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Modeling N fertilization impact on water cycle and water use efficiency of maize, finger-millet, and lablab crops in South India

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Abstract

The understanding of the impact of nitrogen (N) fertilization on the field water cycle and corresponding water use efficiency (WUE) is very important for optimizing fertilization rates and conserving stressed water resources. We modeled soil moisture dynamics of maize (*Zea mays* L.), finger millet (*Eleusine coracana Gaertn*.), and lablab [*Lablab purpureus* (L..) *Sweet*] plots using calibrated HYDRUS-1D model on two experimental sites (rain-fed and irrigated) for three seasons under different N treatments. The results indicate that the effects of N depended on plant specific properties such as N-fixation and drought tolerance, and on plant available water content governed by soil structure and rainfall seasonal variability. Maize WUE of plots which received 150 kg/ha of urea (46 % N) were 10–30 kg/ha/mm higher than plots which received none; likewise, millet that received 50 kg/ha of urea had a 7–10 kg/ha/mm higher WUE than control plots in both experiments. However, differences in water cycle components were noticeable between N treatments only in the rain-fed experiment, where higher N levels led to around 60 and 30 mm higher transpiration, 30 and 20 mm lower evaporation, and 30 and 15 mm lower percolation per season for maize and millet, respectively. In 2018, which was the driest year, the difference in maize WUE between the high and low N treatments was only 1 kg/ha/mm, which corresponded with low actual to potential transpiration ratios (<50%). This indicates higher sensitivity of maize to water stress compared to the other crops. The results of lablab indicate a positive impact of N fertilization on WUE only under water-limited conditions.

1 | INTRODUCTION

The city of Bengaluru has experienced a rapid expansion over the last decades, which have seen it growing into a mega city with over 10 million inhabitants (Government of India, Ministry of Home Affairs, 2011; Narayana, 2011). This resulted in a transformation of the agricultural production toward more intense crop management practices associated with higher fertilization rates (Bora, 2022) and increased irrigation (Mishra et al., 2020; Sankar et al., 2011) which led to higher annual crop yields in rural and urban areas (Government of Karnataka, 2007, 2011, 2014b; Lakshmi Kumar et al., 2019;

Abbreviations: DP, deep penetration; SCE-UA, shuffled complex evolution algorithm; TR, transpiration reduction; WUE, water use efficiency.

Ritchie et al., 2022). On the other hand, the city has been facing serious challenges to meet the growing water demand, and groundwater resources have been over-exploited, which has led to the main river in the Arkavathy catchment to dry up since 1990 (Raj, 2016; Srinivasan et al., 2015). It is therefore essential to understand the impact of those management practices on the soil water cycle and to estimate water use efficiencies as a function of nitrogen (N) fertilization and irrigation under different weather conditions.

Finger millet (*Eleusine coracana Gaertn.*), maize (*Zea mays* L.), and lablab [*Lablab purpureus* (L..) *Sweet*] are widely cultivated crops in the region of Bengaluru during the monsoon (Kharif) season (Government of Karnataka, 2014b, 2021). While several studies investigated the effects of N and water management practices on water use efficiency (WUE) of maize, little information is available on secondary crops like finger millet and lablab.

A study from Bengaluru (Sankar et al., 2011) showed that millet yields are determined by the distribution and amount of rainfall, nutrient availability, and their interactions. Other studies on maize crops showed that higher N application rates increase both grain yield and WUE under nonlimiting water conditions (Al-Kaisi & Yin, 2003; Di Paolo & Rinaldi, 2008; Kim et al., 2008). However, results under limited water availability are contrasting. While Di Paolo and Rinaldi (2008) and Hernández et al. (2015) found that grain WUEs were not affected by N rates; Teixeira et al. (2014) and Eissa and Roshdy (2019) showed the opposite. These studies were mainly focused on WUE and utilized empirical water budget models.

Several crop models, such as DSSAT (Jones et al., 1998) and APSIM (McCown et al., 1996), have been used to model crops yields under different irrigation and nutrient management practices (Asadi & Clemente, 2003; Babel et al., 2018; Dokoohaki et al., 2017). These model are primarily focused on the crop part and adopt a simple tipping bucket approach for simulating water flow dynamics. In contrast, mechanistic hydrological models proved to be better suited for simulating soil moisture dynamics and determining water cycle components on different scales (Baek et al., 2020; O et al., 2020; Palla et al., 2012), while they do tend to simplify crop growth dynamic. Some studies attempted to complement hydrological models with crop models (Bonfante et al., 2010; Kroes & Supit, 2011; Kuang et al., 2021; Shelia et al., 2018). Soil hydraulic properties can be determined based on laboratory measurements of undisturbed field samples such as soil water retention curves and saturated hydraulic conductivity. However, several studies (Ritter et al., 2003; Wöhling et al., 2008) reported disagreements between measured and modeled soil moisture content when such an approach was adopted. This is due to the fact that laboratory measurements are not necessarily representative of the flow behavior in the field, as well as due to the high degree of spatial heterogeneity of soils and potential preferential flow pathways in structured soils.

Core Ideas

- HYDRUS models calibrated and validated based on soil moisture of minimum three soil profiles per crop per treatment.
- Transpiration reduction was calculated as a proxy for water stress and used to distinguish between nitrogen (N) and water stress effect.
- Favorable soil conditions such as good pH and water availability appear to minimize N effect on field water cycle.
- Precipitation amounts and plant-specific properties interact to determine how N affects water balance and water use efficiency.

Alternatively, inverse methods emerged to overcome some of those shortcomings. In these approaches, parameters are estimated by calibrating models based on in situ measurements such as soil moisture, pressure head, soil temperature, or flow measurements. This results in an effective set of parameters (Wollschläger et al., 2009) that minimize the deviation between modeled and measured values. A good summary of inverse methods has been provided by Hopmans and Šimůnek (1999) and Vrugt et al. (2008). Numerous optimization algorithms have been developed for inverse methods that vary in their robustness and complexity. Local optimization algorithms such as the gradient-based Marquardt–Levenberg algorithm used in HYDRUS models (Simunek et al., 2009) are quite fast and simple to use. Their application, however, can be limited when optimizing more than five parameters (Nakhaei & Šimůnek, 2014). Furthermore, factors like poorly defined boundary conditions and the high sensitivity to the initial values of optimized parameters may result in non-uniqueness of the parameter estimation (Simunek et al., 2012). Global optimization algorithms on the other hand like AMALGAM, NASGA II, and SCE-UA are more robust and better suited when optimizing parameters of soil profiles with multiple horizons, and many studies have proven their superiority in finding more optimal solutions (Scott et al., 2000; Vrugt et al., 2001; Wöhling et al., 2008).

Several agronomic studies utilized mechanistic hydrological models in their water cycle modeling. Among the crops studied, most of the literature focused on crop management of maize. For instance, some studies have looked at the water cycle under mulching (He et al., 2018) or cover cropping (Gabriel et al., 2012), while others focused on irrigation management (Dash et al., 2016; González et al., 2015; Zhou & Zhao, 2019). To the best of our knowledge, so far no studies were conducted on finger millet and lablab. Overall, reports on the effects of N fertilization rates in rain-fed and irrigated conditions were mostly limited to maize. They mainly used simplistic water budget models, based on soil moisture measurements that are limited to few soil profiles and/or weekly observations. Moreover, most studies were primarily focused on estimating WUE and, due to their modeling approaches, ignore processes such as deep percolation, preferential flow, and capillary rise. In summary, there is a lack of studies which use calibrated mechanistic hydraulic models to estimate the impact of N fertilization rates on field scale water dynamics of maize, finger millet, and lablab under limiting and non-limiting water conditions.

In this study, we addressed those gaps by establishing two experimental field trials under conditions that resemble the typical range of common crop management practices in Bengaluru and the intensity gradient of nutrient and water supply reflecting management transformation in a fast growing mega city of SE Asia (Buerkert et al., 2021; Hoffmann et al., 2021). Those conditions comprised different N application rates for the three crops maize, finger millet, and lablab under irrigated and rain-fed conditions. We simulated soil water flow for each treatment and each crop using HYDRUS-ID and calibrated it with high-resolution soil moisture data from sensors we installed in each replicate using the SCE-UA algorithm (Duan et al., 1993).

The objectives of our study are: (1) To check whether the calibrated model would simulate soil moisture adequately over several seasons, (2) to determine the impact of N treatments on water cycle components and WUE under seasonal rainfall variability, and (3) to examine how plant specific properties such as N_2-fixing ability and drought tolerance, water availability, and site-specific soil conditions would influence the extent of N treatments.

2 | MATERIALS AND METHODS

2.1 | Site description and experimental design

The study area is located at the premises of the University of Agricultural Science (GKVK Campus) in Bengaluru, India (13˚05″19.7″N 77˚34″14.9″E, 920 m a.s.l.). The climate is moderate with distinct dry and wet seasons, which are locally called as “Rabi” and “Kharif.” The long-term average annual rainfall is 873 mm and the mean temperature is 34˚C in summer and 27˚C in winter (Buerkert et al., 2021; Murugan et al., 2019).

The rain-fed and irrigated field experiments established to mimic typical intensity levels along the rural-urban interface of Bengaluru were located at 500-m distance from each other. Prior to the project, the two field experiments had different management histories. While the irrigated field was formerly planted with eucalyptus trees, the rain-fed field was cultivated with annual crops. Each field consisted of 36 plots (6 m × 12 m) that are arranged in a randomized blocked split plot design. The study started in the rainy season of 2016 (August to December) where the plots were planted with the three crops (maize, finger millet, and lablab), while vegetables (tomato—*Solanum lycopersicum* L., eggplant—*Solanum melongena* L., and cabbage—*Brassica oleracea* L.) were planted only on the irrigated field during the dry season (January–May). The rain-fed field remained fallow during that season. Furthermore, crops of rainy seasons were systematically rotated in a cycle of lablab, maize, and millet, consecutively. For instance, if lablab was grown in certain plots in the rainy season of 2017, the following season saw maize planted in those same plots.

The crops received fertilization with urea (46% N) at three distinct levels: high (H), medium (M), and low (L). Moreover, it was administered in two doses, with 50% applied at sowing and the remaining 50% around 40 days later. The N application rates of the N treatments were adjusted with the start of the 2018 cropping season so that they correspond to the N quantities applied by local farmers. A summary of crop specifications and fertilization rates are summarized in Table 1, and more detailed description of the experiment can be found in Buerkert et al. (2021).

Crops on the irrigated experiment were watered by deficit drip irrigation and quantities were recorded with a water meter. Crops in the rain-fed experiment were irrigated only in emergencies when rainfall was scarce, using water tankers. This kind of practice is usually carried out by local farmers in the region in such management systems, especially in the case of a delayed monsoon onset. The irrigation quantities on the irrigated experiment in 2018 were 74.2 mm for millet and maize and 33 mm for lablab, while the respective amounts on the rain-fed experiment were 47 and 19 mm. In 2017, the applied irrigation quantities on the irrigated experiment were 24 mm for millet and maize and 13 mm for lablab, while on the rain-fed, they were 86 and 36 mm, respectively. Crops were rarely irrigated in 2021 due to high rainfall amounts, and no irrigation data were supplied to us from our field management partners.

2.2 | Soil sampling and measurements

We collected disturbed soil samples and undisturbed soil cores (height = 4 cm, diameter = 5.5 cm) in each plot at 15, 40, and 70 cm depths below ground surface to determine soil physical parameters (texture, bulk density, saturated hydraulic conductivity [Ksat], and the water retention curve). Following the World Reference Base for Soil Resources (WRB) (FAO, 2014), the soil is classified as Nitisol, with a texture of sandy clay loam in the plough horizon and sandy clay in the subsoil layers.

TABLE 1 Summary of crop specifications and fertilization levels—High (H), medium (M), and low (L)-in both irrigated (IE) and rain-fed (RE) experiments.

						N fertilization rate (kg/ha)		
Year	Crop	Spacing (cm)	Field	Sowing date	Harvesting date	L	M	H
2017	Maize	30 × 60	IE	15.07.2017	11.11.2017	50	100	150
			RE	14.07.2017	10.11.2017	50	75	100
	Finger millet	15 × 30	IE	15.07.2017	22.11.2017	50	75	100
			RE	14.07.2017	18.11.2017	25	37.5	50
	Lablab	15 × 30	IE	15.07.2017	15.10.2017	10	15	25
			RE	14.07.2017	16.10.2017	10	15	25
2018	Maize	30 × 60	IE	07.08.2018	09.12.2018	0	50	150
			RE	13.08.2018	01.12.2018	0	50	150
	Finger millet	15 × 30	IE	07.08.2018	01.12.2018	0	25	50
			RE	13.08.2018	12.12.2018	0	25	50
	Lablab	15 × 30	IE	07.08.2018	15.11.2018	0	12.5	25
			RE	13.08.2018	15.11.2018	0	12.5	25
2021	Maize	30 × 60	IE	25.08.2021	15.12.2021	0	50	150
			RE	25.08.2021	14.12.2021	0	50	150
	Finger millet	15 × 30	IE	25.08.2021	12.12.2021	0	25	50
			RE	25.08.2021	10.12.2021	0	25	50
	Lablab	15 × 30	IE	25.08.2021	30.11.2021	0	12.5	25
			RE	25.08.2021	26.11.2021	0	12.5	25

Based on laboratory analysis, we observed slightly lower bulk density corresponding with higher pore volume and significantly higher *K*sat values in the samples of the irrigated field. This might be due to the different management history of the two fields and slight differences in texture. Details of the measurements and soil physical properties are published in Almawazreh et al. (2021).

We installed a soil sensor network (SMT-100 TDT), which recorded soil moisture and temperature at 15, 40, and 70 cm below ground surface, in 10-min intervals in each plot on both experiments since February 2017. An on-site weather station measured temperature, relative humidity, wind speed, rainfall, and sunshine hours, which we used to calculate reference evapotranspiration (ET_o) according to Penman–Monteith FAO56 (Allen, 1998).

Figure 1 shows rainfall and reference evapotranspiration of the rainy seasons (Kharifs) of 2017, 2018, and 2021. We focused on those years because of data availability, as the project suffered from the consequences of the COVID-19 pandemic, which prevented us from regularly exchanging batteries of the installed devices. Over the project's study period, the highest precipitation was recorded in 2017, while 2018 was extremely dry and ET_o exceeded season precipitation. In comparison to previous years, the lowest ET_o occurred in 2021, when rainfall was rather erratic and fell on rather late growth stages of the crops.

Crop growth was monitored by measuring the leaf area index (LAI) using a LI-COR LAI-2000 plant canopy analyser when the crops reached their maximum height and before reaching maturity. We used these data later to separate transpiration and evaporation from the modeled ET.

2.3 | Hydrologic model

We used HYDRUS-1D version 4.08 (Simunek et al., 2009) that was implemented in a python interface using phydrus (Collenteur et al., 2019). The model simulates one-dimensional water flow according to Richards' equation (Jury et al., 1991):

$$\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial z}\left[K\left(\frac{\partial h}{\partial z} - 1\right)\right] - S, \tag{1}$$

where θ (-) is the volumetric water content, t (days) is time, z (cm) is the depth, K (cm/day) is the hydraulic conductivity, h (cm) is the matric potential, and S is the sink term accounting for plant water uptake.

We adopted the Mualem–van Genuchten model (Mualem, 1976; van Genuchten, 1980) for deriving the unsaturated hydraulic parameters:

$$\theta(h) = \begin{cases} \theta_r + \frac{\theta_s - \theta_r}{[1+|\alpha h|^n]^{1-1/n}} & h < 0 \\ \theta_s & h \geq 0 \end{cases}, \tag{2}$$

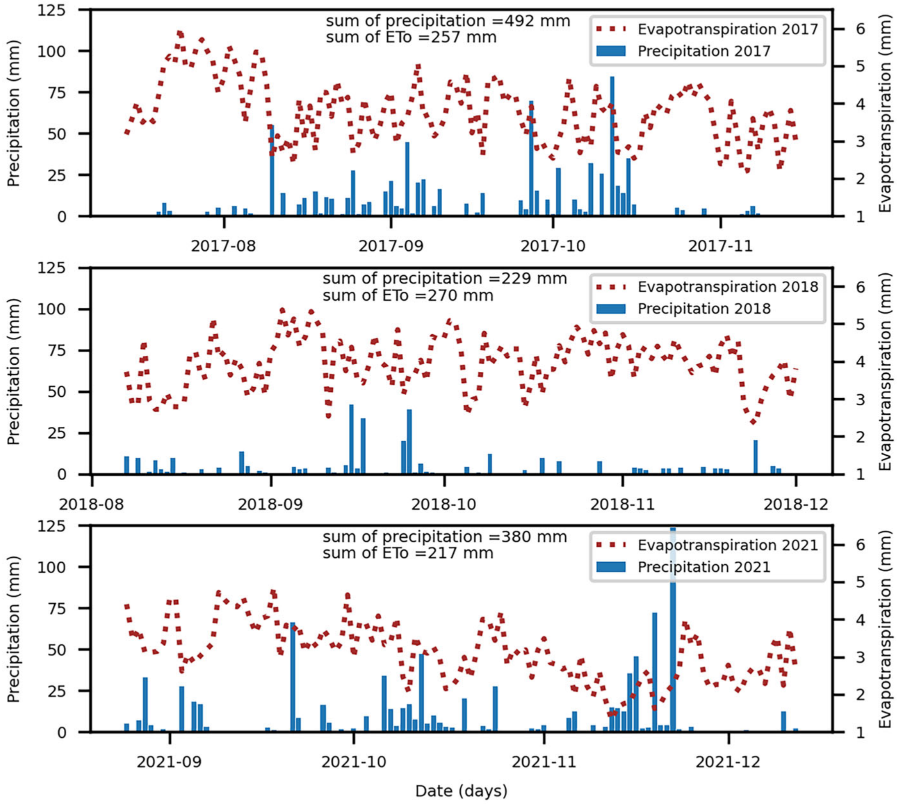

FIGURE 1 Daily sums of precipitation and daily averages of reference evapotranspiration (ET_o) during the growing season (rainy season) over 2017, 2018, and 2021. The sums of both were calculated from 2 weeks after sowing to 80 days after sowing, a period at which crops require water and energy the most.

$$K = K_s S_e^l \left[1 - \left(1 - S_e^{\frac{n}{n-1}}\right)^{1-1/n}\right]^2, \tag{3}$$

$$S_e = \frac{\theta - \theta_r}{\theta_s - \theta_r}, \tag{4}$$

where θ_s(-) and θ_r(-) are the saturated and residual moisture contents, respectively, l(-) is the tortuosity, α(1/cm) and n(-) are shape parameters, K_s(cm/day) is the Ksat, and S_e(-) is the effective saturation.

We used Feddes' model (Feddes, 1978) to calculate root water uptake as:

$$S(h) = \alpha(h) S_p, \tag{5}$$

where S(h) is the actual root water uptake rate as function of water availability, α(h)(-) is the root water stress response function, and S_p (day^{-1}) is the potential root water uptake rate. According to this definition, the potential transpiration is reduced under non-optimal conditions (i.e., when the soil is too dry or too wet) by α, which is a function of soil water pressure head (h). As depicted in Figure 2, The value of α is

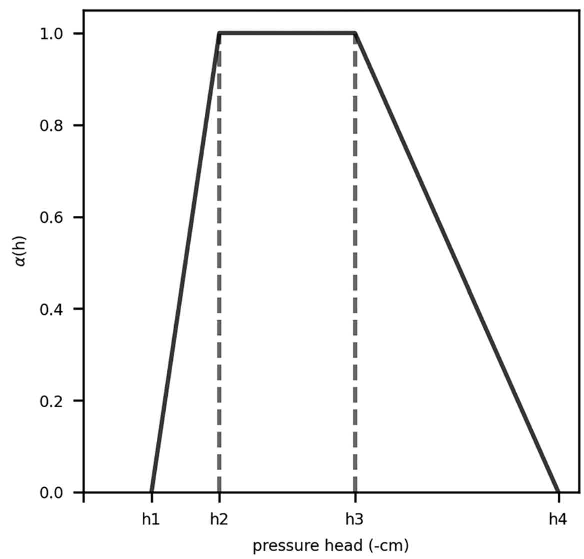

FIGURE 2 Plant water uptake reduction function, adapted from Feddes (1978).

assumed to be zero close to saturation when h is close to $h1$, or near the wilting point at $h4$. The water uptake is assumed to be highest when h is between $h2$ and $h3$, and increase or decrease linearly when it falls between h1 and h2 or h3 and h4, respectively. The water stress function parameters are crop specific, and their values were chosen from the database in HYDRUS, which are derived from Wesseling et al. (1991) and Taylor and Ashcroft (1972). Since finger millet and lablab are neither included in the database nor found in the literature, we assumed that their parameters are similar to those of small grains and bean plants, respectively. Since no root distribution data was available, we used a logistic growth function embedded in HYDRUS that assumes that 50% of the root depth is reached by the mid season and the remaining 50% continues growing until the harvest. Based on Allen (1998), we assumed the maximum root depth to be 200 cm for maize, 100 cm for millet, and 75 cm for lablab. Referring to the principle of effective rooting depth as introduced by Renger and Strebel (1980), which designates the depth delineating the extent of the soil profile responsible for supplying water to the root within the physical limits of availability, we considered modeling the top 90 cm of the soil profile. We estimated the depth based on the soil texture in our experiments using data from Ehlers and Goss (2016). Taking into account the soil moisture sensor locations (15, 40, and 70 cm depth), we divided the profile into three horizons with 25-, 25-, and 40-cm thicknesses to allow simulating the observed soil moisture as close as possible.

We set the upper boundary condition allowing runoff and at the bottom as deep drainage due to the very deep water levels recorded around the area (Kulkarni et al., 2021). We determined the initial boundary conditions based on the measured soil moisture content at the three depths and linearly interpolating it from the surface to 90 cm. Then, we calculated the reference evapotranspiration, ET_o, using the FAO Penman–Monteith equation based on the averaged daily atmospheric parameters obtained from the weather station:

$$ET_o = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)}, \qquad (6)$$

where Δ (kPa °C^{-1}) is the slope of the vapour pressure curve, R_n (MJ m^{-2} day^{-1}) is the net radiation, G (MJ m^{-2} day^{-1}) is the soil heat flux density, which we ignored since its value is small compared to the net radiation when calculating evapotranspiration based on daily values (Allen, 1998). T (°C) is the daily mean air temperature at 2-m height, u_2 (m/s) is the mean wind speed at 2-m height, e_s (kPa) is the saturation vapor pressure, e_a(kPa) is the actual vapor pressure, and γ (kPa °C^{-1}) is the psychrometric constant. Since R_n was not measured directly, we calculated it using the daily sunshine hours, which were obtained from the weather station based on the following equations:

$$R_n = R_{ns} - R_{nl}, \qquad (7)$$

$$R_{ns} = 0.77R_s, \qquad (8)$$

$$R_s = (0.25 + 0.5\frac{n}{N})R_a, \qquad (9)$$

$$R_{so} = (0.75 + 2 * 10^{-5} * z)R_a, \qquad (10)$$

$$R_s = (0.25 + 0.5\frac{n}{N})R_a, \qquad (11)$$

$$R_{nl} = 4.903 * 10^{-9}\left[\frac{T_{\max}^4 + T_{\min}^4}{2}\right](0.34 - 0.14\sqrt{e_a})(1.35\frac{R_s}{R_{so}} - 0.35), \qquad (12)$$

where R_{ns} (MJ m^{-2} day^{-1}) is incoming net shortwave radiation, R_{nl} (MJ m^{-2} day^{-1}) is the outgoing net longwave radiation, R_s (MJ m^{-2} day^{-1}) is the solar radiation, R_a (MJ m^{-2} day^{-1}) is the extraterrestrial radiation, n (h) is the actual sunshine duration, N (h) is the maximal possible sunshine, z (m) is the elevation above sea level, and $T_{\max}$ and $T_{\min}$ (K) are the maximum and minimum absolute daily temperatures, respectively. R_a was calculated for each day based on the latitude and solar constant according to Allen (1998). Then, we calculated the crop evapotranspiration following the dual crop coefficient method (Allen, 1998). Using this approach, potential transpiration, T_p, and potential evaporation, E_p, were calculated based on crop-specific coefficients and the growing stages, both of which are available in tables in FAO 56. Since these coefficients reflect standard conditions, we adjusted them based on the actual weather data and the measured LAI values to account for the real situation on the fields based on the following equations:

$$K_{\text{cb,full}} = K_{\text{cb mid,Table}} + [0.04(u_2 - 2) - 0.004(RH_{\min} - 45)]\left(\frac{h}{3}\right)^{0.3}, \qquad (13)$$

$$K_{\text{cb}} = K_{\text{init,Table}} + (K_{\text{cb,full}} - K_{\text{init,Table}})(1 - e^{-0.7*LAI}), \qquad (14)$$

$$K_{\text{c,max}} = \max\left\{1.2 + [0.04(u_2 - 2) - 0.004(RH_{\min} - 45)]\left(\frac{h}{3}\right)^{0.3}, K_{\text{cb}} + 0.05\right\}, \qquad (15)$$

$$K_e = K_{c,\max} - K_{cb}, \tag{16}$$

$$E_p = K_e \times ET_o, \tag{17}$$

$$T_p = K_{cb} \times ET_o, \tag{18}$$

where $K_{cb\ mid,Table}$(-) and $K_{init,Table}$(-) are crop coefficients at the middle and initial crop growth stage, taken from the tables in Allen (1998). RH_{min}(%) is the daily minimum relative humidity, h (m) is the crop height, $K_{cb,full}$(-) is the estimated basal crop coefficient during the mid-season at peak plant height, K_{cb}(-) is the basal crop coefficient, K_{cmax}(-) is the maximum value of crop coefficient following rain or irrigation, and K_e(-) is the soil evaporation coefficient.

2.4 | Water use efficiency and field water cycle

We calculated water use efficiency (kg/ha/mm) based on the sum of actual transpiration that we extracted from the corresponding HYDRUS model as:

$$\mathrm{WUE} = \frac{\mathrm{GY}_{\mathrm{dm}}}{T_a}, \tag{19}$$

where $\mathrm{GY}_{\mathrm{dm}}$ (kg/ha) is the generative dry matter and T_a(mm) is the actual transpiration. The generative dry matter was calculated by gathering samples from the generative components of the crops-such as maize cobs, millet ears, and lablab pods-and drying them at 60°C until reaching a constant weight. As an indication for water stress, we calculated transpiration reduction (TR; %), which describes the reduced percentage of potential transpiration due to limited water availability as:

$$\mathrm{TR} = (1 - \frac{T_a}{T_p}) \times 100\%, \tag{20}$$

where T_a (mm) and T_p (mm) are the actual and potential transpiration, respectively.

2.5 | Calibration and validation

The estimation of the soil hydraulic parameters was based on minimizing the differences between the measured and modeled soil moisture content using the root mean squared error (RMSE) as an objective function:

$$\Phi(u) = \sqrt{\frac{\sum_{i=1}^{N}[\theta_{obs} - \theta_{mod}(u)]^2}{N}} \tag{21}$$

where Φ is the objective function, u is the parameters vector to be estimated by the model, N is the number of the observed moisture data, and θ_{obs} and θ_{mod} are the observed and modeled moisture data, respectively. Out of the six hydraulic parameters (θ_r, θ_s, α, n, K_s, l), we excluded θ_r and the tortuosity parameter l from the estimation. We assigned the value of l to 0.5 as estimated by Mualem (1976) and the value of θ_r close to zero based on the findings of several studies (Šimůnek et al., 1998; Vrugt et al., 2001; Zurmühl & Durner, 1998), which demonstrated that it is the least sensitive parameter among the others. This resulted in the calibration of a total of 12 parameters (4 per layer).

We set the limits of θ_s based on information derived from the water retention curve. Accordingly, we defined a Gaussian prior distribution function (with a mean of 0.39, and a standard deviation of 0.035) from which the algorithm may draw its samples. However, we set the limits of the other parameters based on values we found in the literature (Brunetti et al., 2019; Werisch et al., 2014), as well as based on our initial calibration attempts. This was due to the fact that the shape parameters α and n do not have a well-defined physical meaning and due to the large variations in measured K_s values. These limits are 0.0001–0.1 (cm^{-1}) for α, 1.01–1.8 (-) for n, and 0.1–10000 (cm/day) for K_s.

We used the python package spotpy (Houska et al., 2015) to calibrate the model using the shuffled complex evolution algorithm (SCE-UA) algorithm based on those parameter limits. The main algorithm parameter to be set is the number of complexes, which we set to 14. In the algorithm, a pre-specified population (n) representing a set of model parameters to be optimized (in our case, the 12 soil hydraulic parameters) is drawn from the prior distribution function. These n population points are then run through the model and ranked based on their evaluation (RMSE). The population is subsequently divided randomly into m complexes. Within each complex, a cycle of k evolutions is initiated, during which new points are generated based on a triangular probability distribution function derived from the points in that complex. These new points are evaluated in the model and replace only the worst-performing points in that complex (i.e., those with the worst RMSE). At the end of these evolution cycles, points are collected back from the complexes and convergence is checked. The algorithm considers the model to have converged if the optimized parameters (referred to as the population in the algorithm) fall within a prespecified parameter space, that is, the normalized geometric range is less than or equal to 0.1, or if the RMSE of model evaluations within the last 10 evolution loops has not improved by more than 1%. A more detailed description of the algorithm can be found in Duan et al. (1993). The python implementation allowed us to run the optimization in parallel computational nodes, which helped to reduce the optimization time drastically.

For each experiment, we calibrated and validated HYDRUS model for nine soil profiles. Each profile represents a group of plots that are cultivated with a certain crop and treated with certain N-fertilization level. The averaged soil moisture content of the replicates *n* was used for calibrating and validating each plot group. We chose calibration and validation time spans such that each model included soil moisture data of at least three of the four replicates per treatment as well as dry and wet spells. For calibration, we utilized data from May 2017 to January 2018, with two rounds of validation: first in 2018 from June to December and then in 2021 during the same months. Table 2 provides information on those time spans and exceptions caused by malfunctioning sensors, as well as details about the plot groups, their corresponding crops, and N treatment level.

3 | RESULTS

3.1 | Model performance and soil moisture dynamics

For both experimental fields, the model showed very good performance (see RMSE values in Table 2). The model for the irrigated experiment was consistent over both validation periods and had an averaged RMSE value of 0.026. The same level of performance applies to the rain-fed model, which performed equally well during the 2017 and 2018 seasons with an RMSE of 0.024. However, its performance dropped in 2021. It must be noted that in some cases, a few moisture sensors at certain depths malfunctioned. In such cases, calibration or validation was limited to the moisture data at one or two depths (e.g., at 15 and 40 cm only). Those cases are summarized and footnoted in Table 2. The effective soil hydraulic parameters resulting from model calibration are listed in Table A2 in the appendices.

The models of both experiments simulated soil moisture specially good under wet conditions during the monsoon period (August to December) and sometimes under performed under dry conditions when the model overestimated water contents in January and February in 2018 or at the beginning of the modeling period until the first wetting event. Nonetheless, the models were also able to simulate soil moisture very good in the dry season of year 2018 (Figures 3 and 4). The data also show how higher rainfall quantities in season 2017 led to an average of 5%–8% higher soil moisture content observed on both experiments. Moreover, around 5% higher soil moisture values were recorded on irrigated experiment plots compared with the rain-fed plots, which is due to the higher pore volume as measured from the soil samples. The irrigation effect is also more visible in 2018, when the higher irrigation quantities have led to a higher soil moisture on irrigated experiment plots during September and October (Figure 3). The validation results from year 2021 of the very same plots shown here are listed in Figures A1 and A2 in the Appendix.

3.2 | N treatments impact on water cycle components and WUE

Transpiration, TR percentage, as well as WUE are depicted in Figures 5–7 for maize, millet, and lablab, respectively. The water cycle components and WUE are also summarized in Table A1 in the Appendix. The correlation between N fertilization rates and transpiration, TR, and WUE is evident (Figure 5a). Maize plots which have received higher N had higher transpiration, less TR, and accordingly better water use efficiency. However, the degree of this impact on WUE varied through the seasons, where it was the largest in 2017 and very low in 2018. For instance, WUE of plots receiving highest N was only 10% higher than those that received none in 2018. Furthermore, plots that received less N seem to have experienced more water stress, which is translated to having higher TR percentages. In season 2021, maize crops without N had 11% higher TR than crops receiving 150 kg/ha N and their WUE was 27 kg/ha/mm lower. This difference in TR was comparably higher in season 2018, where it was 20%. Unlike in the rain-fed experiment, transpiration and TR of irrigated maize plots did not vary as much across the different N-levels (Figure 5b). For instance, in season 2017, the difference in TR was only 0.3% between the lowest and highest N-levels, while in 2018, it was 4.3%. Similar to rain-fed fields, WUE increased with applied N but at a smaller correlation, with season 2018 showing the smallest differences. Overall, WUE of maize is higher on the irrigated fields in comparison with rain-fed fields.

Transpiration and WUE of millet plots correlated to a lesser degree with N rates in comparison with the maize plots, with the exception of season 2017 on the irrigated experiment (Figure 6). In that season, the lowest applied N rate was 50 kg/ha, a rate at which those quantities seem to have plateaued. Moreover, TR percentage differed only in seasons 2018 and 2021 on the rain-fed experiment, while in season 2017 as well as in all seasons in the irrigated experiment, they did not differ that much. Surprisingly, transpiration and WUE of millet on both experiments were higher in 2018 compared with 2021, despite the fact that crops in 2018 received the lowest rainfall that was 40% less than 2021.

Results from the lablab plots varied a lot across the season (Figure 7). The correlation between N levels and transpiration is not clear, and plots which have received less N did not necessarily have the lowest WUE. We excluded the harvest results of 2018 on the irrigated experiment due to unreasonably high values, which could be only explained by a mistake in measurements.

TABLE 2 Calibration and validation time spans as well as the goodness of fit RMSE for both irrigated and rain-fed fields.

PG	N level	*n*	Calibration Time span	crop	RMSE	Validation 1 Time span	Crop	RMSE	Validation 2 Time span	Crop	RMSE
Irrigated experiment											
1	high	4	21.05.2017–31.12.2017	lablab	0.025	15.07.2018–22.09.2018	maize	0.026 ξ	–	maize	–
2	medium	4	21.05.2017–31.12.2017	lablab	0.024	15.07.2018–22.09.2018	maize	0.022ϱ	–	maize	–
3	low	4	21.05.2017–31.12.2017	lablab	0.026	15.07.2018–22.09.2018	maize	0.023ϱ /ζ	–	maize	–
4	high	4	21.05.2017–20.01.2018	millet	0.027	15.06.2018–22.09.2018	lablab	0.036	15.05.2021–05.12.2021	lablab	0.026
5	medium	4	21.05.2017–20.01.2018	millet	0.029	15.06.2018–22.09.2018	lablab	0.034	15.05.2021–05.12.2021	lablab	0.025
6	low	4	21.05.2017–20.01.2018	millet	0.029	15.06.2018–22.09.2018	lablab	0.037	15.05.2021–05.12.2021	lablab	0.032
7	high	4	21.05.2017–31.12.2017	maize	0.026	15.06.2018–22.09.2018	millet	0.029	15.05.2021–05.12.2021	millet	0.024ϱ
8	medium	4	21.05.2017–31.12.2017	maize	0.026	15.06.2018–22.09.2018	millet	0.024	15.05.2021–05.12.2021	millet	0.024ϱ
9	low	4	21.05.2017–31.12.2017	maize	0.024	15.06.2018–22.09.2018	millet	0.028	15.05.2021–05.12.2021	millet	0.024ϱ
Rain-fed experiment											
1	high	4	21.05.2017–01.02.2018	lablab	0.029	01.06.2018–01.12.2018	maize	0.02	01.08.2021–05.12.2021	maize	0.03κ
2	medium	4	21.05.2017–01.02.2018	lablab	0.021	01.06.2018–01.12.2018	maize	0.017	01.08.2021–05.12.2021	maize	0.054
3	low	4	21.05.2017–01.02.2018	lablab	0.021	01.06.2018–01.12.2018	maize	0.023	01.08.2021–05.12.2021	maize	0.056
4	high	3	21.05.2017–01.02.2018	millet	0.019	01.03.2018–18.07.2018	lablab	0.027	–	lablab	–
5Ψ	medium	3	21.05.2017–01.02.2018	millet	0.021	01.03.2018–18.07.2018	lablab	0.027	–	lablab	–
6	low	3	21.05.2017–01.02.2018	millet	0.043	01.06.2018–01.12.2018	lablab	0.021	01.08.2021–05.12.2021	lablab	0.037
7	high	4	01.01.2018–22.09.2018	millet	0.018	01.04.2019–10.08.2019	maize	0.022	–	millet	–
8	medium	4	01.01.2018–22.09.2018	millet	0.017	21.05.2017–01.02.2018	maize	0.039ϱ	01.08.2021–05.12.2021	millet	0.035
9	low	3	16.05.2018–22.09.2018	millet	0.014	01.04.2019–20.11.2019	maize	0.032	–	millet	–

Note: PG, plot group number; n, number of replicas of the treatment used for calibration and validation; Ψ, calibration and validation based on soil moisture data at 15 and 40 cm depths; ϱ, unlike calibration the validation was based on averaged soil moisture of 3 replicas; ξ, soil moisture data for validation available only at a depth of 70 cm; ζ, soil moisture data available for validation at 40 and 70 cm depths; κ, soil moisture data available for validation at 15 and 40 cm depths.

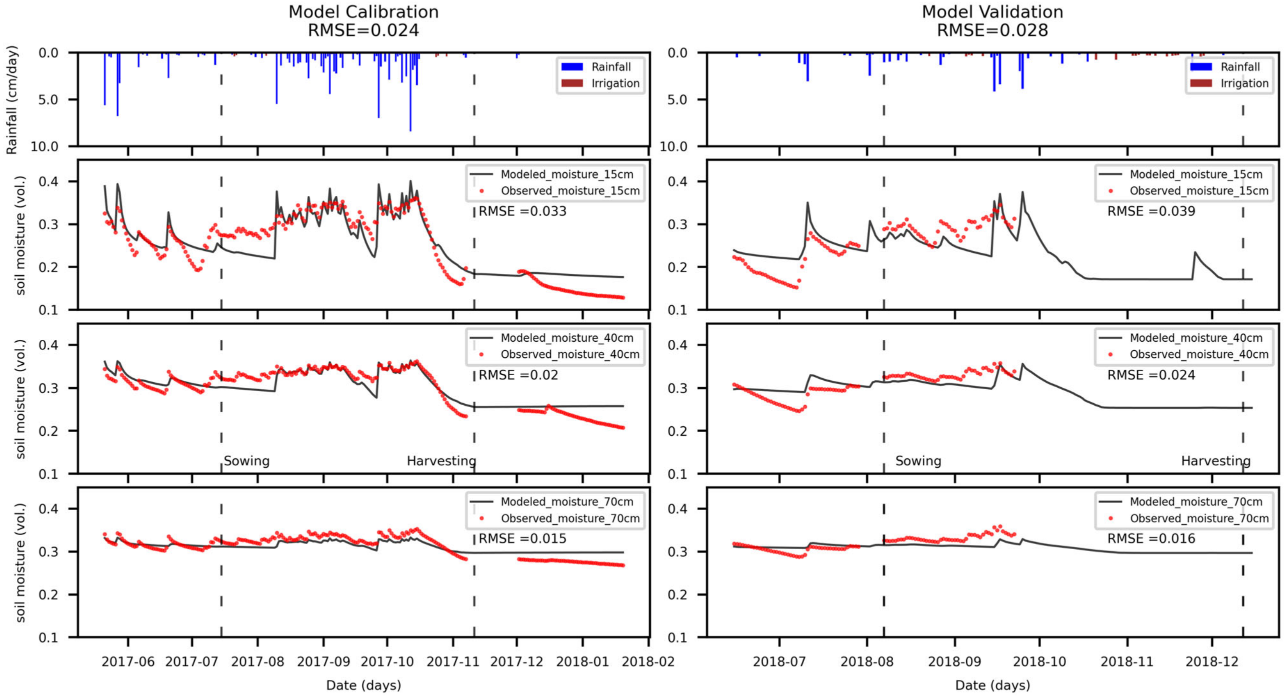

FIGURE 3 Model calibration and validation of plot group 9 in the irrigated experiment at University of Agricultural Sciences Bengaluru, GKVK Campus, South India. RMSE, root mean squared error.

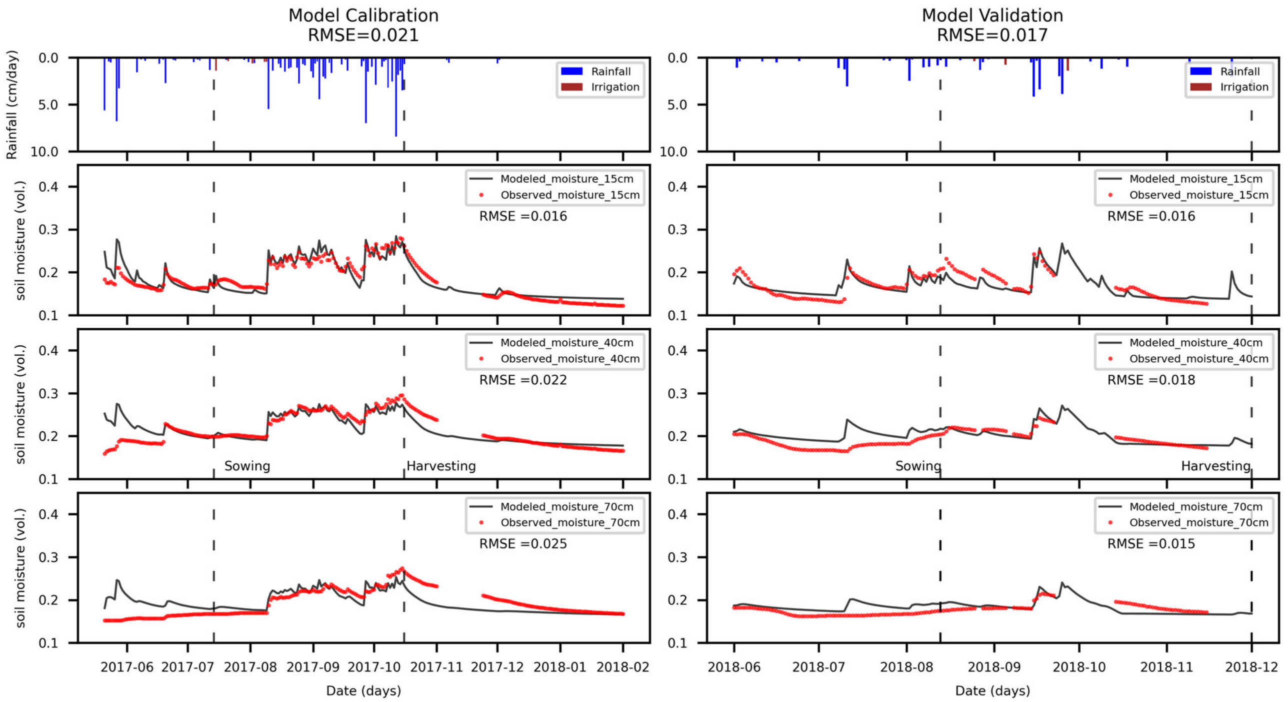

FIGURE 4 Model calibration and validation of plot group 2 in the rain-fed experiment at University of Agricultural Sciences Bengaluru, GKVK Campus, South India. RMSE, root mean squared error.

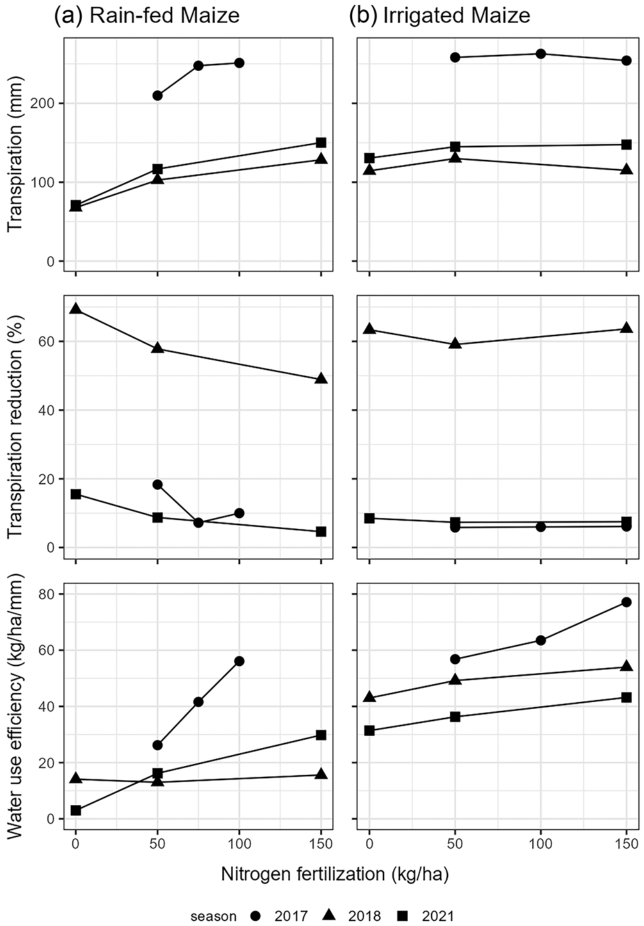

FIGURE 5 Transpiration, transpiration reduction (TR), and water use efficiency (WUE) of maize as a function of nitrogen fertilization rates on both irrigated and rain-fed experiments.

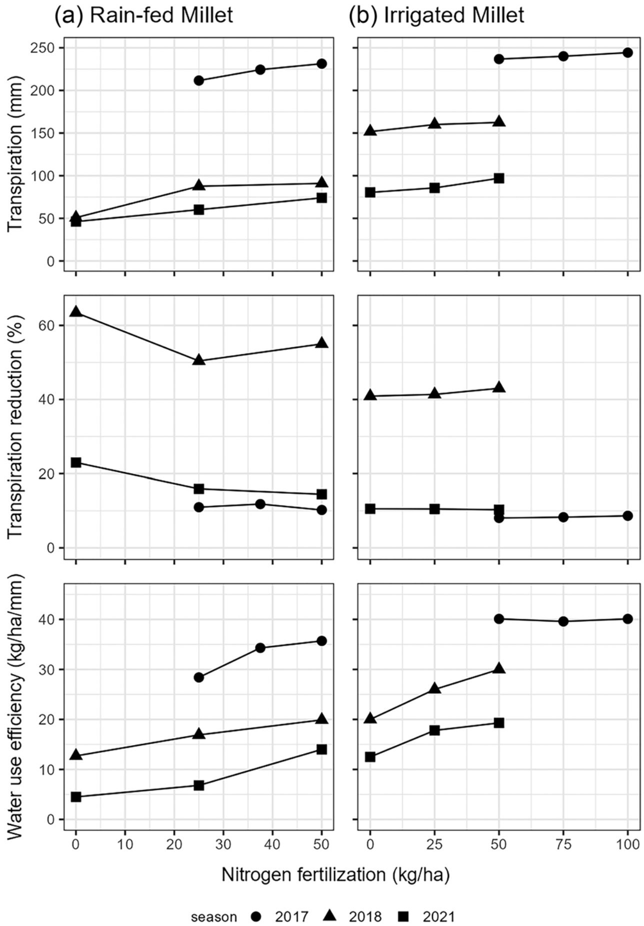

FIGURE 6 Transpiration, transpiration reduction (TR), and water use efficiency (WUE) of millet as a function of nitrogen fertilization rates on both irrigated and rain-fed experiments.

Deep percolation (DP) sums are illustrated in Figure 8. These values correlate with N levels of maize and millet in the rain-fed experiment, where they slightly decreased with the increased N application with the exception of season 2017 for millet. This trend, however, was not observed on the irrigated experiment where DP sums were similar regardless of N application rate. Similar to transpiration, DP sums for the lablab plots also varied from season to season, where in 2017 in the rain-fed experimental plot receiving lower N had higher percolation while the opposite happened in season 2018. Overall, in all plots, percolation sums were highest in seasons 2017 and 2021 and very low in 2018.

4 | DISCUSSION

Our modeling approach simulated soil moisture dynamics on both experimental fields very well. This gives us confidence in relying on the models to extract the water cycle components of the crops under the different N treatments.

Despite the limited soil moisture data in 2021, the results of models on the irrigated experiment showed a steady model performance. On the other hand, a drop in performance of the rain-fed models was observed as indicated by higher RMSE in that period (Table 2). We can only speculate that the longer exposure of those plots to dryness in the following fallow seasons has led to the formations of soil crusts, which may have altered hydraulic properties of the upper soil horizon. Since our models calculate root water uptake using crop-specific water functions and are calibrated with high soil moisture data, we were able to extract the actual crop transpiration T_a, which we have used to calculate both the crops' WUEs and a proxy for water stress by the transpiration reduction percentage, TR. This proxy helped us to differentiate between N treatments effects and water stress effects.

The results indicate that the extent of N effects on water cycle components (T_a, DP, E) and WUE are different between the two experimental fields. While the trivial explanation of that would be the irrigation effect, this cannot explain the differences in season 2017, at which higher precipitation occurred and as a result differences in applied

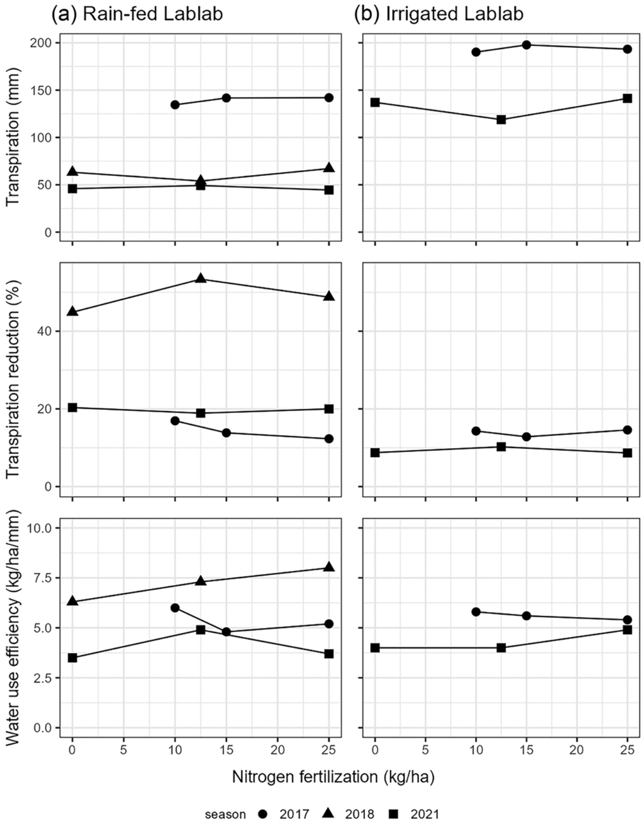

FIGURE 7 Transpiration, transpiration reduction (TR) and water use efficiency (WUE) of lablab as a function of nitrogen fertilization rates on both irrigated and rain-fed experiments.

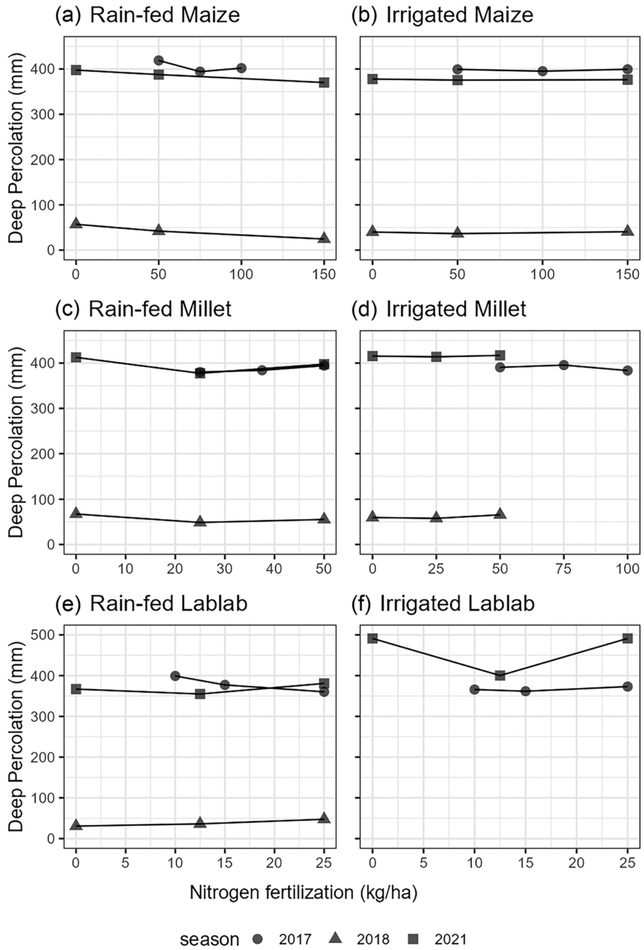

FIGURE 8 Sum of deep percolation as a function of nitrogen fertilization rates for all crops on both irrigated and rain-fed experiments.

irrigation quantities between the two sites were rather low. The detected differences can be rather explained by the higher pore volumes on the irrigated experiments that have resulted in higher observed soil moisture in these plots and accordingly to higher plant available water percentages (Almawazreh et al., 2021) (Figures 3 and 4). Furthermore, according to Buerkert et al. (2021), the higher pH of 5.1 on the irrigated field compared to 4.4 on the rain-fed field and the twice higher C and N content have led to more favorable plant growth conditions on that field (Msimbira & Smith, 2020). This may explain why the effects of N application were more tangible in the rain-fed experiment than in irrigated experiment. We expected that higher N rates would lead to higher biomass production of maize and millet accompanied by higher transpiration rates and lower evaporation and deep percolation. The results partly confirmed this effect (Figures 5, 6, and 8). However, they also confirm that water availability represented by rainfall and irrigation quantities as well as specific crop properties such N fixation abilities or tolerance to water scarcity affects the impact of N treatments. For instance, maize WUE in the rain-fed site only varied by 1.0 kg/ha/mm between the highest and lowest N treatment in 2018, compared to 30 and 27 kg/ha/mm in 2017 and 2021, respectively, which confirm a similar finding by Kim et al. (2008). This illustrates a case where water availability fell below a minimum threshold (TR >49%) required by the plants to be able to utilize more N, a result which confirms the findings of Hernández et al. (2015). Furthermore, transpiration, TR, and DP of maize plots varied much less between the N treatments in the irrigated experiment; nonetheless, WUE varied among the treatments. We can infer from this that these differences were largely explained by the N effect, while on the rain-fed experiment, the differences in yields were a combination of both water stress and N effects.

Millet results also showed a couple of particularities (Figure 6). First, on the irrigated experiment season 2017 where higher N quantities were applied, the application of >50 kg/ha seemed to be exceeding the millet demands. This is reflected by very close yield and WUE quantities between the treatments. Second, millet plants seemed to be rather resistant to limited water, for instance on the rain-fed experiment in season 2017; TR did not vary as much among the N levels meaning that water was not a limiting factor in that year. Furthermore, the yields and WUE in season 2018 were surprisingly not the lowest, but rather those in season 2021. While this can be explained for the irrigated experiment by the higher irrigation quantities that bridged the gap between the two seasons, it does not explain it for the rain-fed experiment where irrigation was very limited. We can only speculate that the lower radiation (sunshine hours), which has led to a lower reference evapotranspiration compared to the previous seasons, and the late intense rainfall in 2021 have negatively impacted the yields of millet in that year see (Figure 1). In this case, a crop growth model that is based on photosynthetic processes such as WOSFOT (van Diepen et al., 1989) could be used to explore this. Unlike the maize and millet crops, lablab results do not suggest a positive correlation between transpiration and WUE. This is may be attributed to N_2-fixing ability of lablab which seemed to mask out the N effect such as in season 2017. Moreover, in almost all seasons on both fields, N had either no impact or only very small impact on WUE and TR.

The correlation of high N levels with lower (DP and E) in the case of maize and millet may be explained by the less-exposed soil surface in the plots that received more N due to higher plants biomass, which also led to higher plant water uptake, resulting in less evaporation and DP values. Moreover, the ratio of DP to rainfall and applied irrigation ranged in the wet seasons of 2017 and 2021 between 45% and 60%, whereas in the drier season of 2018, it ranged between 9% and 20%, which emphasizes the importance of including it in water budget models. By calibrating every model with an averaged soil moisture of at least three soil profiles, we incorporated to a certain degree the local heterogeneity of soil structure and texture, but we do ignore the variance and the extreme variations of these heterogeneities which add uncertainties to calculated water components. These uncertainties would have more impact on T_a, for example, under water limited conditions where the plants are under water stress, such as in 2018. A calibration of each single replicate (plot) would have meant a calibration of 72 models (36 at each experiment), which would have not been time efficient as even when using parallel computational nodes, a calibration needed up to 72 h. Moreover, this would not have been possible in any case due to limited data on some plots. Nonetheless, we recommend this approach to field studies of including soil moisture data from several soil profiles as it better represents field water cycles compared to laboratory derived soil hydraulic parameters.

In our study, we utilized one type of measurement, the soil moisture content, for model calibration, which may introduce uncertainties in the resulting water cycle components. Using other measurements such as pressure head would have reduced such uncertainties (Wöhling et al., 2013), but the installation of such sensors in addition to the soil moisture sensors would be financially expensive and laborious, especially on the scale of our study. Finally, we opted to use Phydrus, the python implementation of HYDRUS (Collenteur et al., 2019), as it was easier to couple with the SCEUA for calibration purposes. The compensation for plant water uptake in case of dry condition is not yet implanted in Phydrus, which led us to the usage of the Feddes model instead, that may introduce some uncertainties to calculated actual transpiration values. Nevertheless, a study by Cai et al. (2018) compared two water uptake models considering compensation with the Feddes model and found that cumulative actual water uptake differed only slightly, at around 2%, while other water cycle components such as evaporation, drainage, and soil water storage were very similar.

5 | CONCLUSIONS

The approach of using the calibrated soil hydrologic model HYDRUS allowed to successfully simulate moisture dynamics in the short and long term, specially when dry and wet spells were included in the model calibration. This was particularly effective during wet spells and allowed for good estimation of water cycle components in both experiments.

The impact of N on water cycle components for the crops was affected by water availability (amount and distribution), soil structure, and crop-specific physiological characteristics. Moreover, its impact on water cycle components was diminished under more favorable growing conditions such as higher plant water availability and irrigation. However, it still did have a positive impact on grain yields and WUE of maize and finger millet.

As known from earlier studies, maize proved to have high water and N demands compared with finger millet and lablab. As a result, water shortages impede its ability of N recovery and decrease its WUE, which increases the probability of N losses through volatilization and leaching, and made it more suited to irrigated systems. Finger millet on the contrary seems to be less sensitive to water scarcity and as such better adapted to rain-fed conditions. Both crops performed always better with higher N levels, with high N plots having higher transpiration, lower deep percolation and evaporation, and higher WUE. Moreover, the results suggest that N application exceeding 50 kg/ha seems to be exceeding the demands of finger millet at the yield levels obtained.

Lablab on the other hand had a very low N demand due to its N_2 fixation ability. As a result, effects of N fertilization were less clear and varied between the years most probably due to water availability; it only had a positive impact on yields under limiting water conditions.

AUTHOR CONTRIBUTIONS

Albara Almawazreh: Data curation; formal analysis; investigation and visualization; methodology; software; writing—original draft; writing—review and editing. **Daniel Uteau**:

Conceptualization; supervision and validation; writing—review and editing. **C. T.Subbarayappa**: Resources; project administration. **Andreas Buerkert**: Resources; writing—review editing. **Sybille Lehmann**: Data curation; investigation. **Stephan Peth**: Conceptualization; funding acquisition; project administration; resources; supervision and validation; writing—review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest that could be perceived as prejudicing the impartiality of the research reported.

DATA AVAILABILITY STATEMENT

The data used in this study are available upon request from the corresponding author.

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APPENDIX A

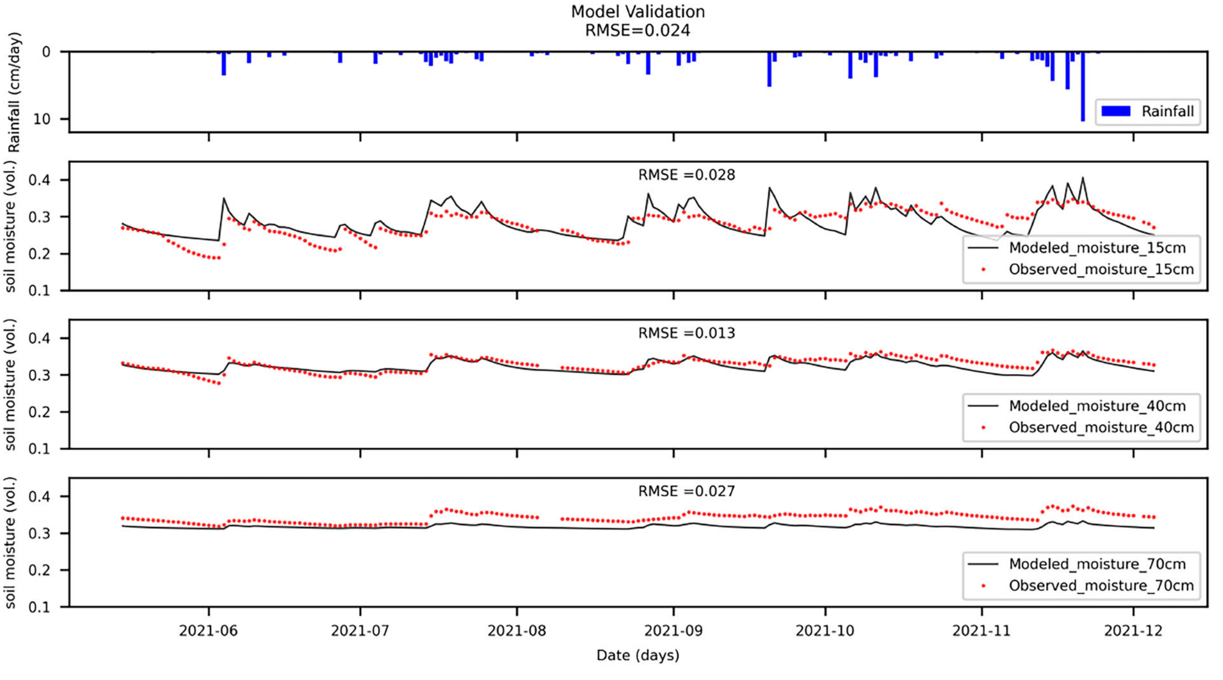

FIGURE A1 Model validation in 2021 of plot group 9 in the irrigated experiment at UASB, GKVK Campus, S-india.

TABLE A1 Water cycle components in (cm) and water use efficiency in (kg/ha/mm).

Crop	N level	2017 P+I	2017 Ta	2017 Ea	2017 DP	2017 WUE	2018 P+I	2018 Ta	2018 Ea	2018 DP	2018 WUE	2021 P+I	2021 Ta	2021 Ea	2021 DP	2021 WUE
Rain-fed experiment																
Maize	L	85.1	21	21.71	41.88	26.2	26.8	6.78	15.34	5.70	14.1	68.9	7.09	22.96	39.77	3.0
	M	85.1	24.76	22.29	39.42	41.6	26.8	10.27	14.65	4.21	13.0	68.9	11.67	18.76	38.77	16.2
	H	85.1	25.12	20.77	40.192	56.1	26.8	12.84	14.40	2.45	15.6	68.9	15.02	16.14	37.02	29.8
Millet	L	84.6	21.16	26.91	38.01	28.4	27.8	5.084	16.44	6.74	12.7	68.9	4.62	24.34	41.26	4.5
	M	84.6	22.44	24.39	38.42	34.3	27.8	8.76	16.10	4.88	16.9	68.9	6.02	24.31	37.75	4.5
	H	84.6	23.14	23.37	39.44	35.7	27.8	9.10	14.52	5.54	19.9	68.9	7.41	22.43	39.77	14.0
Lablab	L	79	13.45	20.98	39.91	6.0	24	6.32	16.51	3.068	6.3	68.9	4.59	25.00	36.69	3.5
	M	79	14.17	21.24	37.72	4.8	24	5.40	17.35	3.62	7.3	68.9	4.92	24.93	35.49	4.9
	H	79	14.2	21.62	36.02	5.2	24	6.71	15.53	4.75	8.0	68.9	4.46	24.50	38.08	3.7
Irrigated experiment																
Maize	L	79.3	25.82	16.68	39.92	56.8	33.8	11.45	18.9	4	43.0	68.9	13.06	17.52	37.78	31.4
	M	79.3	26.28	16.40	39.52	63.5	33.8	13	18.1	3.65	49.2	68.9	14.45	16.12	37.55	36.3
	H	79.3	25.42	17.00	39.93	77.1	33.8	11.5	18.61	4.06	54.0	68.9	14.76	15.94	37.64	43.2
Millet	L	79.3	23.68	19.93	39.06	40.1	33.8	15.17	17.1	6	20	68.9	8.045	20.43	41.55	12.5
	M	79.3	24.00	19.29	39.56	39.6	33.8	16	16.23	5.78	26.0	68.9	8.57	20.12	41.38	17.8
	H	79.3	24.43	19.58	38.36	40.1	33.8	16.25	15.4	6.57	30	68.9	9.70	18.65	41.70	19.3
Lablab	L	76.2	19.02	13.31	36.59	5.8	–	–	–	–	–	68.9	13.70	18.78	49.12	4.0
	M	76.2	19.78	12.93	36.17	5.6	–	–	–	–	–	68.9	11.90	16.43	40.02	4.0
	H	76.2	19.33	12.74	37.31	5.4	–	–	–	–	–	68.92	14.13	18.35	49.13	4.9

Abbreviations: P+I, precipitation and irrigation; Ta, actual transpiration; Ea, actual evaporation; DP, deep percolation; WUE, water use efficiency.

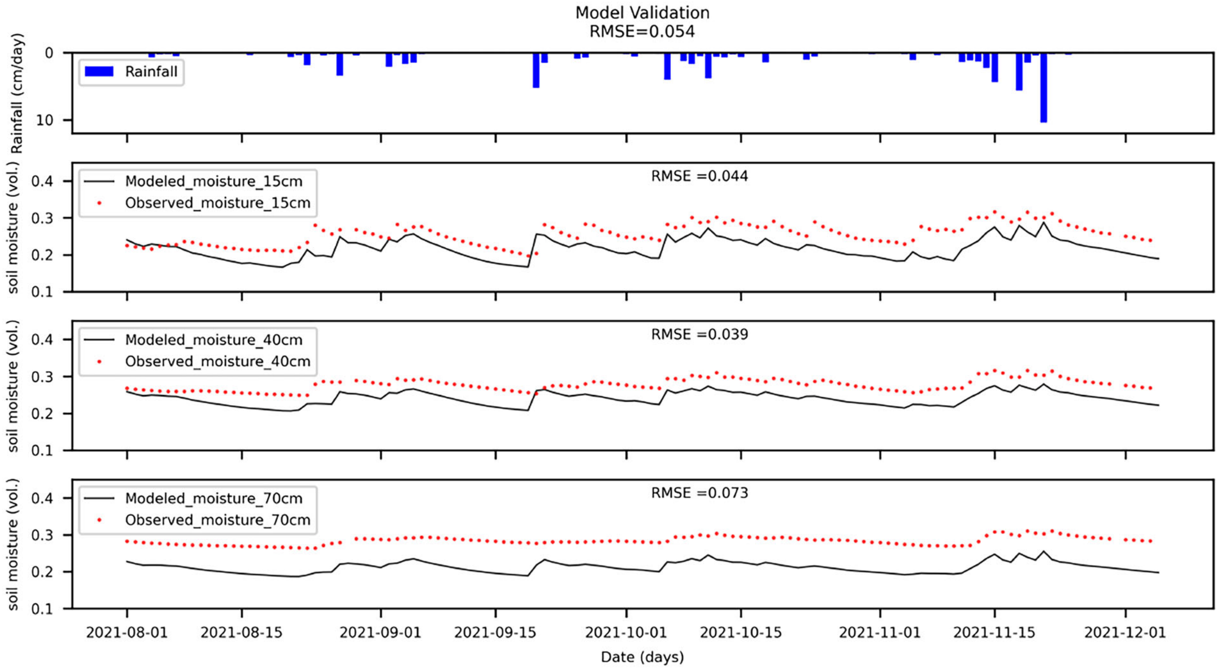

FIGURE A2 Model validation in 2021 of plot group 2 in the rain-fed experiment at UASB, GKVK Campus, S-india.

TABLE A2 Effective soil hydraulic parameters for each plot group (pg) resulting from model calibration.

Irrigated experiment												
	First horizon				**Second horizon**				**Third horizon**			
PG	θ_s **(-)**	α **(1/cm)**	n **(-)**	**Ks (cm/day)**	θ_s **(-)**	α **(1/cm)**	n **(-)**	**Ks (cm/day)**	θ_s **(-)**	α **(1/cm)**	n **(-)**	**Ks (cm/day)**
1	0.41	0.040	1.09	7124	0.34	0.038	1.05	9520	0.34	0.093	1.03	385
2	0.41	0.020	1.12	432	0.37	0.041	1.05	5856	0.33	0.083	1.04	580
3	0.45	0.057	1.10	3610	0.40	0.037	1.05	5956	0.37	0.076	1.04	1212
4	0.47	0.097	1.16	628	0.38	0.017	1.09	3288	0.38	0.082	1.07	410
5	0.47	0.061	1.16	168	0.40	0.018	1.12	2854	0.38	0.090	1.07	973
6	0.47	0.082	1.16	205	0.38	0.060	1.10	3962	0.34	0.090	1.05	190
7	0.46	0.088	1.15	115	0.41	0.029	1.10	2738	0.35	0.097	1.03	349
8	0.47	0.071	1.15	120	0.43	0.040	1.10	3978	0.37	0.078	1.05	468
9	0.45	0.089	1.16	107	0.38	0.029	1.08	2312	0.34	0.093	1.02	125
Rain-fed experiment												
	First horizon				**Second horizon**				**Third horizon**			
PG	θ_s **(-)**	α **(1/cm)**	n **(-)**	**Ks (cm/day)**	θ_s **(-)**	α **(1/cm)**	n **(-)**	**Ks (cm/day)**	θ_s **(-)**	α **(1/cm)**	n **(-)**	**Ks (cm/day)**
1	0.37	0.068	1.17	730	0.34	0.024	1.09	2796	0.34	0.097	1.06	30
2	0.35	0.052	1.16	812	0.29	0.009	1.11	3860	0.29	0.099	1.09	1008
3	0.43	0.065	1.15	2882	0.31	0.015	1.07	3488	0.29	0.069	1.04	2994
4	0.51	0.043	1.19	739	0.39	0.035	1.09	3758	0.33	0.096	1.06	3024
5	0.48	0.080	1.16	3438	0.30	0.086	1.07	9624	0.49	0.070	1.05	987
6	0.38	0.055	1.17	2938	0.41	0.064	1.12	218.6	0.41	0.072	1.08	1137
7	0.49	0.053	1.20	735	0.36	0.059	1.10	5116	0.28	0.099	1.02	1363
8	0.50	0.058	1.22	1517	0.39	0.015	1.10	6308	0.35	0.087	1.04	1566
9	0.41	0.067	1.19	3882	0.30	0.021	1.09	8040	0.28	0.075	1.05	6772