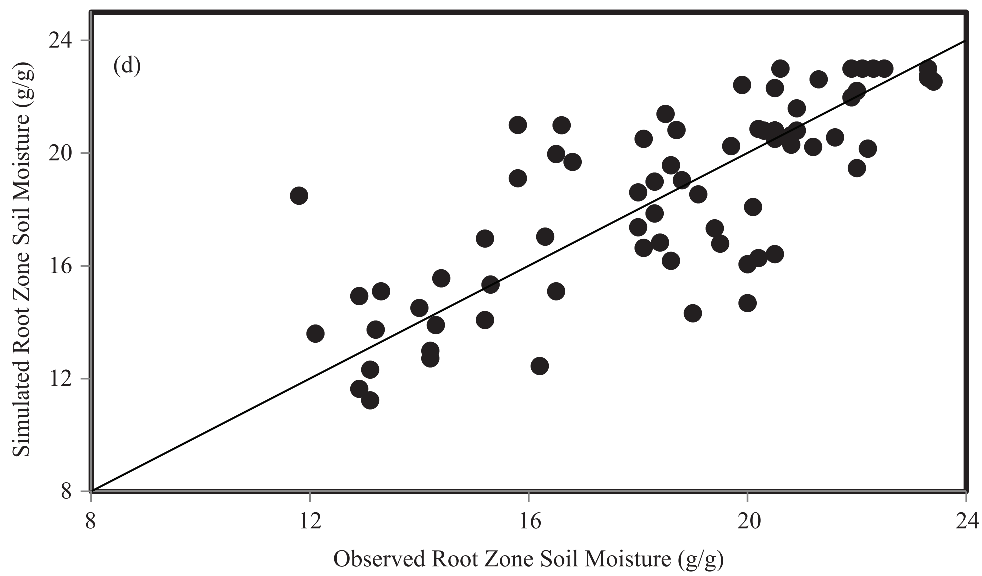


Figure 6: Continued.

Table 3: Relative error (REi) for HCC1, HCC2 and EPC2 for the various combinations L1 to L7.

Likelihood combination	Relative error (REi)		
	HCC(1)	HCC(2)	EPC(2)
L1	0.09	0.19	0.36
L2	0.94	0.62	0.88
L3	0.1	0.44	1.4
L4	0.09	0.28	0.39
L5	0.88	0.9	0.92
L6	0.99	0.63	0.88
L7	0.11	0.84	1.51

gave better estimates than L3 (SSM + LAI), showing that among crop canopy variables, BM holds more information than LAI. Combination of the 3 observed variables (L1) gave same kind of results as L4, showing that additional information on crop canopy is not improving much parameter estimability. Though this method is found to be applicable for the crop consider here, it has to be evaluated under varying agro-climatic conditions with several crop-soil combinations.

Crop variables like Leaf Area Index (LAI) and biomass can be estimated by optical and microwave remote sensing techniques, which make this approach a potential tool for estimating soil properties at catchment scales. The availability of multi-satellite microwave data (RADARSAT-2, RISAT-1, SMAP etc. apart from optical remote sensing data) on crop variables and soil moisture can be useful to map soil hydraulic properties. Here we demonstrate an example of estimating soil hydraulic properties from satellite data. Figure 7 shows the mean and uncertainty of the estimates of HCC1 and HCC2 using field and satellite data for the case of turmeric crop. Uncertainty in the estimate of HCC1 is very low in the case of satellite data inversion. The mean of the estimate of HCC1 is similar in both field and satellite inversion case.

Satellite inversion case slightly underestimates the mean of HCC2, whereas the uncertainty range in HCC2 is similar in both field and satellite inversion cases. The mean of the estimate of EPC2 of field case is very close to that of the satellite inversion case but uncertainty in the satellite inversion case is on the higher side (Fig. 8). This is because of

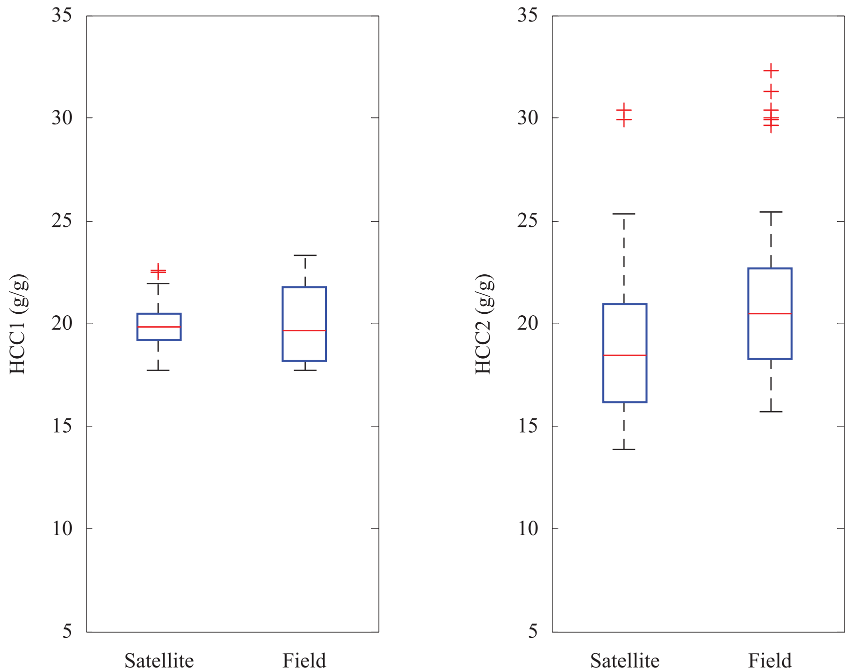


Figure 7: Box plot of HCC1 and HCC2 for field and satellite inversions.

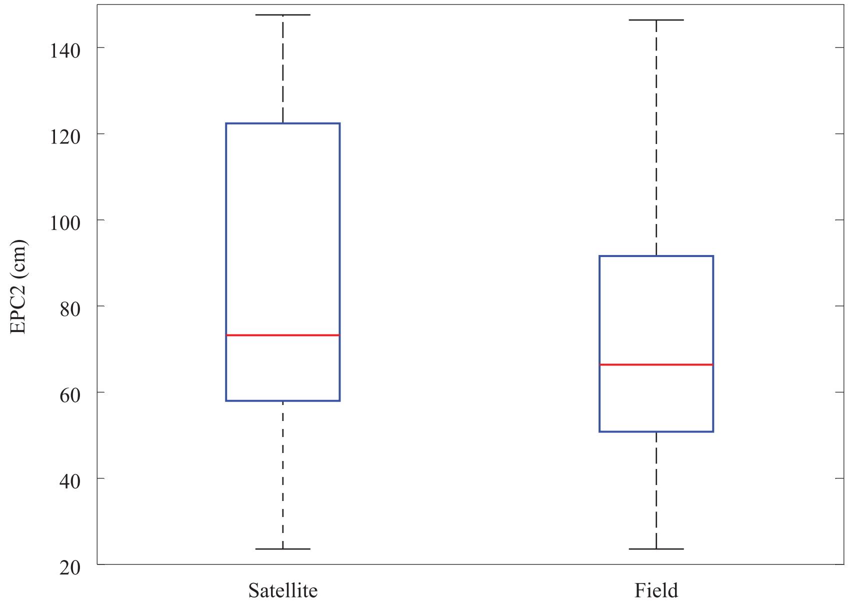


Figure 8: Box plot of EPC2 for field and satellite inversions.

the higher RMSE in the estimate of the LAI from satellite data.

The observed mean of the estimate of HCC1 is 19.5 g/g, which is very close to the estimates obtained from field inversion (19.79 g/g) than that from satellite inversion (19.93 g/g). In case of HCC2 the observed mean is 20 g/g. The mean of the field inversion estimates is closer to the observed mean, whereas the satellite inversion case underestimates HCC2. This is because of the higher RMSE in the estimate of LAI from satellite data and the estimate of HCC2 and EPC2 are sensitive to the value of the LAI. The estimate of EPC2 from both field and satellite inversion case are close to the observed mean which is 70 cm. These results indicate that the satellite data has a good potential to estimate soil hydraulic properties.

3.3 *Estimation of spatial variation of potential recharge using STICS crop model*

The soil hydraulic parameters are estimated using the inversion approach described in the previous section, the ensemble of behavioural parameters for each soil group is selected based on the likelihood function. Using the ensemble of the behavioural parameters in the STICS model, the potential recharge and its variability corresponding to each soil group is simulated and is shown in Fig. 9. The hydrological budget and the inter-soil variability of potential recharge simulated for irrigated turmeric crop is shown in Fig. 9.

The inter-soil variability of potential recharge is captured well by the crop model, thus underlining the theory that crop models are best suited to simulate the potential recharge and its spatial and temporal variability. The simulated and observed root zone soil moisture for the case of sandy loam and clay soil are shown in Fig. 10 (a) and (b) respectively. The observed root zone soil moisture and the simulated root zone soil moisture closely agree in both the soil types demonstrating the model's ability to simulate the soil moisture and hence the potential recharge.

In general, the approach discussed here shows promise as a method for estimating potential recharge from a semi-arid agricultural area. Even though the crop model approach is more data intensive when compared with other traditional approaches, often soil parameters are available from existing databases or can be built by the crop

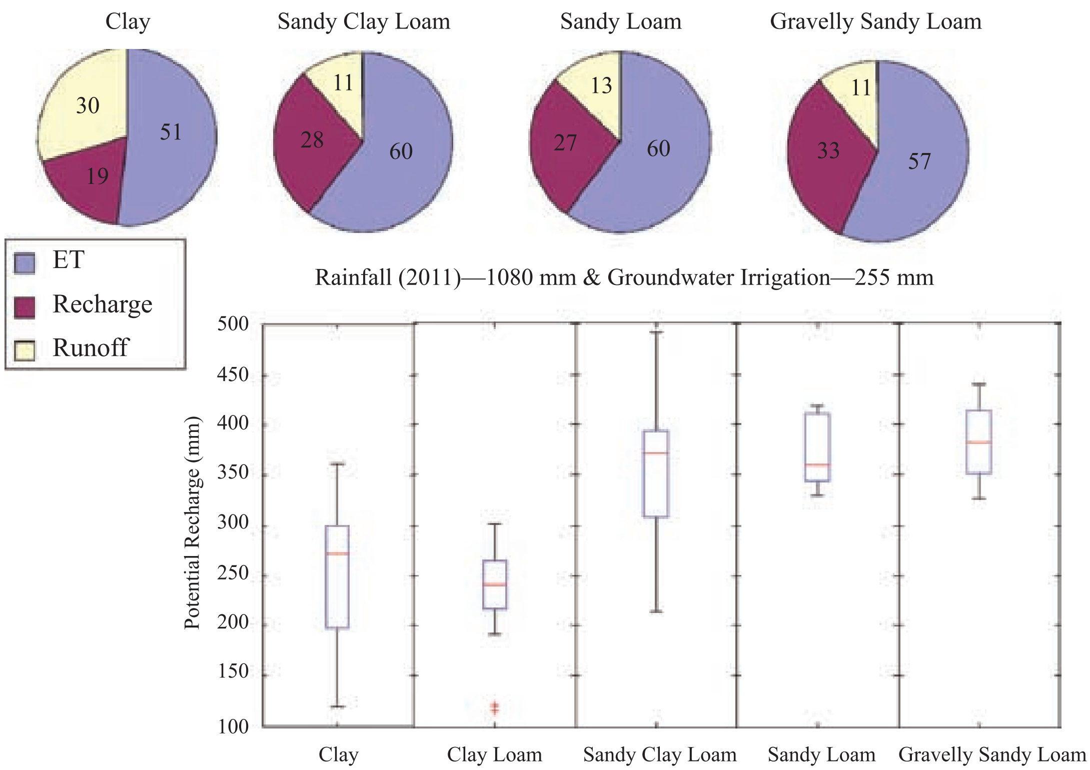


Figure 9: Hydrological budget: Inter-soil variability and potential recharge among various soil types (ET—evapotranspiration, recharge and runoff are in mm).

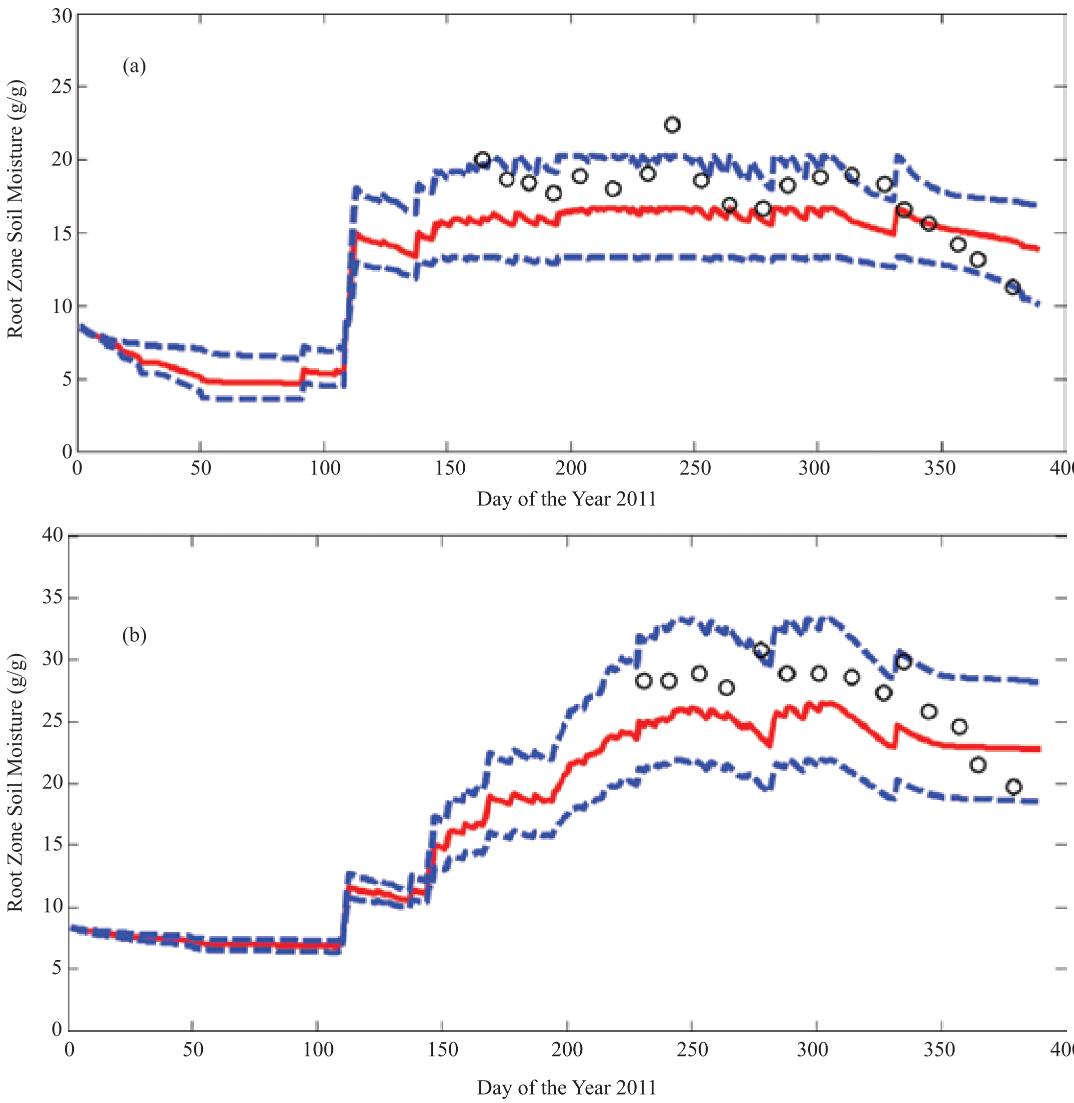


Figure 10: Simulated (red line) and observed (circles) root zone soil moisture and 95% upper and lower confidence interval (blue dashed line) for (a) Sandy loam soil and (b) Clay soil.

model inversion methodology described in the previous section. The results presented here are based on the experiments and simulations on irrigated turmeric crop, future study in this aspect is aimed at quantifying the potential recharge and its uncertainty with multiple soil-crop matrix.

3.4 *Application of satellite weather products for simulating STICS crop model*

The Kalpana rainfall estimates showed an error of 10% when compared with the Maddur gage data. The number of rainy days also differed by 12% with Kalpana data on the higher side. Number of days of significant rainfall (>5 mm) differed by 25%, with Kalpana estimates showing more number of rainy days. These indicate that Kalpana data is over estimating the rainfall by about 10%. It was observed also that in a wet year, a 10% error in satellite rainfall data induces an error of 10% in crop growth variables such as biomass and leaf area index, whereas crop yield varied by 15%. The simulated LAI and crop yield from gauge and satellite data are shown in Fig. 11.

The rainfall estimates from TRMM after bias correction, provided good estimates of crop yield, leaf area index and biomass. The comparison of potential recharge simulated by STICS model using gauge and satellite data is shown in Fig. 12. The potential recharge simulated using TRMM data closely agrees with the simulations using gauge data. The error in the estimates of rainfall from Kalpana satellite

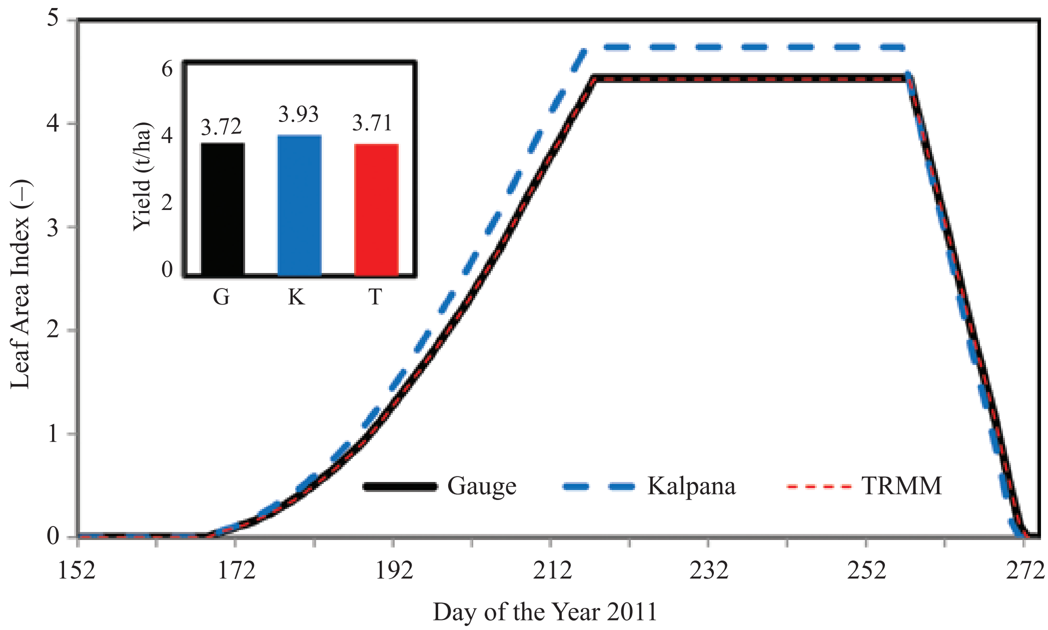


Figure 11: Comparison of LAI and yield (inset figure) simulated by STICS model using gauge and satellite rainfall data.

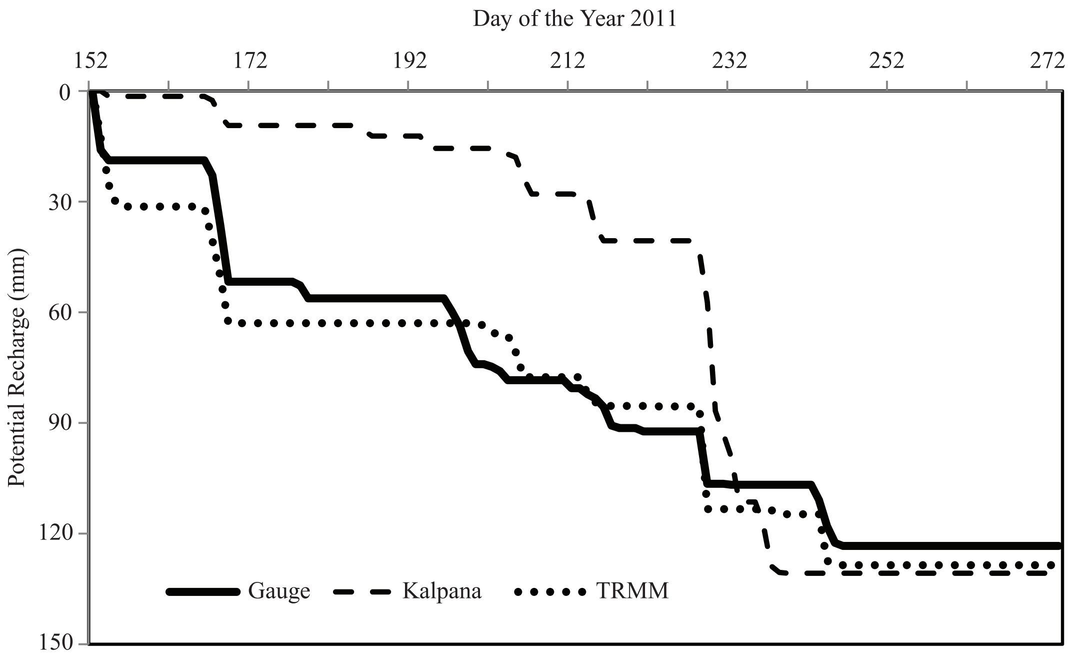


Figure 12: Comparison of potential recharge simulated by STICS model using gauge and satellite rainfall data.

produces an error of similar magnitude in the case of crop variables such crop yield, LAI and biomass, whereas from the TRMM data the error is significantly less. Hence there is a potential to use satellite data for agro-hydrological simulation given that we quantify the propagation of error from data to model.

4 Summary and Perspectives

Groundwater extraction for irrigation is drawing down water tables and reducing base flows; groundwater declines affect water yields especially in hard rock aquifers and affect the irrigated crop productivity; prices of agricultural inputs and products as well as climate change affect irrigation water demand; changes in aquifer recharge and groundwater depletion may feedback to crop productivity. Depletion of water tables, groundwater quality (fluoride and nitrates) and over-extraction of groundwater have become critical issues in several regions. Availability of groundwater resources is critically important in semiarid watersheds, which primarily depend on groundwater irrigation. The effect of groundwater availability and its quality on the agricultural systems can be understood by modeling the feedback between these two systems. Coupling a crop-groundwater model provides a scheme to understand the dynamics of the feedback between a crop and a groundwater system.

Crop models simulate the potential recharge, which may reach the water table and add to the groundwater resource, and in turn groundwater is being pumped out to facilitate irrigation. Fig. 13 shows the scheme by which a coupled crop-groundwater model can be developed. The primary variables of exchange are the groundwater recharge and the groundwater pumping or draft. The potential recharge estimated by the crop model is given as a recharge into the groundwater model and the pumping from the groundwater model is given as irrigation to the crop model. Such a model can be calibrated and validated at field scale by using observations of groundwater level and data on pumping and irrigation practices.

The groundwater recharge and its spatio-temporal variability are critical components of the water balance with respect to sustainability of groundwater resources in a groundwater irrigated semi-arid agricultural catchment. Precise quantification of recharge to groundwater from a soil-crop system is essential to understand the interactions between a crop and groundwater system in a coupled crop-groundwater model. In this we demonstrated that a crop model based approach is best suited to estimate the recharge flux and its variability in a heterogeneous soil/crop system. Accurate representation of soil hydraulic parameters in the crop model is necessary to quantify the potential recharge and its variability because the potential recharge is sensitive to the soil hydraulic parameters. We also demonstrated that a crop model based inversion approach using ground and satellite data is a promising approach for estimating surface and root zone soil hydraulic properties in a multilayered heterogeneous soil system. As these variables can be estimated from remote sensing data (microwave and optical), this approach has the potential to map soil hydraulic properties

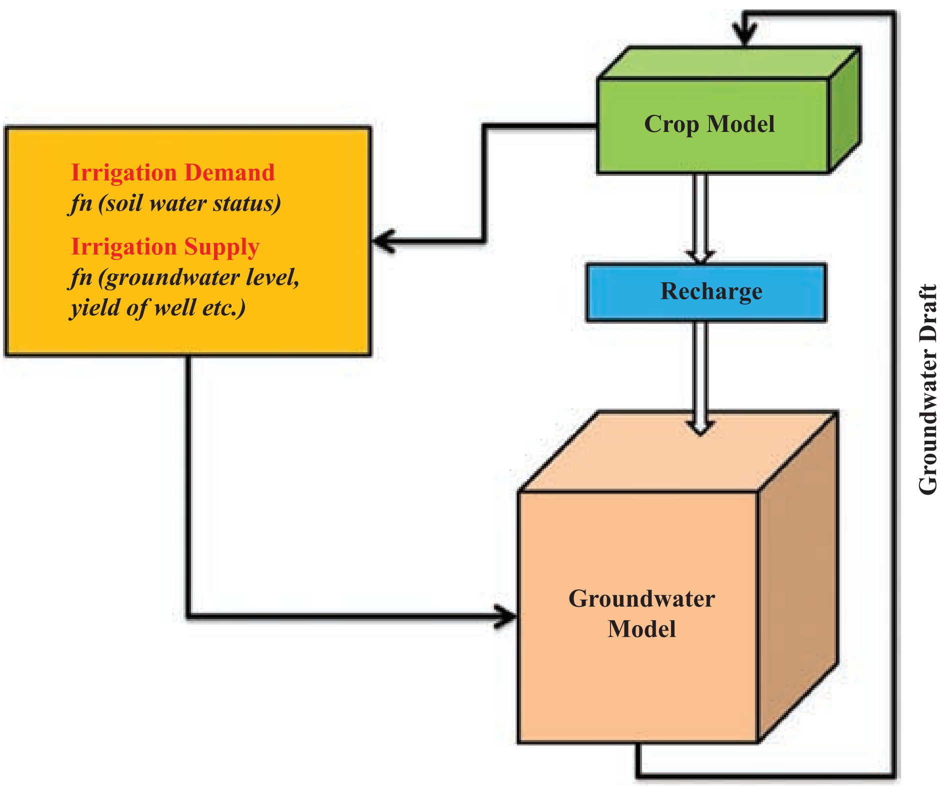


Figure 13: Scheme for coupling a crop-groundwater model.

at large spatial scales. The method needs to be further explored by using multi-satellite data to compensate for the short growing period of most crops. The spatial variability of crop type and farming practices bring in additional uncertainty in the estimation of soil parameters. Future studies should aim at quantifying these uncertainties and understanding the effect of these uncertainties in the model simulations. The satellite based weather data can be used for agro-hydrological simulation given that we quantify the propagation of error from data to model. With the availability of weather satellites and given the high spatial variability of climate variables in semi-arid region, the usefulness of satellite weather data to capture the spatial variability of crop yield, recharge and soil moisture status needs to be explored at large spatial scales. The performance of a coupled agro-hydrological model can be improved by the process of data assimilation. In addition to surface soil moisture, crop variables like leaf area index and biomass can also be estimated from satellite remote sensing. By assimilating these variables into the coupled model, a more realistic representation of variability of crop growth can be obtained.

Acknowledgements

We thank the field survey and GIS team members: Mr. P. Giriraja, Mr. K.N. Sanjiva Murthy and Amit K. Sharma. Apart from the specific support from the French Institute of Research for Development (IRD), the Embassy of France in India and the Indian Institute of Science, the research was funded by the Indo-French programme IFCPAR (Indo-French Center for the Promotion of Advanced Research) through the project 4700 WA "Adaptation of Irrigated Agriculture to Climate Change" (AICHA).

Received 24 April 2013.

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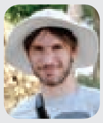

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