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Uncertainty Analysis of Water Balance Module of Control Release Urea Fertilizer (CRUF) Model for Flooded Rice

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Abstract

Available water and nitrogen balance models for flooded rice field are only applicable for conventional fertilizer. Alternatively application of control release fertilizer (CRF) is improving to protect environment quality from agriculture non-point pollution largely due to rice cultivation. An attempt of develop Control Release Urea Fertilizer (CRUF) model can help to identified the quantity and frequency of CRF application and water balance in flooded rice field. This developed model (integration of water balance, nitrogen release rate and nitrogen balance module)essentially to be accurate and reliable for user. The current study presents the uncertainty analysis of water balance module of CRUF model using Taylor series method. Two seasons of field studies were carried out to calculate uncertainty of water balance module, respectively. Five percent uncertainty (95% confidence interval) was assigned to input variable for uncertainty computation. From the result it is concluded that uncertainty of water balance module is about 26 percent. Uncertainty of all variables in water balance equation is vary according to season of cultivation while experiment carried out in the same field with similar instrument/sensor.

Key word: Uncertainty analysis; Taylor series method; CRUF model; flooded rice.

Introduction

The process of water and nitrogen loss is very important and complicated in flooded rice field[1]. Application of control release fertilizers (CRF)is intensified in rice field due to low environmental losses and high plant uptake of nitrogen[2,3,4]. Nitrogen and water balance in CRF is a different phenomenon due to slow and synchronized release of nitrogen compared to conventional urea[5,6]. Numerous simulation models have been developed over past decade based on empirical, semi-empirical and mechanistic approaches for describing the release of nutrients from CRFs[5,6,7,8,9].

The conceptual modelssimulating water and nutrients' movement in rice are unable to model nitrogen release rate from CRF or nitrogen balance from coated urea fertilizers. Dubey and Mailapalli (2017)[10] developed a control release urea fertilizer (CRUF) model to simulate nitrogen release rate, water balance and nitrogen balance in CRF treated rice fields. In the CRUF model, water and nitrogen balance models were integrated with a nitrogen release rate model and the effect of coated urea on nitrogen transformations was studied in CRF applied flooded rice field. Generally, the nitrogen transport models require water balance module, which is a driving force for transporting plant nutrients in soil-plant-atmosphere continuum.

Application of any model brings some kind of uncertainty dealing with model structure, model parameter and input data. Traditionally, these uncertainties are handled through model calibration and data adjustment[11] and probabilistic approaches such as Taylor series, Monte Carlo simulation and Bayesian approaches[12,13]. Model results for the water balance are always different from the actual field condition due to the model assumptions, and spatial and temporal climatic conditions[1,14,15]. Analysing models without incorporating the parameter uncertainties may provide misleading results[16].

Precision and accuracy of a model must be quantified so user could comprehend the degree of uncertainty surrounding the data collection/processing to advance the simulated model result for existing field conditions. The uncertainty analyses are based on traditional method (simplified assumptions based on instrumentation)[11], Taylor series[12], Monte Carlo simulation[13], and Bayesian approaches.

Taylor seriesapproach is associated to mathematical evaluation of model equations[12]. It is an analytical method, which includes differentiation of model equation and solution of a set of uncertainty equations. Uncertainty study of lake water balance indicated that error in estimation of evaporation vary according to the instrumentation and methodology, while energy budget equation is the most accurate method of calculating the evaporation with 10-15% uncertainty[17]. Mun et al. (2015)[17] calculated uncertainty for the Mississippi Irrigation Scheduling Tool (MIST) irrigation scheduling model using Taylor series method and concluded that accurate measurement of irrigation and rainfall are critical to minimize errors for water balance model.

Monte Carlo simulation involves sampling the model using the parameter's probability distribution function to provide parameter values[13]. Major disadvantage of this method is that it required several model runs to reliably present all probable results in the presence of number of random variables[13].Bayesian approach involves dynamic analysis of data based on probability sensitivity analysis. Engel and et al. (2005)[18] assessed uncertainty in water balance model by using Bayesian methodology. They considered two sources of uncertainty, one is in model parameter and the other is in model structure and concluded that parameter uncertainty is less important than the uncertainty caused by the model parameters. Source of data collection andbasin characteristics had vast influence on model uncertainty. Precision and accuracy of model must be quantified so user could be comprehended the degree of uncertainty surrounding the data collection/processing to advance the simulated model result for existent field condition. The objective of this study was to determine relative uncertainties of water balance module to diminish the associated error of CRUF model. This study helps to identify the source of errors in the calculated parameters used in CRUF model calculations. This information will be assisted in accurate validation of model for flooded rice field treated with CRF for wet and dry seasons.

Material and Methods

Description of CRUF model

CRUF model is integration of water balance, nitrogen release rate and nitrogen balance modules, in which water balance module is more uncertain and vulnerable to errors compared to other two modules.

Water balance module

The water balance module simulates temporal dynamics of soil water components resulted from the water applied to rice field. In the traditional rice culture, a known depth of ponding water (5-10 cm depth) is maintained most of the growing season of the crop. Bunds are constructed across the field to prevent surface runoff and to maintain the desired ponding water depth. Figure 1 shows the different water balance components considered for flooded rice field. The basic water balance equation used to estimate hydrology components is given by:

$$FR_t = R + IR + FR_{t-1} - ET_c - DP \qquad (1)$$

Where, FR_t is the water depth in the rice field, R is the rainfall reaching the surface, IR is the amount of irrigation, ET_c is the crop evapo transpiration, DP is the deep percolation; and FR_{t-1} is the water depth (all these components are in mm per day).

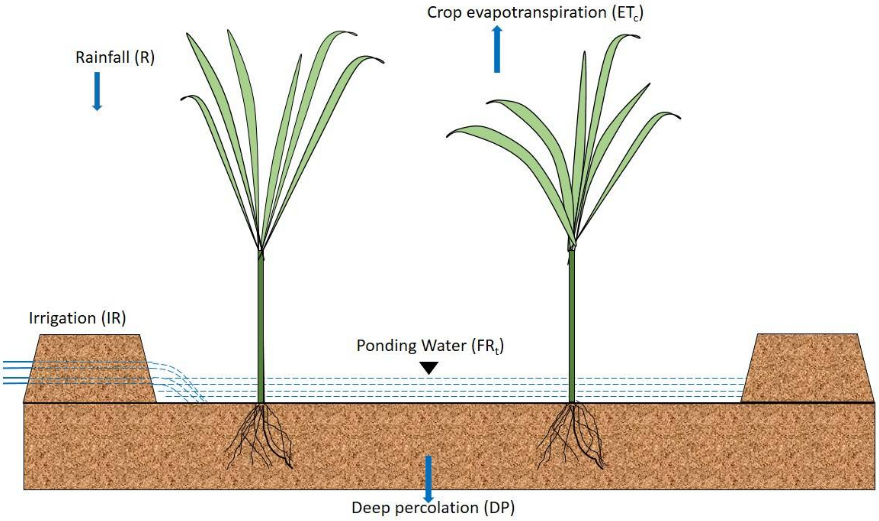


Figure 1: Schematic view of different water balance components in flooded rice field

This soil water balance module is used to estimate the amount of N under different N-transformations associated with the hydrological pathways. Estimation of hydrological pathways is based on the mass conservation law, in which sum of water components in a control volume determines its changes in stored soil water, at a given time interval. In the flooded water zone, hydrolysis (NH_4^+), volatilization (NH_3) and nitrification (NO_3^-) are the dominating processes of N-transformations. Ammonium (NH_4^+-N) and nitrate (NO_3^--N) infiltrate in to root zone with infiltrated water. In the root zone, NH_4^+ is taken by plant root with ET_c however; uptake of nitrate is limited due to high nitrate mobility. Therefore, many plants prefer ammonium over nitrate for nitrogen uptake. Nitrates (NO_3^-) are leached out from the root zone with percolated water.

Modified Penman-Monteith equation[19] was used to calculate the reference crop evapotranspiration (ET_0)

$$ET_0 = \frac{0.408\,\Delta R_n + \gamma\left(\frac{900}{T_{mean}+273.16}\right)u_2\,(e_s - e_a)}{\Delta + \gamma\,(1 + 0.34\,u_2)} \qquad (2)$$

Where, R_n is the net radiation at the crop surface (MJ/m^2/day), T_{mean} is the mean of the daily maximum and minimum temperature (^{o}C), u_2 is the wind speed at slandered 2 m height (m/s), e_s is the saturation vapor pressure (kPa), e_a is actual vapor pressure (kPa), Δ is the slope of vapor pressure curve (kPa/^{o}C), and γ is the psychrometric constant (kPa/^{o}C).

The net radiation R_n is expressed by:

$$R_n = R_{ns} + R_{nl} \qquad (3)$$

$$R_{ns} = (1-\alpha)R_s \qquad (4)$$

$$R_{nl} = \sigma\left(\frac{T_{max}^4 + T_{min}^4}{2}\right)\left(0.34 - 0.14\sqrt{e_a}\right)\left(1.35\frac{R_s}{R_{so}} - 0.35\right) \qquad (5)$$

Where, R_{ns} is the net solar radiation, R_{nl} is the net long-wave radiation, α is the reflection coefficient (α=0.23), R_s is the solar radiation, σ is the Stefan-Boltzmann constant (4.903×10^{-9} MJ K^4 m^2), T_{max} and T_{min} are the maximum and minimum absolute temperatures (^{o}C) during the 24-h period, R_{so} is the maximum solar radiation in the clear sky at the same location.

The equation for R_{so} is expressed as below:

$$R_{so} = 0.7492\frac{24(60)}{\pi}G_{sc}d_r(\omega_s\sin(\varphi)\sin(\delta) + \cos(\varphi)\cos(\delta)\sin(\omega_s)) \qquad (6)$$

Where, G_{sc} is the solar constant (0.0820 MJ m^{-2} min), d_r is the inverse relative distance of earth sun, $d_r = 1 + 0.033cos\left(\frac{2\pi}{365}J\right)$, J is the number of days in a year, ω_s is the sunset hour angle in radian $\omega_s = \mathrm{acos}\,(-\tan(\varphi)\tan(\delta))$, φ is the latitude in radian (0.389 for Kharagpur, India), δ is the solar declination.

The saturated vapour pressure e_s of the atmosphere is given by the following equation:

$$e_s = \left(\frac{e^0(T_{max}) + e^0(T_{min})}{2}\right) \qquad (7)$$

Actual vapour pressure e_a of the atmosphere is given by the equation:

$$e_a = \frac{e^0(T_{min})(RH_{max}/100) + e^0(T_{max})(RH_{min}/100)}{2} \qquad (8)$$

Where, RH_{max} and RH_{min} are the maximum and minimum relative humidities. The slope of the saturated vapour pressure curve (Δ) is calculated by the following formula:

$$\Delta = \frac{4098e_s}{(T_{mean} + 237.3)^2} \qquad (9)$$

Uncertainty analysis

CRUF model includes integration of water balance, N-release rate and N-balance modules, in which water balance module is more uncertain and vulnerable to errors compared to other two modules. The soil water balance module (Eq. 1) simulates temporal dynamics of soil water components resulted from the water applied to rice field.

Equation (1) suggested that uncertainty of FR_t depends on errors in R, IR, FR_{t-1}, ET_c and DP. Taylor Series Method[16] was used to estimate model uncertainty (Eq. 1) and the detailed discussion of this concept was given by Mum et al. (2015)[17]. In order to determine the uncertainty of the experimental result (U_r), the bias (W_r) and precision limit (P_r) must be combined. This is accomplished using the root sum square method by providing 95% confidence interval:

$$U_r = \sqrt{W_r^2 + P_r^2} \qquad (10)$$

If experimental result r is a function of j measured variables X_j($j$is the variable count)then:

$$r = f(X_1, X_2, \dots \dots, X_j) \qquad (11)$$

Uncertainty of the equation (10) is given by:

$$U_r^2 = \left(\frac{\partial r}{\partial X_1}\right)^2 U_{X_1}^2 + \left(\frac{\partial r}{\partial X_2}\right)^2 U_{X_2}^2 + \cdots + \left(\frac{\partial r}{\partial X_j}\right)^2 U_{X_j}^2 \qquad (12)$$

Where, $U_{X_j}$is the uncertainty in the measured variablesX_j. Equation (12) is continuous and has continuous derivatives. However, measured variables $X_j$are independent of one another, so the uncertainty in the measured variables are independent of one another. Eq. (12) can be written as:

$$\frac{U_r^2}{r^2} = \left(\frac{X_1}{r}\frac{\partial r}{\partial X_1}\right)^2 \left(\frac{U_{X_1}}{X_1}\right)^2 + \left(\frac{X_2}{r}\frac{\partial r}{\partial X_2}\right)^2 \left(\frac{U_{X_2}}{X_2}\right)^2 + \cdots + \left(\frac{X_j}{r}\frac{\partial r}{\partial X_j}\right)^2 \left(\frac{U_{X_j}}{X_j}\right)^2 \qquad (13)$$

The terms $\left(\frac{X_j}{r}\frac{\partial r}{\partial X_j}\right)$is the uncertainty magnification factor (UMF)and$\left(\frac{U_{X_1}}{X_1}\right)$ is the relative uncertainty. The UMF for a given U_r indicates the influence of the uncertainty in the variable on the uncertainty in the output. A UMF value greater than 1 indicates that the influence of the uncertainty in the variable is magnified as it propagates through the uncertainty equation. The UMF value less than 1 indicates that the influence of uncertainty in the variable is diminished. The uncertainty of FR$_t$(mm^{-1} day) can be calculated as

$$\frac{U_{FR}}{FR} = \left[\left(\frac{R}{FR}\frac{\partial FR}{\partial R}\right)^2 \left(\frac{U_R}{R}\right)^2 + \left(\frac{IR}{FR}\frac{\partial FR}{\partial IR}\right)^2 \left(\frac{U_{IR}}{IR}\right)^2 + \left(\frac{FR_{t-1}}{FR}\frac{\partial FR_{t-1}}{\partial FR_{t-1}}\right)^2 \left(\frac{UFR_{t-1}}{FR_{t-1}}\right)^2 + \left(\frac{ET_C}{FR}\frac{\partial FR}{ET_C}\right)^2 \left(\frac{UET_C}{ET_C}\right)^2 + \left(\frac{DP}{FR}\frac{\partial FR}{\partial DP}\right)^2 \left(\frac{U_{DP}}{DP}\right)^2\right]^{\frac{1}{2}} \qquad (14)$$

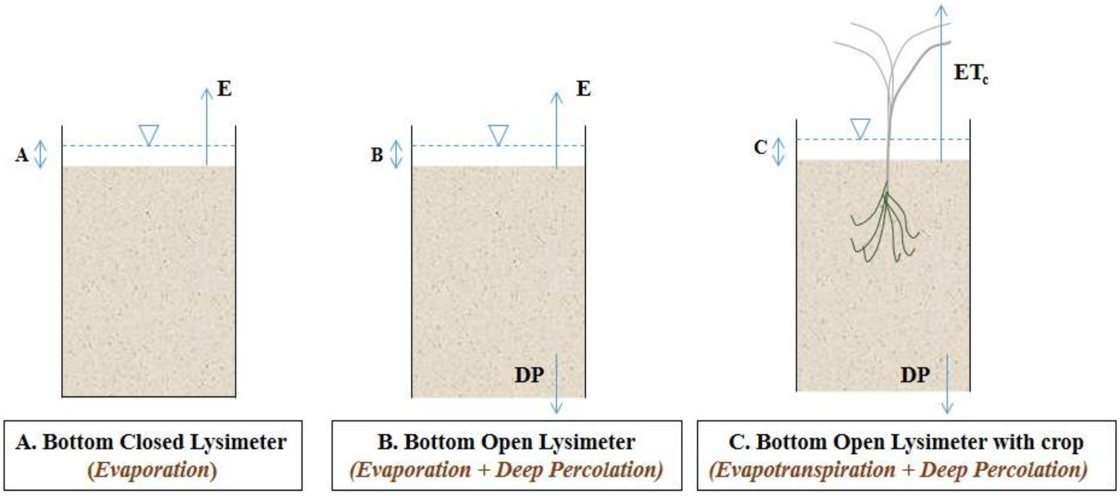
Where, $U_R/R$is the relative uncertainty of the rainfall at the time of measurement, $U_{IR}/IR$is the relative uncertainty of measurement in irrigation water, $U_{FT_{t-1}}/FT_{t-1}$ is the relative uncertainty from previous day water balance, and U_{DP}/DP is the relative uncertainty in deep percolation. The uncertainty of *R*, *IR*, *FR*$_{t-1}$, and *DP* depends uponerror in the measurement of parameter at that day whereas uncertainty of crop evapotranspiration, ET_cdepends on $ET_0$and K_c($ET_C = K_C \times ET_0$). The uncertainty of $K_c$was not considered in the calculation as the data were taken from Allen et al., (1998)[20]The uncertainty of$ET_0$is propagated by the following equation (Mum et al., 2015):

$$\frac{U_{ET_0}}{ET_0} = \left[\left(\frac{\Delta}{ET_0}\frac{\partial ET_0}{\partial \Delta}\right)^2 \left(\frac{U_\Delta}{\Delta}\right)^2 + \left(\frac{R_n}{ET_0}\frac{\partial ET_0}{\partial R_n}\right)^2 \left(\frac{U_{R_n}}{R_n}\right)^2 + \left(\frac{T_{meanC}}{ET_0}\frac{\partial ET_0}{\partial T_{meanC}}\right)^2 \left(\frac{UT_{meanC}}{T_{meanC}}\right)^2 + \left(\frac{Y}{ET_0}\frac{\partial ET_0}{\partial Y}\right)^2 \left(\frac{U_Y}{Y}\right)^2 + \left(\frac{u_2}{ET_0}\frac{\partial ET_0}{\partial u_2}\right)^2 \left(\frac{U_{u_2}}{u_2}\right)^2 + \left(\frac{e_s}{ET_0}\frac{\partial ET_0}{\partial e_s}\right)^2 \left(\frac{U_{e_s}}{e_s}\right)^2 + \left(\frac{e_a}{ET_0}\frac{\partial ET_0}{\partial e_a}\right)^2 \left(\frac{U_{e_a}}{e_a}\right)^2\right]^{\frac{1}{2}} \qquad (15)$$

Data collection

In order to estimate uncertainty in the model, experimental data of Kharif and Rabi seasons of 2015-16 were used. Field experiments were carried out in 6 (1m x 1m) lysimeter plots at the Agriculture and Food Engineering Department (AgFE), Indian Institute of Technology Kharagpur, India to study the water balance in Kharif and Rabi seasons for determining the uncertainty of water balance module. The six lysimeters comprised four bottom open and two bottom closed non-weighing lysimeters of 1.25m x 1.25m x 1m (length x width x depth) (Fig. 2). The bottom of each lysimeter was kept at 80 cm below the ground surface and water infiltrating beyond 80 cm was considered as percolation loss. The combination of two bottom open and one bottom closed lysimeter was used to measure deep percolation loss from the plots under ponded water condition (Fig. 3). A ponding water depth of 3-5 cm was maintained for first 15 and 25 days during Kharif and Rabi seasons, respectively. The initial ponding water depth in Rabi season was extended to 10 days more due to slower plant growth resulted from unfavorable temperatures.

Daily meteorological data were collected from the meteorological station located about 200 m from the experimental fields throughout the season. Table 1 shows the weather data during the cropping session used for calculating ET_c for Kharif and Rabi seasons.Table 2 presents the uncertainty (95% confidence interval), assigned to input variables used to compute the uncertainty in the water balance components. Zero percentage of uncertainty was considered in the variables such as $\varphi, G_{SC}, \omega_S, \sigma, d_r, \delta, R_{SO}, \alpha,$ and K_C[17].



A. Bottom Closed Lysimeter *(Evaporation)*

B. Bottom Open Lysimeter *(Evaporation + Deep Percolation)*

C. Bottom Open Lysimeter with crop *(Evapotranspiration + Deep Percolation)*

Figure 2: Schematic view of different type of the lysimeters used inexperimental plots

Figure 3 Lysimeters installation in field to compute deep percolation of water balance component

Table 1 Summary of the selected meteorological parameters during Kharif and Rabi seasons of 2015-16

Parameter	Kharif season (August – November, 2015)			Rabi season (January – April, 2016)		
	minimum	maximum	mean	minimum	maximum	mean
Wind speed (km h^{-1})	3.8	23.6	6.5	5.8	81.9	5.5
Min Temperature (°C)	19.0	30.5	25.1	15.8	29.0	20.7
Max Temperature (°C)	27.4	36.6	32.3	19.3	42.0	32.0
Solar radiation (W m^2)	1.8	1321.8	267.4	1.2	1006.2	350.3
Minimum relative humidity (%)	31.9	92.2	62.4	11.6	96.0	44.3
Maximum relative humidity (%)	44.9	99.8	89.4	33.6	99.5	89.7
Precipitation (mm)	0.0	53.2	2.7	0.0	14.0	1.2

Table 2 The uncertainty (95% confidence interval) assigned to input variables used to compute the model uncertainty in the water balance module.

Variable	Symbol	Percentage error
Latitude	$\varphi\theta$	0*
Solar constant	G_{sc}	0
Stefan-Boltzmann constant	σ	0
Relative distance	dr	0
Solar declination	δ§	0
Sunset hour angle	ω_s	0
Maximum solar radiation	R_{so}	0
Reflection coefficient	α	0
Crop coefficient	K_c	0
Rainfall	R	5
Wind speed	U_2	5
Relative humidity	RH	5
Temperature	T	5
Solar radiation	R_n	5
Deep percolation	DP	5
Irrigation	I	5

Note: zero uncertainty was assumed for constant value.

Figure 4 (a, and b) shows the daily variations of water balance components in paddy field for Kharif and Rabi seasons of 2015-16. Deep percolation (DP) and ET_c were considered as water loss from paddy field. The standing water was available for long-time in Kharif season (Fig. 4) as compare to Rabi season due to high and frequent rainfall and the local shallow groundwater table during Kharif season. The presence of hard clay pan at about 1 m soil depth in the experimental site developed a perched water table during Kharif season. The deep percolation rate was increased in the later part of Kharif season as groundwater table started depleting.

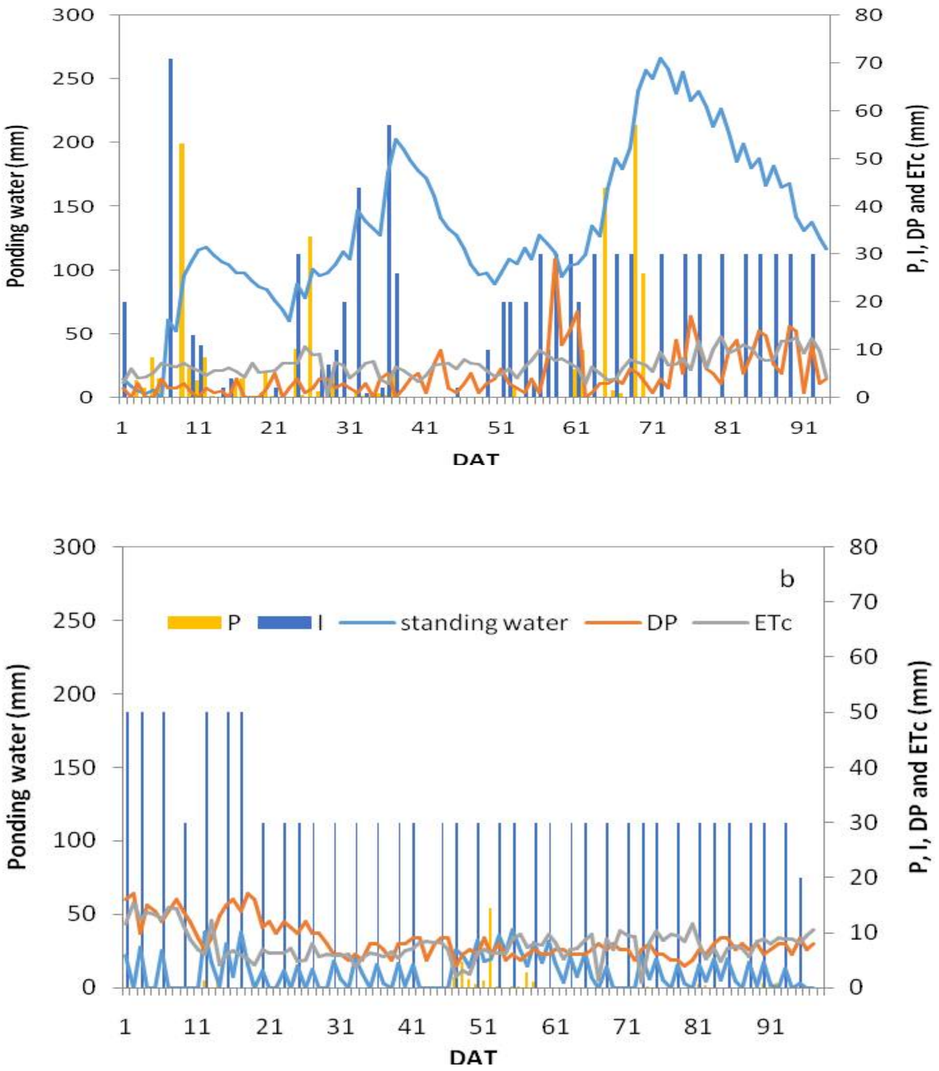


Figure 4: Water balance components in paddy field for (a) Kharifand (b) Rabi seasons

Results and Discussion

Figure 5 represents the calculated uncertainty of different parameters of water balance equation. If equal error is considered in all instruments or sensors, the uncertainty in $ET_c$was estimated to be increased by 24.4% due to the uncertainty in R_n(net radiation) and R_{nl} (net long wave solar radiation), which resulted 26.4% uncertainty in SW (Fig. 5).

Figure 6 and 7 show the uncertainty magnification factors (UMFs) and uncertainty percentage for all calculated parameters used in water balance equation for Kharif and Rabi seasons, respectively for 94 days from the day after transplanting (DAT). The UMF values were less than 3 in Kharif season whereas they were increased up to 10 for DP and ET_c in Rabi season. In *Kharif* season uncertainty was obtained maximum (up to 40%). for R_{nl} (net long wave solar radiation) R_{nl} was depended on input parametersR_s, T_{max} , T_{min},, R_{so},, and e_a(eq 3.5) and uncertainty of these parameters was higher in *Kharif* season where as in *Rabi* season input variable R_n(net radiation) was more uncertain. A wide variation of uncertainty was presented in input parameters of ET_c but still in both the seasons, the final uncertainty of ET_c

was similar, about to 10% because the equation of ET_c depends upon a number of sub-equations and uncertainty was compensated due to error variation in these parameters. The uncertainty of other measuring parameters such as DP, I, and P was depended upon soil saturation condition, ground water table, and frequency of irrigation which were varied in both the seasons.

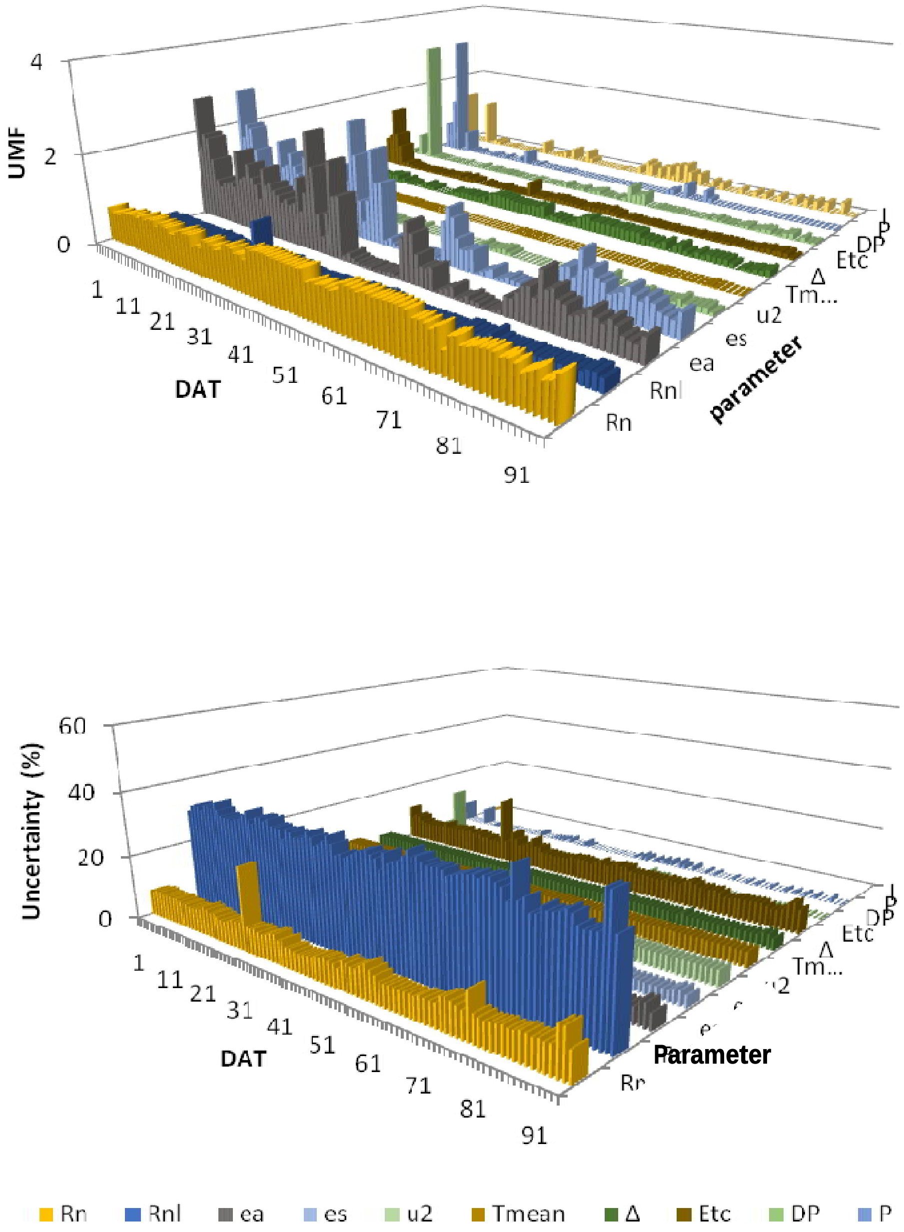


Figure 6: Dimensional plot of uncertainty magnification factors (UMFs) and uncertainty for all parameters used in water balance equation for Kharif season.

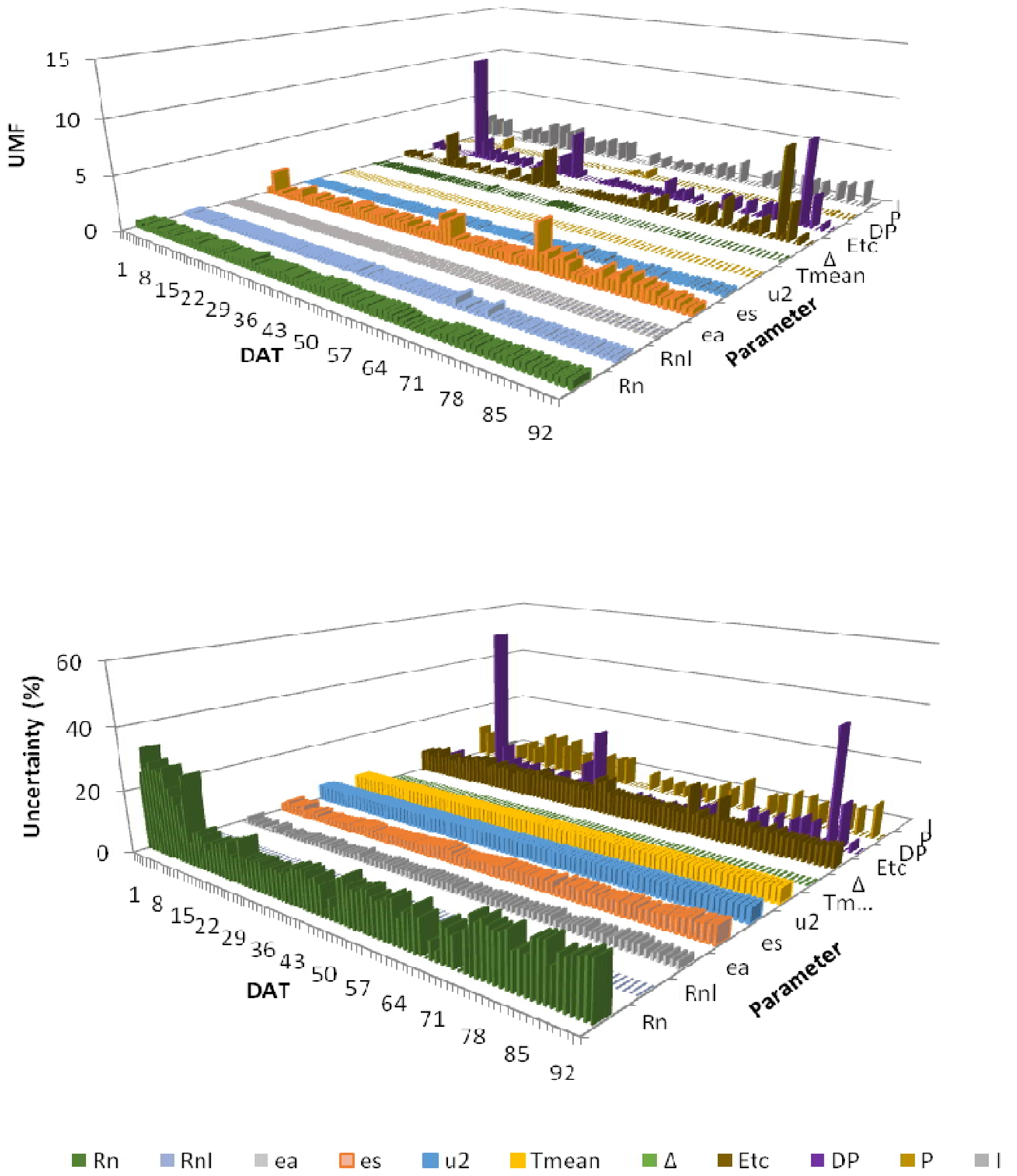


Figure 7: Dimensional plot of uncertainty magnification factors (UMFs) and uncertainty percentage for all parameters used in water balance equation for Rabi season

Figures 8 to 11 show the temporal changes in the UMFs and the associated uncertainties of the water balance components for both growing seasons. The UMFs of DP, ET_c, P, and I were less than one for Kharif season with few peaks up to two. In the case of DP, UMF was affected the uncertainty (Fig 8a) of that day such as UMF of DP was very high at 14th and 40th DAT and the associated uncertainty of these days were 53 and 22% higher than the other days, respectively. The uncertainty resulted for ET_c(Fig 9b) was upto 10% throughout the Kharif season with a higher peak of 21% at 28th DAT. The uncertainty of DP, P and I was very less in Kharif season whereas uncertainty of ET_c was high compared to other components. The water balance results showed an acceptable uncertainty variability of 10% for all components for Kharif season.

During Rabi season UMF was less than one for P and reached upto10 for DP and ET_c whereas it varied between 1 and 2 for I. Based on the previous studies on piezometer data from different soil depths of the study area, water table was observed to be shallow in Rabi season compared to *Kharif* season thus it increased the magnitude of DP. Due to higher and rapid movement of water, it improved the chance of error to measure DP. The uncertainties of DP and I of Rabi season were not significantly equivalent with Kharif season (Fig 8b and 10b). Relative uncertainty of DP was raised from 4-50% for Rabi season and was 1-5% (with single extreme peak of 15% at the 6th DAT) for Kharif season. The uncertainty of I was near to 10% with a peak point of 35% at 95th DAT for Rabi season and was about to 5% for Kharif season. DP was the most uncertain parameter of water balance equation as its relative uncertainty was about 50% for Rabi season.

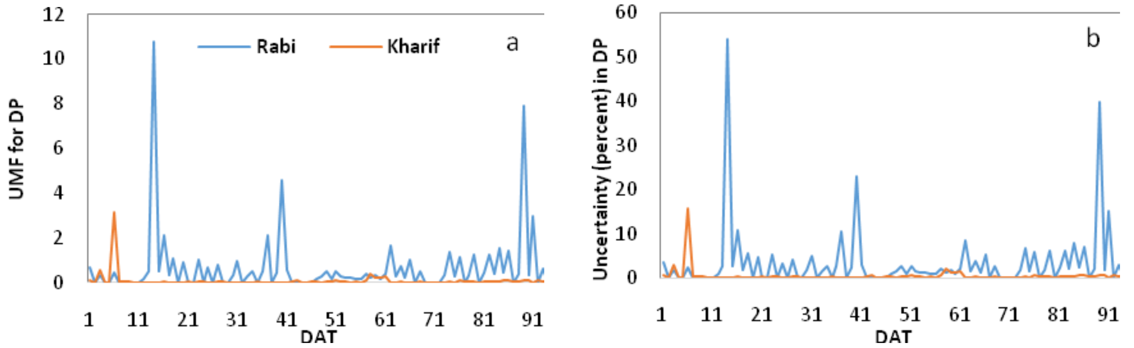


Figure 8: Uncertainty magnification factor (UMF) and Uncertainty of DP for Rabi and Kharif seasons

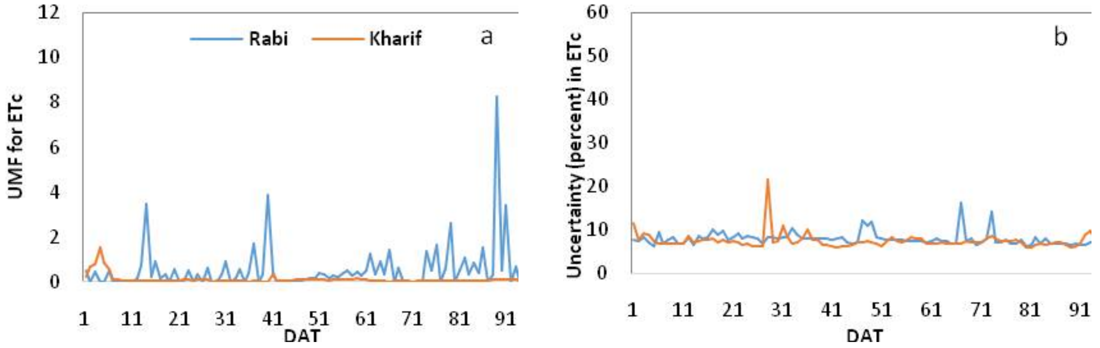


Figure 9: Uncertainty magnification factor (UMF) and Uncertainty of ET_c for Rabi and Kharif seasons

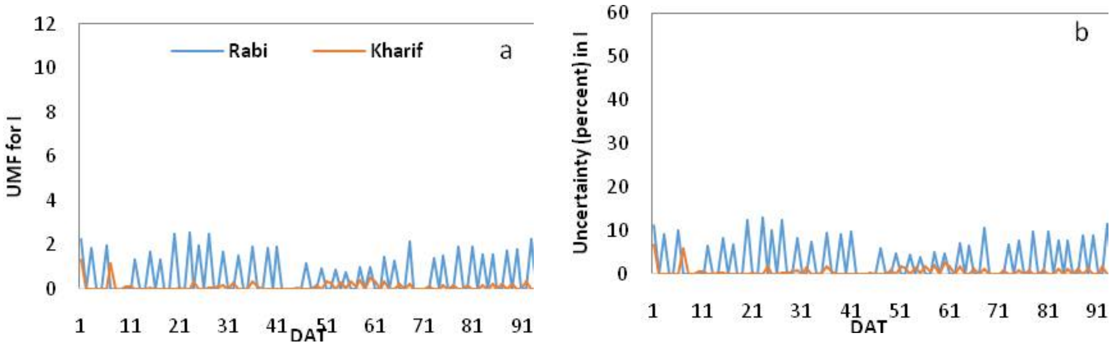


Figure 10: Uncertainty magnification factor (UMF) and Uncertainty of I for Rabi and Kharif seasons

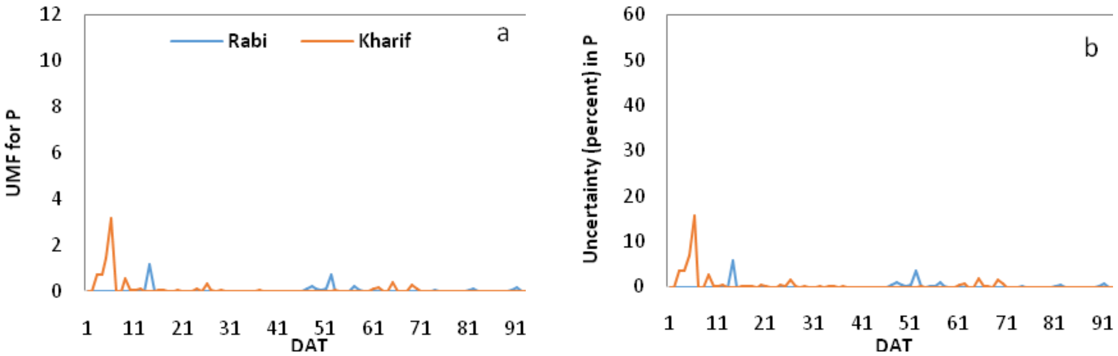


Figure 11: Uncertainty magnification factor (UMF) and Uncertainty of P for Rabi and Kharif seasons

Conclusions

Water balance module was considered for estimating uncertainty of CRUF model. Five percent uncertainty (at 95% confidence interval) was assigned to input variable for uncertainty computation. Uncertainty analysis of water module of CRUF model was conducted for two crop seasons (rabi and kharif). Water balance equation was found to be vulnerable to DP and I for rabi season due to high temporal fluctuation of uncertainty of these two variables. Most of the error comes from DP and I parameters. It is concluded that high and rapid uncertainty in rabi season is due to low water table, high surface temperature which increased ET_c resulting frequent irrigation application. These factors strongly influence the error in ET_c field measurement and the associate uncertainty of water balance variables. Uncertainty of all variables in water balance equation was also vary according to the season if experiment carried out in the same field with similar instrument/sensor. Sudden and large increase in uncertainties of some parameters resulted in sharply higher uncertainty in water balance calculation. After detailed study of uncertainty of CRUF model it is suggested that during the field data collection in rice field extra precision should be taken during rabi season. Frequent irrigation application and high deep percolation enhance the susceptibility of data collection.

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