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Interlinkages between human agency, water use efficiency and sustainable food production

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Abstract:

Efficient use of water and nutrients in crop production are critical for sustainable water and crop production systems. Understanding the role of humans in ensuring water and nutrient use efficiency is therefore an important ingredient of sustainable development. Crop production functions are often defined either as functions of water and nutrient deficiency or are based on economic production theory that conceptualizes production as a result of economic activities that take in inputs such as water, capital and labor and produce crop biomass as output. This paper fills a gap by consistently treating water and nutrient use and human agency in crop production, thus providing a better understanding of the role humans play in crop production. Uptake of water and nutrients are two dominant biophysical processes of crop growth while human agency, including irrigation machine power, land-preparing machine power and human labor force, determine limits of water and nutrient resources that are accessible to crops. Two crops, i.e., winter wheat and rice, which account for the majority of food crop production are considered in a rapidly developing region of the world, Jiangsu Province, China, that is witnessing the phenomenon of rural to urban migration. Its production is modeled in two steps. First water and nutrient efficiencies, defined as the ratios of observed uptake to quantities applied, are modeled as functions of labor and machine power (representing human agency). In the second step, crop yields are modeled as functions of water and nutrient efficiencies multiplied by amounts of water and fertilizers applied. As a result, crop production is predicted by first simulating water and nutrient uptake efficiencies and then determining yield as a function of water and nutrients that are actually taken up by crops. Results show that modeled relationship between water use efficiency and human agency explains 68% of observed variance for wheat and 49% for rice. The modeled relationship between nutrient use efficiency and human agency explains 49% of the variance for wheat and 56% for rice. The modeled relationships between yields and actual uptakes in the second step explain even higher percentages of observed the variance: 73% for wheat and 84% for rice. Leave-one-out cross validation of yield predictions shows that relative errors are on average within 5% of the observed yields, reinforcing the robustness of the estimated relationship and of conceptualizing crop production as a composite function of bio-physical mechanism and human agency. Interpretations based on the model reveal that after 2005, mechanization gradually led to less labor being used relative to machinery to achieve same levels of water use efficiency. Labor and irrigation equipment, on the other hand, were found to be complimentary inputs to water use efficiency. While the results suggest interventions targeting machinery are most instrumental in increasing wheat productivity, they may exasperate rural – urban migration. Policy strategies for alleviating rural-urban migration while ensuring regional food security can nonetheless be devised where appropriate data are available.

1. Introduction

Changing climate and growing population in the Anthropocene (Vörösmarty et al., 2013; Savenije, H. H. G et al., 2014) are amplifying the tension between water supply and demand across the planet (Vörösmarty et al., 2000; Arnell and Lloyd-Hughes, 2014; Flörke et al., 2018; Duan et al., 2019; Brown et al., 2019; Di Baldassarre et al., 2019). Increased average temperatures and variability in rainfall are making water infrastructures for urban and agriculture water supply obsolete as they have often been designed for a stationary climate (Milly et al., 2008; Wagener et al., 2010). Such changes are coupled with rising population in emerging, mostly agrarian, economies such as China and India that rely on agricultural water (Parry, 2019). Such changes are major threats for sustainable development as it renders societies water insecure, food insecure and at the same time stripping rural communities of livelihood opportunities (Novoa et al., 2019).

Often human ingenuity is assumed to be able to overcome water and food challenges posed by changing climate, by conquering climate determinism of human fate and engender human prosperity through technological innovation in spite of climatic adversity (Kreibich et al., 2017; Kendall and Spang, 2019). Technological innovations are assumed to not only mitigate water insecurity but also adapt to it by internalizing climate change in new water infrastructure and technological designs (Fletcher et al., 2019; Levin-Koopman et al., 2019; Allen et al., 2019). As part of the solutions offered, it is assumed that human agency makes the use of water and other related inputs in food production more efficient, thereby releasing pressures of increasing water scarcity and sustaining food production and human wellbeing (Sivapalan et al., 2014; Konar et al., 2016).

Human well-being comprising of food and economic security in water insecure rural areas depends on crop production that efficiently uses water and nutrients (Haines-Young & Potschin, 2010; Herrero et al., 2012). This includes the production of feed for livestock production, thereby making it the foundation of agricultural systems in general and linking it to phenomena such as migration, agrarian crisis across the globe and even dispersal of agrarian societies (Afifi et al., 2014; Elshafei et al., 2014; Pande et al., 2014; FAO et al., 2018). Agricultural systems in Jiangsu Province, China are one such example, where crop production is a major consumer of water, accounting for nearly 73.5% of total water consumption in Jiangsu Province, China (BSJ, 2018). It is also a major human activity, employing 5.82 million people in Jiangsu province in 2017 (BSJ, 2018). Crop production critically couples wellbeing of human with water and nutrient cycles and has been shown to be linked with rural to urban migration in Jiangsu Province, China (Lyu et al., 2019).

Crop production is influenced both by hydro-climatic variability and the interventions of humans in terms of provisioning of irrigation and labor. There are therefore several conceptualizations of interactions between human agency and the environment (Sivapalan et al., 2015) in how crops are produced, often reflecting the disciplines from which such models have originated. Water proxies such as transpiration, nutrient proxies such as fertilizer use and their joint-effect effects have been incorporated in multivariate linear regressions to estimate crop yield–input relationships in agricultural sciences community (Insam et al., 1991; Heaton et al., 2004). Meanwhile biophysical models such as CROPWAT (Smith, 1992), Aquacrop (Steduto et al., 2009; Raes et al., 2009; Hsiao et al., 2009), WOFOST (WOrld FOod STudies) (de Wit et al., 2018; Lecerf et al., 2018; Ceglar et al., 2019), APSIM (The Agricultural Production Systems sIMulator) (Holzworth et al., 2014; Gaydon et al., 2017), and statistical models such as by Sheldrick et al. (2003) explicitly explain the underlying mechanisms. Similarly, Hatirli et al. (2006) focus on nonlinear water, temperature and nutrients constraints on biomass production (Ferrero et al., 2018; Hoffman et al., 2018). These models emphasize the critical role of water and other nutrients in crop yields and incorporate the role of humans as multipliers that scale optimal yields to reflect less than optimal efforts of humans. For example, less than optimal crop yield is often linked to water deficit via linear function, i.e., $1 - \frac{Y_a}{Y_x} = K_y(1 - \frac{ET_a}{ET_x})$, where the crop yield response factor K_y changes with crop characteristics (FAO, 2012; Liu et al. 2002).

On the other side of the spectrum are conceptualizations of production models based on economic theory, which emphasize less on biophysical constraints but more on human agency based on the principles of economics. Models derived based on Cobb-Douglas production functions (Cobb and Douglas, 1928) have often been applied, such as by Goldsmith et al. (2004), which consider water as an input alongside other inputs such as machinery and labor in the production of a crop as an economic good. Other forms of production functions have also been used in this context, see e.g. McCarl (1982). Others examples include linear programming models of agricultural production (Howitt, 1995, Pattanayak and Sills 2001), multi-crop micro-econometric models to interpret farmers' production acreage choice (Femenia et al., 2018), complex integrated economic-hydrologic models to model the interactions between water allocation, farmer input choice, agricultural productivity and water demand (Rosegrant et al. 2000, Roobavannan et al. 2017a) and system dynamics based socio-hydrological models to understand the interlinkages between water availability, labor demand and migration (Roobavannan et al. 2017b).

While such models have proved powerful in simulating yields and modeling labor employment in the agriculture sector as a function of water availability and other inputs, it remains a challenge to consistently estimate both yield and labor demand from the same function. Bio-physical models represent labor as a scaling factor on potential yields, while economic theory-based models often include water as one of the inputs into an economic activity while deemphasizing the biophysical role played by water in biomass production.

The present paper fills this gap by focusing not only on the bio-physical relationships of crop yield with water and nutrient inputs, but also by considering how humans, e.g.

through irrigation and land-preparation, which would influence the efficiencies of water and nutrients uptake. The paper acknowledges that understanding the critical role played by human agency in efficient use of water and nutrients for crop production is key to facilitating a sustainable future, especially in fast developing parts of the world. Jiangsu Province in China is one such region, a typical example of rapidly urbanizing region with a significant flow of economic migrants from rural to urban areas. Jiangsu is a producer of crops such as rice and wheat, which occupy almost 60% of the total planted area. Though agriculture production is closely linked to water availability and is influenced by climatic factors, several government initiatives have produced rapid development and industrialization of agriculture in Jiangsu Province. At the same time, it is undergoing an industrial revolution. The proportion of agriculture output is being gradually reduced by modern secondary and tertiary industries, affecting income sources of rural families and exasperating rural to urban migration. Understanding the interlinkages between water security, water and nutrient efficiency and food production would therefore enable policy makers to devise and implement appropriate hydrological or economic instruments to address the migration phenomenon in the province.

The paper is organized as follows. Section 2 introduces the methodology of incorporating both bio-physical mechanisms and human agency into a single crop-production modeling framework and the study area. Modeling results including the calibrated parameters of the crop production model, together with the results of cross validation, are then shown in section 3. Section 4 then discusses how substitutions between labor and machinery have changed over time in Jiangsu China, how it matches with patterns estimated based on independent data and what it means in terms of rapid mechanization of agriculture in China. Section 5 gives the conclusions of the study.

2. Methodology

The light reactions of photosynthesis absorb energy from the sun that is then used by the dark reactions to convert nutrients into crop biomass (Foyer, 1984; Leegood et al., 2000; Ke, 2001; Allakhverdiev, 2015). Crop greenness resulting from energy absorption by light reactions is therefore an important indicator of crop biomass accumulation and can be measured by reflectance-based vegetation indexes (VI). Such indices have been widely used as indicators of crop yields (Quarmby et al., 1993; Ren et al., 2008; Mkhabela et al., 2011; Kogan et al., 2013; Sharma et al., 2015). Given that transpiration, carbon & nitrogen fixation, and phosphorus consumption occur in leaves (Foyer, 1984), reflectance measurements have also been utilized to assess crop water and nutrient status (Sembiring, 1998; Albayrak, 2008; Caturegli et al., 2016).

Human agencies, representing labor force and machinery utilization, on the other hand, contribute to crop production by enabling crops to access water (Allen et al., 1998) and nutrient resources. Irrigation devices such as pumps and drip-irrigation systems (Brouwer et al., 1988) help conveying and concentrating water in the root zone whereas land-preparation machinery, such as tractors create appropriate growing space for seeds to get access to nutrients (Klein and Zaid Date, 2002). Such agencies are crucial for improving the efficiencies of water and nutrients use for variety of crops (Bhiuyan et al. 1992; Erkossa et al., 2005; Johnston and Bruulsema, 2014; Ma et al., 2014).

Given that human agency supplements water and nutrients in order to efficiently produce biomass from photosynthesis, we conceptualize crop production as a (composite) function of human agency induced use efficiency of water and nutrients and resulting biomass production.

2.1 Conceptual Model Structure

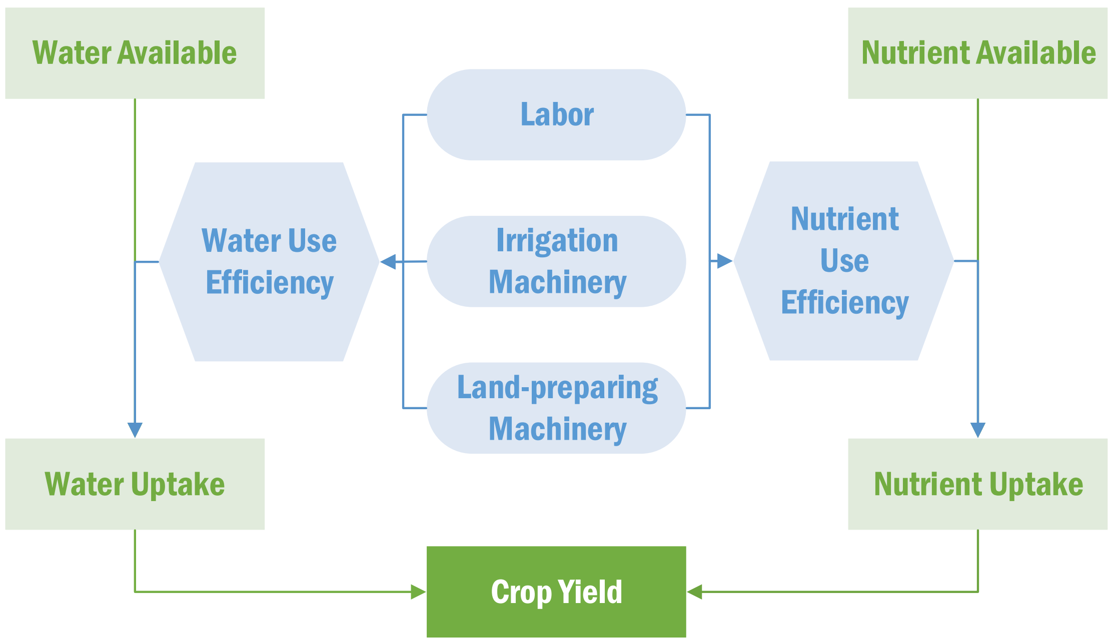


Fig. 1 Crop production conceptualized as a composite function of biophysical mechanisms and human agency. Human agency influences uptake efficiencies, which then influence biomass production for given levels of water and nutrient resources.

Figure 1 illustrates the overall methodology described in detail in Section 2.3. A crop production function is conceptualized as a composite function of biomass production and efficiency with which water and nutrients are used up. Labor, irrigation and land-preparation machinery are considered as factors that impact the efficiency of water and nutrient use by crops. Human agency therefore does not directly contribute to crop biomass accumulation but determines the amounts of accessible water and nutrient resources for crops.

2.2 Research Area and Data

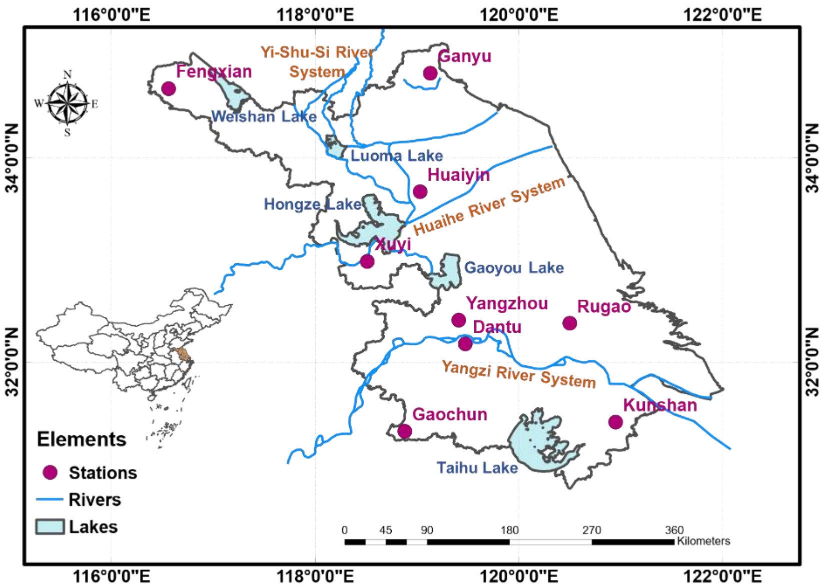


Fig. 2 Study area: Jiangsu Province of China. Also shown are the locations of agro-meteorological stations at which Normalized Difference Vegetation Index (NDVI) and water-crop-related data were used.

Figure 2 shows the study area. Crop production is modelled in Jiangsu Province, China. Jiangsu Province is in the central area of the south-east coast of China. Being a part of the Yangzi River Delta, Jiangsu Province rapidly developing, together with one of the highest population densities in the country. The main climate pattern of Jiangsu Province is subtropical monsoon, with annual precipitation around 1000 mm/year. Dominated by plain terrain, Jiangsu Province has the highest water surface proportion among all the administrative regions in China, taking advantage of abundant surface water resources. The total planted area under food crops in Jiangsu Province reached to about 5.41 million hectares in 2017. Wheat and rice have the highest two proportions of plant area, which are 28.69% and 29.94%, respectively. Jiangsu Province has been undergoing a rapid process of agricultural mechanization, i.e. more and more machines are being used to replace human labor. The total power of agricultural mechanics reached to approx. 50 million Kw in 2017, which is nearly 6 times of the value in 1978 (approx. 8.6 million Kw) (Bureau of Statistics of Jiangsu., 2018). As a result, it is also witnessing rural to urban migration and urgently seeks solutions that increase water and food security while balancing it with employment in rural areas.

Crop growth information, including crop type and growing status, were obtained from nine agro-meteorological monitoring stations across Jiangsu Province (shown in Figure 1). Two major types of food crops, i.e., winter wheat (growing season: starts from October of previous year, 8 months in total) and rice (growing season: starts from May of current year, 5 months in total) were selected as modeling objects. Of the nine stations, six stations located in Fengxian, Ganyu, Xuyi, Huaiyin, Yangzhou and

Kunshan provided crop growth information for winter wheat; three stations, including Ganyu, Dantu and Gaochun, provided information for rice. Time series of precipitation, rootzone moisture, transpiration, and provincial crop yield per area, are also used. The data sources are listed in Table 2.1.

Data categories	***Variables (symbol)***	***Unit***	***Period***	***Spatial Resolution***	***Temporal Resolution***	***Data source***
Hydro-climatic	Precipitation (P)	mm	2000 -2017	0.5*0.5 °	Derived from monthly data. Growing-season-accumulated value for each year.	CRU (CRU, 1901-2017; Harris et al., 2014)
	Transpiration (T)			0.25*0.25 °		GLDAS Noah Land Surface Model L4 monthly 0.25*0.25 ° V2.1 (Rodell et al., 2004)
	Rootzone Moisture (S_W)			0.25*0.25 °		
Crop Information	NDVI (g)	-	2000 -2017	30 meters	Derived from 8-day data. Growing-season-maximum value for each year.	Landsat 7 NDVI (imported from Google Earth Engine: 'LANDSAT/LE07/C01/T1_8DAY_NDVI', Gorelick et al., 2017)
	Crop type & Growing season		1991 -2010	Station-level	Yearly	National Meteorological Information Center of China (2006)

	Provincial crop yield (Y)	kg/ha	2001-2017	Provincial	Yearly	Statistical Yearbook of Jiangsu (BSJ, 2018)
Human Agencies	Labor force in crop cultivation (L_C)	Capita/1000ha	2001-2017	Provincial	Yearly	Statistical Yearbook of Jiangsu (BSJ, 2018)
	Irrigation machinery (M_I)	Kw/1000ha				
	Land-preparing machinery (M_L)					
	Fertilizer use (F)	Ton/1000ha				

Table 2.1 Description of the data sets used. The overlapping period from 2001-2017 was used for regression and related analysis.

2.3 Model Set-up, calibration and validation

Let crop yield Y be represented by a function $G(.,.)$ of actual water, x_W, and nutrient, x_N, uptakes. Then $Y = G(x_W, x_N)$. However, actual amounts of uptakes are often less than total amount of water available W_T in the form of rainfall R, rootzone moisture S_W and nutrients available after fertilizer amount F has been applied. The actual amount of water and nutrient uptakes relative to their available supply defines corresponding efficiencies. Therefore if uptake efficiencies (η_W as water use efficiency and η_N as nutrient use efficiency) as well as the available supplies are known then the amounts taken up by crops can be obtained by multiplying efficiencies with the corresponding available amounts of water and nutrients. This means that $x_W = \eta_W W_T$ and $x_N = \eta_N F$.

Water and nutrient use efficiencies are assumed to be enabled by human agency, *H*, representing variables linked to machinery and labor. This means that efficiencies are functions of *H*, i.e. $\eta_W = \eta_W(H)$ and $\eta_N = \eta_N(H)$. Then crop production can be defined by the following *composite function*,

$$Y = G(x_W, x_N) = G(\eta_W(H)W_T, \eta_N(H)F)\ . \tag{1}$$

Each station $i = 1, .., S$ has its own effects embedded in the functions *G*, η_W and η_N. These station specific fixed effects result lead to station specific yields. Such effect is implemented in Equation (1) as,

$$Y^i = G^i(x_W, x_N) = G^i\left(\eta_W^i(H^i)W_T^i, \eta_N^i(H^i)F^i\right). \tag{1a}$$

Equation 1a is the composite function model of crop production that is calibrated using data available at multiple resolutions. Since the model brings in human agency and biophysical effects in a sequence (being a composite function), the parameters of the model can be estimated in two stages. Therefore panel regressions (Lobell &

Burke, 2010; Cai et al., 2014; Álvarez et al., 2017) are performed in two steps. This also synthesizes observations at different locations and provides general relationships *across stations*.

Fixed Effect Estimation of the model in two stages

Step 1: In order to understand regional water and nutrient use efficiencies across locations, panel regression is performed across stations to estimate η_W and η_N as functions of human activities, *H*. We use the ratios $\eta_W = x_W/W_T$ and $\eta_N = x_N/F$ (efficiencies of water and nutrient uptakes respectively) as dependent variables and use inputs, *H*, such as machineries linked to labor and irrigation as independent variables to estimate the following equations for stations $i = 1, .., S$:

$$\eta_W^i = \Lambda H^i + \delta^i + \epsilon_W$$

$$\eta_N^i = \Theta H^i + \theta^i + \epsilon_N$$

(2a, b)

Here, H^i represent station-specific human activities but its effect on efficiencies, (Λ, Θ), are general across all the stations. Hence, (Λ, Θ) are independent of station *i*. Fixed station-specific effects are quantified by (δ^i, θ^i), and (ϵ_W, ϵ_N) represent the residuals accounting for variance of efficiencies not explained by *H*. The estimation of effects is based on linear regression of equations in Equation 2a,b and implemented by using Álvarez et al. (2017).

Step 2: Panel regressions are again employed to estimate crop yields as functions of observed water and nutrients uptakes, independent of the stations. We assume that $G(x_W, x_N) = k{x_W}^{\alpha}{x_N}^{\beta}$ (Kouka et al., 1994; Gowariker et al., 2009; Xin et al., 2016; Li et al., 2016). This is done by estimating the following equation in log-space, accounting for station specific fixed effects.

$$log(Y^i) = \alpha\, log(x_W^i) + \beta\, log(x_N^i) + log(k) + \pi^i + \epsilon_Y \tag{3}$$

Here (x_W^i, x_N^i) are 'observed' water and nutrient inputs and Y^i corresponding observed yields. Note that the effects (α, β, k) are independent of the stations while π^i is station specific fixed effect and ϵ_Y represents variance of *Y* not explain by the independent variables. The *station independent* prediction of yields are obtained by removing fixed effects $Y = k{x_W}^{\alpha}{x_N}^{\beta}$. The regression is performed using Álvarez et al. (2017).

Model based prediction

When *predicting* yields, predictions of station specific water, $\hat{x}_W^i$, and nutrient uptakes, $\hat{x}_N^i$, are obtained as products of station-specific predictions of water and nutrient use efficiencies with location specific water and nutrient availability respectively.

That is, $\hat{x}_W^i = \hat{\eta}_W^i \mathrm{W}_T^i$ and $\hat{x}_N^i = \hat{\eta}_W^i F^i$ with $\hat{\eta}_W^i = \Lambda H^i + \delta^i$ and $\hat{\eta}_N^i = \Lambda H^i + \theta^i$ being predictions of first stage regressions.

2.3.1 Proxies for water and nutrient uptakes

Transpiration, *T*, is chosen as the proxy for water uptake by plants. Since it is harder to detect nutrient uptake directly, proxy for nutrient uptake is estimated based on Normalized Difference Vegetation Index (NDVI), (Landsat 7, 2001-2017). NDVI reflects the joint effect of water and nutrient uptakes on plant greenness (Quarmby et al., 1993; Ren et al., 2008; Mkhabela et al., 2011; Kogan et al., 2013; Sharma et al., 2015). Therefore, the effect of water uptake on NDVI is first filtered out and the remaining variance of NDVI is then assumed to approximate the uptake of nutrients.

In order to filter out the effect of water uptake from NDVI, a fixed effect regression across the stations, similar to fixed effect regressions described above, is conducted in log space with NDVI as dependent variable, *g*, and water uptake x_W, as represented by transpiration *T*, as the independent variable. This regression provides $\hat{g}$ (an estimate of *g*), which is the part of greenness that is explained only by water uptake. The difference between g and $\hat{g}$ in log space, i.e. residuals, then provides the part of greenness that is only a function of nutrients taken up by crops. Such residuals are then taken as proxy of nutrient uptake *N*, i.e.

$$log(N) = log(g) - log\ (\hat{g}) \tag{4}$$

The yearly maximum value of NDVI during the growing season is chosen to represent the maximum level of crop greenness because peak NDVI is most sensitive to the levels of water and nutrient uptakes (Gamon et al., 1995). We assume that higher peak NDVI also implies that the crop has undergone lower water and nutrient stress during other critical growth stages. The growing season considered for winter wheat was from 1st October of previous year to 1st June of next year (8 months), while the growing period of rice was set as 1st May to 1st of October (5 months).

2.3.2 Water and nutrient use efficiency

Water and nutrient use efficiencies are defined as the ratio of transpiration T and nutrient proxy N to total available water, W_T, and nutrient resources respectively. Total available water resources, W_T, is defined as the sum of root zone moisture S_W at the beginning of crop growing season and precipitation P during crop growing season. Nutrient availability, F, is represented by the total amount of fertilizer applied per unit area – assuming that yield response to increased amounts of residual soil nutrients are much less than to freshly applied fertilizer (Prihar et al., 1985). The *observed* water use efficiency η_W and nutrient use efficiency η_N are then calculated as follows and used to calibrate its predictive equations (equations 2a, b).

$$\eta_W = \frac{T}{P + S_W} \tag{5a}$$

$$\eta_N = \frac{N}{F} \tag{5b}$$

Human factors such as labor used in crop production L_C, irrigation machinery power M_I and land-preparing machinery power M_L per unit area are considered in the set of independent variables H (see equations 2a, b). All combinations of joint and individual effects (such as $L_C M_I M_L$, $L_C M_I$, $M_I M_L$, $L_C M_I$, L_C, M_I and M_L) were first regressed and only those effects that were statistically significant were selected in the final model.

2.3.3 Validation

Leave-one-out cross validation was implemented to test the robustness of estimated crop production for each crop. For each station, data was available for 17 years (2001-2017, see Table 1). In each round of validation, 16 out of 17 years for each station were chosen to train the model, while the remaining year was used to validate the estimated model. This was repeated 17 times, each time with a unique year left out for validation. Boxplots of relative errors show the distribution of relative errors in leave one out cross validation. The calculation of relative errors is defined as:

$$RE = (\hat{y} - y)/x \tag{5}$$

where $\hat{y}$ represents the predicted yield for a crop using all except one year of data, whereas y represents the observed yield.

3. Model interpretation: substitution between labor and machinery in winter

wheat cultivation

The proposed crop production function is a composite function of crop yield and efficiency with which water and nutrients are taken up, as facilitated by human agency.

One can therefore interrogate such a model to understand how tradeoffs between different components of human agencies have evolved over time. The water use efficiency of winter wheat, as shown in Table 3.2, is supported by labor and irrigation machinery (pumps) and land-preparation machinery (tractors and supporting tools). Thus, winter wheat serves as an interesting example to investigate how different elements have substituted one another and shed light on the mechanization of agriculture in Jiangsu. Here we show that such estimations based on the composite production function are consistent with observed data.

Here, by substitution of one factor by another we mean how much of one factor can be substituted by one unit of another factor such that water use efficiency remains the same. This requires, for example, the estimation of $\frac{dL_C}{dM_I}$ such that $d(\eta_W) = 0$ (so that the level of water use efficiency remains the same).

$$d(\eta_W) = \frac{\partial \eta_W}{\partial L_C} dL_C + \frac{\partial \eta_W}{\partial M_I} dM_I + \frac{\partial \eta_W}{\partial M_L} dM_L = 0 \tag{4.1}$$

To obtain $\frac{dL_C}{dM_I}$, we divide both sides of Eq. 4.1 by dM_I:

$$\frac{\partial \eta_W}{\partial L_C}\frac{dL_C}{dM_I}+\frac{\partial \eta_W}{\partial M_I}+\frac{\partial \eta_W}{\partial M_L}\frac{dM_L}{dM_I}=0$$

(4.2)

Obtaining $\frac{dM_L}{dM_I}$ by using data from the statistical yearbooks of the province (BSJ, 2001~2018), $\frac{dL_C}{dM_I}$ can be calculated as

$$\frac{dL_C}{dM_I}=-\frac{\partial L_C}{\partial \eta_W}(\frac{\partial \eta_W}{\partial M_I}+\frac{\partial \eta_W}{\partial M_L}\frac{dM_L}{dM_I})$$

(4.3a)

Note here that partial derivatives can be estimated from the regressed equations in 2.3.2. Similarly, $\frac{dL_C}{dM_L}$ can be calculated as:

$$\frac{dL_C}{dM_L}=-\frac{\partial L_C}{\partial \eta_W}(\frac{\partial \eta_W}{\partial M_L}+\frac{\partial \eta_W}{\partial M_I}\frac{dM_I}{dM_L})$$

(4.3b)

The calculated $\frac{dL_C}{dM_I}$ and $\frac{dL_C}{dM_L}$ are shown in figure 4.1a, b.

4. Model Results

4.1 Yield-uptake relationship

Table 3.1 gives the coefficients of proxies correspond to the effects (i.e., α and β in equation 3) of water and nutrient respectively. It reports that estimated effects for both the crops were significant.

Crops	***X***	***Coefficients***	***Std. Error***
Winter wheat	$(x_W)^\alpha$	*0.53*	*0.06*
	$(x_N)^\beta$	*0.12*	*0.03*
	Overall	*R-squared*	*0.73*
Rice	$(x_W)^\alpha$	*0.17*	*0.02*
	$(x_N)^\beta$	*0.04*	*0.01*
	Overall	*R-squared*	*0.84*

Table 3.1 Yield-uptake fixed effect estimation of α and β for the two crops. All effects are significant with p<0.01.

Figure 3a,b show observed yields in comparison with the modeled yields for rice and wheat. Modeled yields for various stations are obtained by incorporating station specific fixed effects (from equation 3) for stations $i = 1,..,S$ with parameters given in Table 3.1 (fixed effects $k^i = ke^{\pi^i}$ not shown).

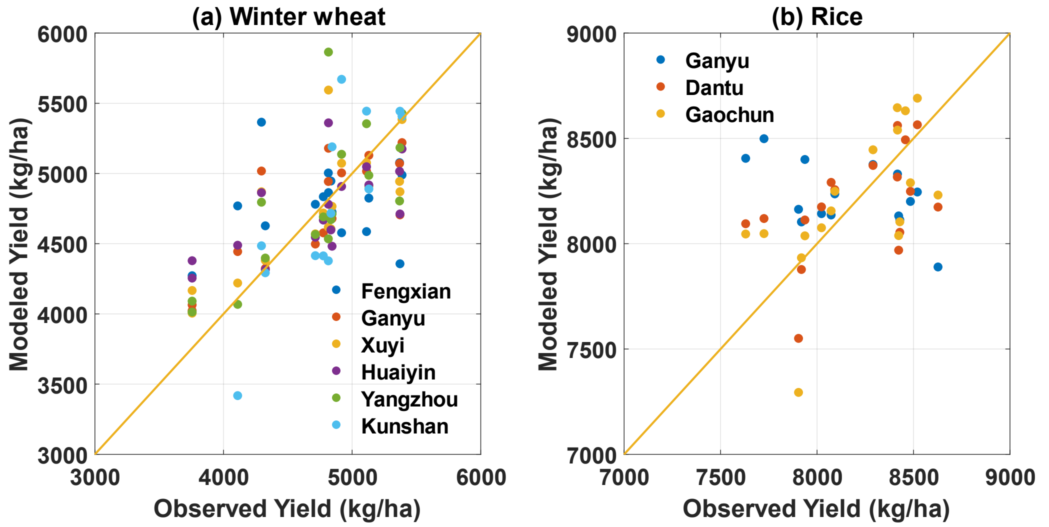


Fig. 3a, b Modeled and observed crop yields based on estimated effects shown in Table 3.1.

4.2 Water Use Efficiency

Table 3.2 shows that several elements of H were found to be statistically significant in explaining water use efficiency of winter wheat. In case of rice, only irrigation machinery M_I demonstrated significant effect (regression coefficient) on water use efficiency, which reflects that water access is most important for its water uptake.

Crops	***H***	***Coefficients***	***Std. Error***
Winter wheat	L_C	*8.57e-3*	*2.76e-3*
	M_I	*5.60e-3*	*2.00e-3*
	M_L	*2.94e-3*	*0.75e-3*
	L_C*M_I	*-9.92e-6*	*0.34e-5*
	L_C*M_L	*-3.77e-6*	*1.05e-6*
	M_I*M_L	*-3.41e-6*	*0.92e-6*
	L_C*M_I*M_L	*4.45e-9*	*1.29e-9*
	Overall	*R-squared*	*0.68*
Rice	M_I	*3.01e-4*	*0.77e-4*
	Overall	*R-squared*	*0.49*

Table 3.2 Fixed effect estimation of water use efficiency for the two crops. All effects are significant at p<0.01.

Again, Figure 4a, b show 'observed' (see equation 5a how water use efficiency, i.e., WUE, has been defined) WUE in comparison with the modeled WUE for rice and wheat (from equation 2a).

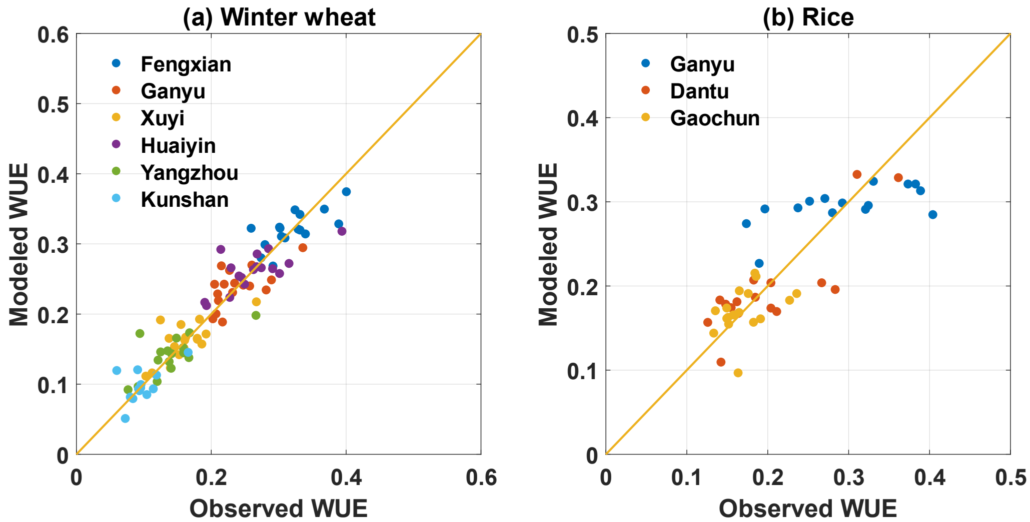


Fig. 4a, b Modeled and observed crop water use efficiency (WUE) across the stations.

4.3 Nutrient Use Efficiency

Table 3.3 shows that land-preparing machinery is the only significant factor for the nutrient use efficiency of winter wheat. This indicates that better-prepared farmland is the only significant factor that facilitated better nutrient access for winter wheat. On the other hand, the major contributing factor to rice nutrient use efficiency is labor power, together with the joint-effect factor of crop labor and land-preparation machinery.

Crops	***X***	***Coefficients***	***Std. Error***
Winter Wheat	M_L	*1.26e-7*	*0.23e-7*
	Overall	*R-squared*	*0.49*
Rice	L_C	*2.35e-8*	*0.58e-8*
	L_C*M_L	*5.35e-12*	*1.25e-12*
	Overall	*R-squared*	*0.56*

Table 3.3 Fixed effect estimation of nutrient use efficiency. All effects are significant at $p<0.01$.

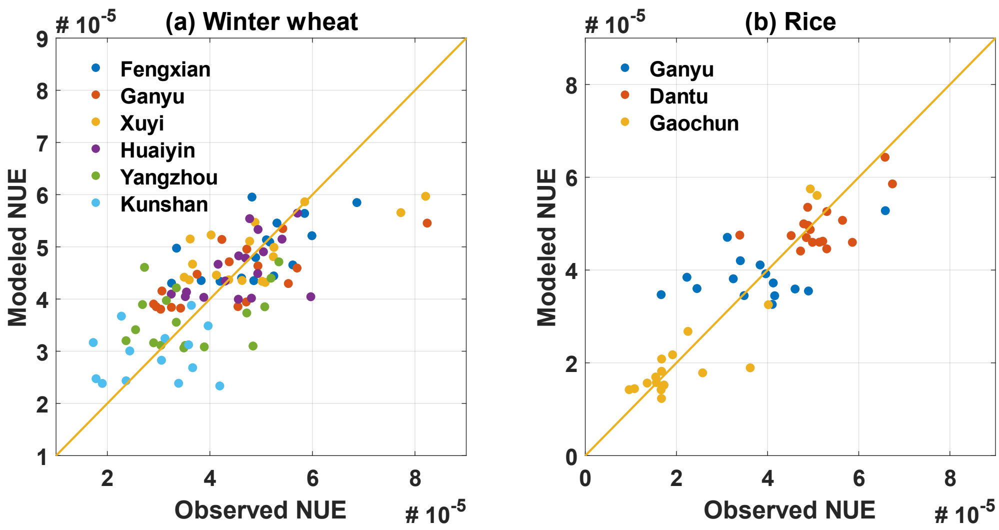
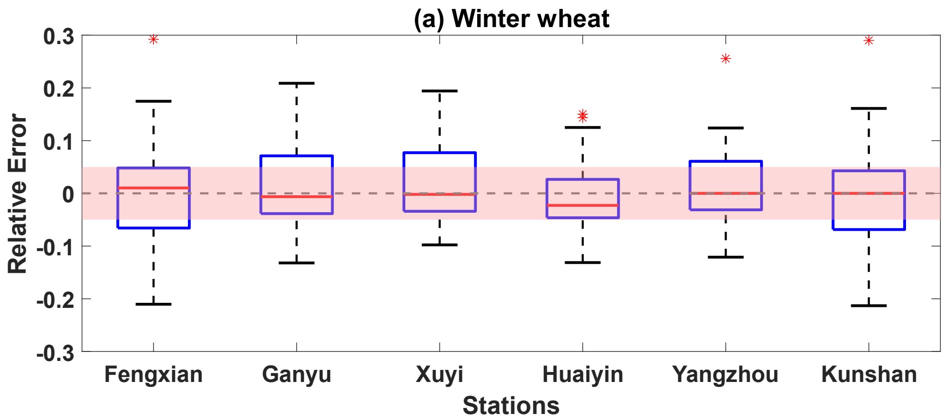


Fig. 5a, b Modeled vs observed crop nutrient use efficiency (NUE) across stations for two crop types.

4.4 Leave-one-out cross validation

According to Fig 6a, b, for all crops at all stations, the median values (shown by red line at the center of the box plots) of relative errors are within ±0.05 of observed values (as indicated by the red shadows). This indicates that the proposed model is robust in modeling winter wheat and rice production within Jiangsu Province.



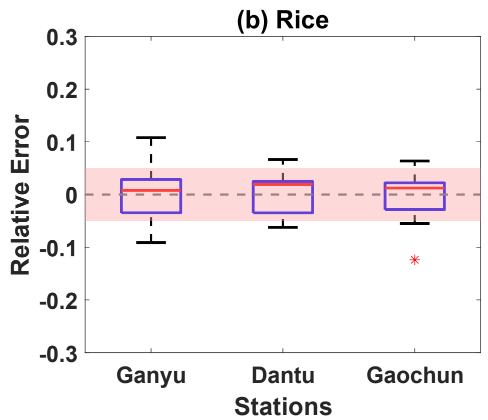


Fig. 6a, b: Leave-one-out cross validation across the stations and two crops. Distribution of relative errors (equation 5) are shown with zero error shown by the grey dashed line, and ±0.05 error shown by the red shadows

4.5 Substitution between labor and machinery in winter wheat cultivation

Fig. 7a, b indicate that during years before 2005, more labor, L_C, was used relative to machinery M_L. After 2005, mechanization gradually led to less labor being used relative to machinery while achieving same level of water use efficiency. The derivative between L_C and M_I, i.e., $\frac{dL_C}{dM_I}$, however fluctuated around 0, indicating that they are complimentary and do not tend to substitute one another. The close resemblance of substitution effects estimated based on regressed relationships, together with those estimated based on statistical year books (indicated as data in Figure 6), further suggests that the proposed production function is capable of providing robust interpretation of how one input has been, or can be, substituted with another without affecting water use efficiency.

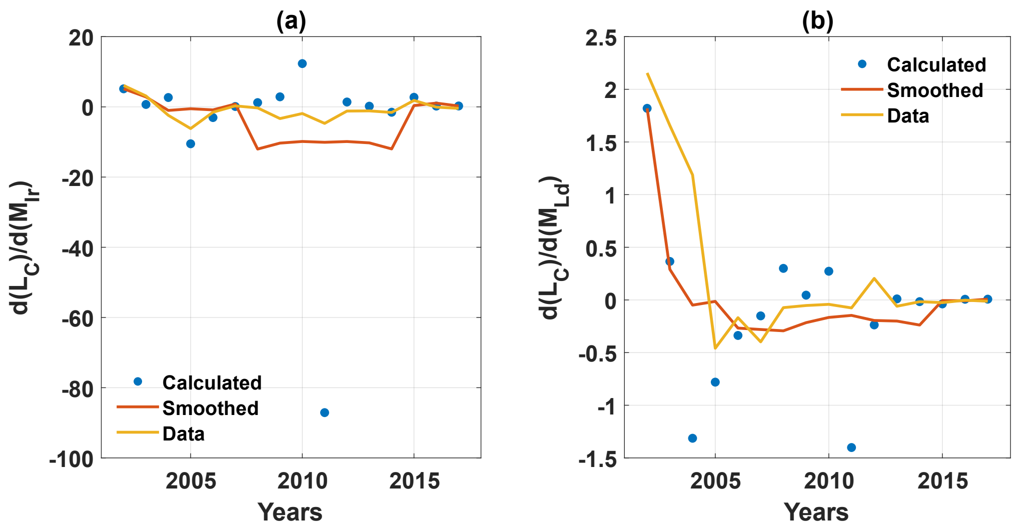


Fig.7a, b Rates of substitution between labor and machinery

5. Discussion and Conclusion

This paper conceptualized crop production as a composite function of bio-physical mechanisms and human-agency. While the former links water and nutrient uptakes to crop biomass production, the latter influences the efficiencies with which water and nutrients are taken up.

The model was calibrated using hydro-climatic and agricultural statistics from 2001 to 2017 for two main food crops in Jiangsu province, i.e., winter wheat and rice, using panel regressions across agro-meteorological monitoring stations (six for winter wheat, three for rice). The median performance of the composite function was found to be within 5% of the observed based on leave one out cross validation.

The fixed effect regressions were used to filter out station specific effects of human agency on use efficiencies and of efficiencies on crop production. This data-driven approach was key to commensurate, to certain extent, different scales of the data sets used and to obtain a generic relationship that is devoid of any station specific effects. The yield data used was at provincial level, transpiration and soil moisture was at 0.25° x 0.25° scale based on GLDAS reanalysis data, and NDVI and human agency data was station specific. However, transpiration and soil moisture data used is at much coarse resolution compared to NDVI, which means that, for example, transpiration would give an aggregate for both (irrigated) crops and native vegetation and other land surfaces. It is assumed that higher peak NDVI also implies that the crop has undergone lower water and nutrient stress during other critical growth stages. Further, irrigation has been ignored when calculating water use efficiency. Results therefore demonstrate a proof of concept at best, which can be made more reliable with higher resolution data sets.

The data driven approach treated crop production as a composite function of water and nutrient use efficiency and human agency. This approach fills a gap in our coupled human-water system understanding of crop production, which either has been focused on bio-physical mechanisms or based on economic production theory. The proposed method demonstrated its novelty by not only modeling the bio-physical relationships of crop yield with water and nutrient inputs, but also considering how humans, e.g. through irrigation and land-preparation, influence the efficiencies of water and nutrients uptake. Crop and labor machinery were found to be important for nutrient use efficiency. Irrigation machinery was most important for water use efficiency of rice production. However, all aspects of human agency were important for water use efficiency of winter wheat production.

These results are intuitive, suggesting the labor and land preparation machinery are key to crop production in the region in general. While the variance explained by human agency in explaining nutrient use efficiency was similar across the two crops, human agency appeared to explain water use efficiency of winter wheat a lot better than rice. This indicates that WUE of rice is less sensitive to human agency and perhaps more dependent on water scarcity. On the other hand water and nutrient use efficiency and therefore crop productivity of winter wheat was sensitive to various aspects of human agency such as labor and land preparation machinery. The differences in the effects between the two crops indicate that rice production is a water intensive crop and its yield exclusively depends on how well the crop is irrigated. Even though rice cultivation is labor intensive, the role of human agency in various stages of the crop growth appears to be less complicated. In contrast, winter wheat, often grown in autumn, relies on a complex interplay of water and nutrient availability that is facilitated by human agency during its growing period.

The substitution analysis revealed that more labor was used relative to machinery in winter wheat production before 2005. Post 2005, mechanization gradually led to less labor being used relative to machinery while achieving similar level of water use efficiency. Labor (L_C) and irrigation machinery (M_I) were found to be complimentary to water use efficiency of winter wheat production. Therefore, interventions targeting machinery are most instrumental in increasing wheat productivity.

Lyu et al. (2019) have recently found that under-employment in rural areas of Jiangsu Province has been fueling the rural to urban migration. Given the gains in efficiency that mechanization produces and the observed transition to mechanization, any sound policy aimed at alleviating under-employment and hence migration should target more skilled employment in the non-agricultural sectors of rural areas. This will ensure rural employment, sustainable rural communities (Li, 2010) as well as regional food security.

The methodology is transferrable to other regions as well. This is because the data sets used are regional agricultural statistics on crop yields and open access hydrological data, such as reanalysis data for transpiration and soil moisture (Rodell et al., 2004) and high resolution LANDSAT7 based NDVI data (Gorelick et al., 2017). Policy strategies for alleviating migration while ensuring regional food security therefore can be devised based on crop production simulations, as shown in this paper, in regions where agricultural statistics data are available. This can be done by analyzing the implications of crop production simulations that ensure food security on rural employment under future climate and socio-economic scenarios. As Lyu et al. (2019) have found, rural under-employment is a major driver of rural-urban migration. Target regions could be fast developing regions such as Maghreb region of Africa and South Asia that are witnessing massive flux of rural to urban economic migrants. Yet, given that the dataset that the approach relies on is either reanalysis or at different scales, such policy designs will need to be handled with caution and be validated based on field campaigns where possible.

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