Improved alternate wetting and drying irrigation increases global water productivity

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Abstract

Rice is the staple food for half of the world's population, but also has the largest water footprint among cereal crops. Alternate wetting and drying (AWD) is a promising irrigation strategy to improve paddy rice's water productivity-defined as the ratio of rice yield to irrigation water use. However, its global adoption has been limited due to concerns about potential yield losses and uncertainties regarding water productivity improvements. Here, using 1,187 paired field observations of rice yield under AWD and continuous flooding to quantify AWD effects (ΔY), we found that variation in ΔY is predominantly explained by the lowest soil water potential during the drying period. We estimate that implementing a soil water potential-based AWD scheme could increase water productivity across 37% of the global irrigated rice area, particularly in India, Bangladesh, and central China. These findings highlight the potential of AWD to promote more sustainable rice production systems and provide a pathway toward the sustainable intensification of rice cultivation worldwide.

Main text

Introduction

Rice is the most irrigation-intensive cereal crop, accounting for 30% of global irrigation water use[1]. By 2050, a 50 to 60% increase in global rice production while a 15% increase in irrigation water use are required to feed the growing population[2], which will intensify water competition between agriculture and other sector, threatening global rice supply[3]. Thus, saving water in rice cultivation is critical to ensure food security of nearly half the world's population with rice as its main staple food.

Alternative wetting and drying (AWD) is a promising and widely recommended water-saving irrigation strategy for paddy rice[4]. With AWD, irrigation water is applied to reflood the field a certain number of days after the subsidence of ponded water. The timing of re-flooding is a key management decision that could be determined by metrics of soil moisture status, such as volumetric or gravimetric water content, soil water potential or field water depth falling below a predetermined threshold[5, 6]. Previous studies showed that AWD could reduce irrigation water use by approximately a quarter compared to continuous flooding[7], and might reduce rice yields in some circumstances (such as alkaline soils)[5, 7]. Trade-offs between water saving and yield losses remain a fundamental obstacle for large-scale application of AWD. To avoid yield losses, several thresholds have been proposed. For example, International Rice Research Institute (IRRI) recommends 15cm below the ground surface (that is, −15 cm) as a safe threshold for the field water depth-based AWD scheme to avoid yield loss[5]. Also, two global meta-analyses indicated −15 to −20 kpa as safe thresholds for the soil water potential-based AWD scheme[6, 7]. However, various case studies also reported varying safe threshold of soil water potential from −70 to −10 kpa across a wide range of global rice cultivation area[8, 9]. This large variation in thresholds underlines that despite increasing research on AWD practices, a spatially explicit application guideline is still lacking. Resolving this challenge requires increased understanding of the factors driving variations in rice yield responses to AWD management practices.

Here, we synthesized 1,187 field observations of AWD-induced changes in rice yield (ΔY) from 123 studies covering all major global rice baskets to identify the predominant driver of ΔY (Fig. S1). The observations in our dataset are up to 7 times larger as those in previous analyses[6, 7, 10, 11], and include the field sites representing >80% of the climatic and edaphic covariate space across global irrigated rice area (Table S1 and Fig. S2). Our overall objectives were to 1) identify the predominant driver of variation in ΔY; 2) develop a spatially explicit AWD scheme to avoid yield loss and improve water productivity (that is, the ratio of rice yield to irrigation water use); and 3) determine the priority areas for implementing the spatially explicit AWD scheme.

Results

Predominant control of the lowest soil water potential on ΔY

The effects of AWD on rice yield (ΔY) in our dataset (see Methods) ranged from −30.5% to 22.1% (5^{th}–95^{th} percentile) (Fig. 1a). We found that the lowest soil water potential at

15-20-cm soil depth during the drying period explained more variation in ΔY than a wide range of environmental and management-related factors, including field water depth below the ground surface (Fig. 1b-c and S3). The superior performance of the lowest soil water potential over field water depth in regulating ΔY was consistent across climatic zones and soil textures (Fig. S4). This was further confirmed by a subset of data with simultaneous observations of field water depth and soil water potential (n = 85) (Fig. S5). This finding underscores the strong influence of soil water potential on plant water uptake and plant water status (e.g., leaf water potential), which further affects crop growth processes such as photosynthesis and grain filling (Fig. S6 and S7)[12, 13, 14]. Interestingly, although field water depth is commonly used in previous studies, the relationship between ΔY and field water depth was much weaker. This is likely because field water depth does not directly connect with plant water uptake, and a specific field water depth can correspond to a wide range of soil water potentials primarily depending on soil properties (Fig. S8).

Although there is a strong quasi-linear relationship between the lowest soil water potential and ΔY, there is still significant site-to-site variation in the threshold of the lowest soil water potential at which ΔY is zero (i.e. no yield loss due to applying AWD). To explore the spatial variations, we used a model selection approach to evaluate the impact of climatic, edaphic, topographic and management-related factors (see Methods). The resulting best model explained 43% of variations in ΔY (Equation 1, $p < 0.001$, root mean squares error = 12%) with its robustness testified by 50 times of fivefold cross-validation (Fig. S9 and Table S3). The model showed significant impacts of upper AWD threshold, climate (growing season temperature and water availability), soil (alkalinity and porosity) and altitude (Fig. S9 and Table S3), in line with findings of previous meta-analyses[6, 7, 10]. These factors alone or in interactions with others determine how fast the predetermined threshold is reached in fields and number of AWD cycles, thereby influencing water and nutrient availability for root uptake. A structural equation model confirmed the importance of soil water potential, the upper AWD threshold and climatological water availability in regulating nitrogen uptake and biomass production (Fig. S11 and Supplementary Text 1) [7, 15]. As a result of the combined effects of these predictors, the lowest allowable soil water potential without yield penalty was less negative in areas with lower temperature and climatological water availability, and in coarse textured or alkaline soils (Fig. S8). These findings suggest that the lowest soil water potential is a good predictor for AWD management to avoid yield losses.

Global mapping of the lowest soil water potential threshold

Using the empirical models we developed (see Methods), we mapped the lowest threshold of soil water potential at 15-20-cm depth that maximizes water productivity and maintains rice yield at the level of continuous flooding at five-arcminute spatial resolution. The average global threshold was estimated at −19 kpa (median) with 5^{th}–95^{th} percentile from −24 to −4 kpa, showing slight interannual variability (Fig. 2a-b, S12, Table S12). The predicted thresholds are broadly consistent with results derived from interpolation (Points in Fig. 2a). Thresholds lower than −20 kpa are found in 35% of irrigated harvested rice areas, primarily in tropical regions with clay-loam and clay soils. This is likely due to the higher water holding capacity and thus water availability of clay soils [8, 16]. By contrast, areas with higher thresholds are located mainly in temperate regions (e.g., north China). The higher threshold is probably related to low precipitation combined with high evapotranspiration requirements in the growing season (Fig. S13). This implies a risk of yield losses for these areas adopting the IRRI recommended safe threshold for AWD (i.e., −15 cm, roughly corresponding to a soil water potential of −10 kpa) (Fig. S8)[17].

Next, we compared our spatially explicit soil water potential thresholds with the field water depth threshold (−15 cm) recommended by the IRRI[5]. To do so, we converted −15 cm to corresponding soil water potential over the global rice paddies using an ensemble of two empirical nonlinear statistical models and a process-based model (Fig. 2c and S14, see Methods and Supplementary Text 2 for details). The three approaches performed similar well in predicting soil water potential ($R^2 > 70\%$, $p < 0.001$) and showed consistency in prediction results, so we used median value of their predictions (Fig. S25). Our results suggest that the field water depth-based thresholds are higher than −10 kpa in more than 90% of irrigated harvested rice areas (Fig. 2c). This result aligns with previous findings [4, 7, 18] and supports the adaptability of the IRRI recommendation across a wide range of circumstances. Large differences between the soil water potential-based and field water depth-based thresholds are especially evident in clay-loam and clay soils (Fig. 2f).

Implications for global application of AWD scheme

We further assessed the change in water productivity from application of the two AWD schemes, i.e., the scheme based on a fixed field water depth threshold of −15 cm, and a scheme that is based on spatially explicit soil water potential thresholds (Methods and Fig. S15). As Figure 3 shows, the soil water potential-based AWD scheme could be potentially adopted at >90% of global irrigated rice harvested areas without yield penalty and additionally improve water productivity by 15% [0 – 53%] (mean [95% prediction interval]) (Fig. 3a and S16). Larger benefits are mainly found in the southern part of China (>50%), due to the substantially lower soil water potential thresholds of the soil water potential-based AWD scheme (Fig. 2e).

Improving water productivity is crucial for areas with tense confliction between irrigation water supply and demand, which could be further intensified by climate change and competition of water use from other sectors in the future [19, 20]. Therefore, we identified priority areas to apply the soil water potential-based AWD scheme in areas where all-sector water use accounted for more than one quarter of renewable freshwater resources according to the United Nations Sustainable Development Goals [21] (See Supplementary Text 3 for water-stressed regions identification). Areas with high salinity (i.e., electricity conductivity > 3 dS m^{-1}) were masked to avoid unexpected yield loss due to aggravated risks of salinity stress in AWD systems [17]. Priority areas account for 37% of global irrigated rice harvested areas, and are mainly distributed in India, Bangladesh, and central China (Fig. 3b, S17 and Table S13). Adopting the soil water potential-based AWD scheme over these areas could improve water productivity by 13% [7 – 52%] relative to the field water depth-based AWD scheme. We also investigated the impacts of rice cultivars on such predictions. Based on different observational subsets (i.e., Japonica or Indica rice, upland or paddy rice, inbred or hybrid rice), we found no significant differences in the predicted lowest soil water potential thresholds (Fig. S18), and small variations (25 – 37% for priorities areas and 13 – 18% for water productivity improvements) due to rice cultivars (Table S15).

In Vietnam, Thailand, China and Indonesia, relatively large additional benefits (>20%) could be realized from implementing the scheme in relatively small areas (<1/3 of the irrigated rice harvested areas) (Table S13). In contrast to the northwestern part of India, southern China (of the same latitude) shows relatively few high priority areas. This is associated with differences in soil texture that adopting AWD could lead to larger reduction in water losses through percolation over more sandy soils (common in India) than over clay soils (common in southern China)[16]. The alignment of the rice growing season with the wet season in southern China is another reason why the soil water potential-based AWD scheme may not significantly enhance water productivity on average. However, even low priority areas may still benefit from the soil water potential-based AWD scheme in years when drought exacerbate the confliction between water supplies and demands.

Discussion

Overall, our study provides observational evidence that optimizing soil water potential is a promising approach to minimize tradeoffs between water conservation and food security under AWD management. We further provided a spatially-explicit map of the lowest safe thresholds of soil water potential. Priority areas for the new soil water potential-based AWD scheme cover over 37% of global irrigated rice areas, highlighting the potential for AWD to save more water while preserving rice productivity.

We acknowledged that the assessment of water productivity is subject to several sources of uncertainties. For factors affecting the rice yield, we did not explicitly quantify physiological processes changes and their combined effects to predict yield responses (See Supplementary Text 1 for detailed discussions). We also did not quantify impacts of weed growth, insect-pest attack or diseases pressure (e.g, rice blast)[22], rice cultivar used (e.g., more drought-resistant and disease-resistant cultivars) and stage-dependent thresholds due to limited spatially-explicit information (Fig. S18-S20 and Table S11). On the irrigation practices, we assumed no water recycling between rice field and nearby reservoirs or ponds, which may overestimate water saving benefits from the fish-rice ecosystems[4, 23]. In contrast, we did not consider applying stage-dependent thresholds, which may underestimate the co-benefits of saving more water while maintaining yield. Further investigation is needed to clarify how above factors would regulate spatial variations in AWD impacts, though our research still provides a valid benchmark for improving process-based models to account for and refine AWD strategies. Despite these uncertainties, our results could provide the requested information for policy makers on priority areas where soil water potential-based AWD can be applied to alleviate water scarcity.

There are indeed many challenges ahead in helping smallholder rice farmers, such as in India and China[24, 25], to apply soil water potential-based AWD scheme. For these farmers, using tensiometers to monitor and control soil water potential is not a straightforward given the aging farming population[26], rather accustomed to using field water tube to monitor field water depth[15]. To facilitate the best practice of the soil water potential-based AWD scheme, an extensive survey of soil physical properties is required, especially in the relatively underrepresented Southeast Asia (Fig. S1). This will provide the parameters that can convert the spatially explicit threshold of soil water potential to field water depth at each rice farm (Supplementary Text 2). Such survey may also increase our understanding of the impacts of soil quality on yield and climate resilience[27, 28]. Although the instrumentation and expertise necessary to obtain reliable soil properties are not easily accessible for smallholder farmers, cooperative arrangements, knowledge transfer and technological development (e.g., microwave remoting sensing) could help to overcome the barrier[13]. Besides, increasing farmers' incentives for adopting AWD by conducting comprehensive cost and benefits analyses and identifying the most beneficial AWD schemes is vital for successful dissemination of AWD[4].

In the context of rapid ongoing climate change, adopting AWD practices offers benefits beyond alleviating water scarcity, including the widely-concerned reduction of methane emissions [29]. Since rice cultivation in major rice-producing countries (e.g., Philippines, Vietnam, Bangladesh, Indonesia) contributes up to 40% of their food-system methane emissions[30], smart AWD application is particularly appealing. When its effects on methane emission reduction are accurately assessed, AWD can be an integral part of climate mitigation strategies in their Nationally Determined Contribution[31]. Current estimates suggested that AWD could reduce methane emissions by 30~80% depending on unflooded days during rice growing period[11, 32]. Because the lowest threshold of the soil water potential-based AWD is generally lower than that of the field water depth-based AWD, our new AWD scheme could lead to longer unflooded intervals, thereby reducing methane emissions. However, it is important to note that there could be increased nitrous oxide emissions from alternating aerobic and anaerobic processes in AWD systems. The overall net impact on greenhouse gas emissions requires further assessments in future studies [11, 32].

Methods

Definitions

Rice irrigation is generally scheduled based on predefined upper and lower water threshold, that is, irrigating to the level of an upper threshold when field water reaches the level of a lower threshold (Fig. S21) [10]. Traditionally, the fields are continuously flooded (CF) from initial flooding (i.e., transplanting in transplanted systems, sowing in water seeded systems or 3-4 leaf stage in dry seeded systems) until drainage in preparation for harvest (i.e., one to three weeks before harvesting). Under AWD management, the lower threshold is lower than the soil water holding capacity, allowing the field to undergo alternate cycles of saturated and unsaturated conditions [5, 10].

AWD schemes mainly differ in terms of irrigation threshold, AWD timing (that is, when the AWD cycles are imposed in the growing season), and number of AWD cycles (irrigation times). There are two commonly used quantifiable indicators of lower threshold under AWD[7], i.e., the field water depth below soil surface and the soil water potential in the rooting zone (typically measured at the soil depth of 15-20 cm, Fig. S22). Accordingly, this study defined and compared two AWD schemes, i.e., a field water depth-based AWD scheme and a soil water potential-based AWD scheme (Fig. S21). In the field water depth-based AWD scheme, the lower threshold is set as −15 cm following IRRI's recommendation[5], with perched field water depth monitored by a field water tube. In the soil water potential-based AWD scheme, the lower threshold is specifically determined according to local climatic and edaphic conditions (See the *Methods* section '*Mapping the lowest AWD threshold of soil water potential*') and a tensiometer is used to measure soil water potential at 15-20-cm soil depth. The field is reflooded to a depth of 2-10 cm until the perched water table in the water tube or the measured soil water potential reaches the predetermined threshold. To represent the degree of soil water drying, lower AWD threshold was categorized into safe (i.e., field water depth ≥ −15cm or soil water potential ≥ −10kpa), moderate (i.e., field water depth ≥ −20cm or soil water potential ≥ −20kpa) and severe level (i.e., field water depth < −20cm or soil water potential < −20kpa)[17]. AWD timing was categorized into two types: 1) throughout the entire growing season, if AWD cycles occurred during both the vegetative and reproductive stage; 2) vegetative or reproductive growing period, if all AWD cycles occurred only during the vegetative or reproductive stage[7] (Fig. S20). The number of AWD cycles (irrigation times) varied depending on interactions between the predefined irrigation thresholds and environmental conditions (Fig. S23).

Data compilation

We compiled a global dataset of AWD effects on various target variables in rice cultivation, including rice yield, irrigation water use (IRR) and physiological traits (see Supplementary Text 1 for details about physiological traits) from peer-reviewed articles published from 2000 to 2022 through the Web of Science, the Google Scholar, and the China Knowledge Resource Integrated (CNKI) databases (Table S2). Relevant articles had to meet the following criteria: (1) only full season field experiments were included (pot and laboratory experiments under controlled environmental conditions were excluded), (2) AWD effects on at least one of the target variables were studied, (3) lower AWD threshold indicator was either soil water potential or field water depth, with the lowest threshold level explicitly reported, (4) if soil water potential was measured, the measurement should be conducted at the soil depth of 15-20 cm (the depth with most observations available), while measurements from the other soil depth were excluded (Fig. S22), (5) the control and AWD treatment(s) only differed in water management, with all other aspects being the same (e.g., cropping intensity, fertilizer management, and tillage). This yielded a dataset covering 19 countries and 106 sites (Fig. S1), comprising 1,187 paired observations for yield and 233 for IRR from 781 AWD experiments. The full dataset was split into two subsets based on the indicator of lower AWD threshold to compare their efficacy in explaining variation in ΔY. There were 744 measurements for soil water potential and 523 for field water depth. The compiled dataset is organized using Microsoft Excel Office 2019 and available online from Supplementary Data.

For each paired observation, five categories of information were collected. First, records of each target variable included observations under control and different AWD gradients. AWD effects on each target variable were calculated as the natural log of the ratio of the target variable under AWD to that under the control, that is, $\ln R = \ln(X_{AWD}/X_{CF})$[33]. In the control, we included studies with a mid-season drain with continuous flooding (a mid-season drainage is a common practice in China and is thus a control treatment for those AWD studies). We conducted a sensitivity test and found that including mid-season drainage treatments as part of the control treatments did not bias the predicted ΔY and ΔIRR, so we included all observations for calibrating the empirical models (Fig. S24, Equation 1-2). Second, climatic variables included mean daily air temperature (T) and climatological water availability (CWA, cumulative growing season precipitation minus crop evapotranspiration). Third, soil topographical variables included sand content and pH. Fourth, management-related variables included N application rate (Nrate), lower AWD threshold (indicated by soil water potential [SWP] or field water depth [FWD]), upper AWD threshold (U_{AWD}), AWD application period [AWD Timing] and number of irrigation events [AWD Times]. Fifth, experimental parameters included location (latitude, longitude and altitude), seeding dates (also transplanting date in transplanted systems) and harvest dates. Climate, altitude and soil variables, if unreported, were extracted from ERA5 [34], NOAA ETOPO dataset [35], and Global Soil Dataset [36]. The definition and unit of each variable can be found in Table S2. For the two subsets of soil water potential and field water depth, we used the method of van den Hoogen et al. [37] to investigate how well our dataset spread throughout the global layers' full multivariate covariate space (all environmental and management-related variables). Interpolation percentage is defined by estimating how adequately our dataset captures the multivariate covariate space of the global layers (Fig. S2).

Modelling AWD effects on rice yield and irrigation water use

We performed the multi-model inference procedures based on the Akaike information criterion (AIC) to select the best-fitting model for predicting AWD effects on rice yield and irrigation water use. We first generated a full model including environmental and management-related predictors, and two-way interactions between upper or lower

AWD threshold with the other predictors (Table S2). The categorical variable AWD timing was not included in the model due to unbalanced observations of the two types (i.e., 719 for AWD applied throughout the entire growing season and 25 for AWD applied only at vegetative or reproductive stage). To reduce uncertainty related to AWD timing, we removed ΔY under AWD applied only at vegetative or reproductive stage (n = 25, Fig. S20). Therefore, the AWD scheme of this study refers to AWD cycles imposed from tillering to pre-harvesting using a constant lower threshold for all growth stages. We took the ln-transformed ΔY and ΔIRR as dependent variables (i.e., $\ln R = \ln(\Delta Y/100+1)$) and values of the predictors were standardized to reduce the magnitude of possible correlations of the interaction terms with their constituent terms, and thus reduce the multicollinearity. We also computed the variance inflation factor (VIF), which measures the multicollinearity of predictors in the model, and used VIF < 3 to represent no multicollinearity. The relative importance of each predictor was estimated as the sum of the Akaike weights for the models in which the predictor appeared. Generally, a cutoff relative importance value of 0.8 was set to differentiate between the important and unimportant predictors (Fig. S9). We then determined the best-fitting models for predicting AWD effects on yield and irrigation water use based on the important predictors (Equation 1 and 2, model details in Table S3 and S4). The best model of ΔY and ΔIRR explained 43% and 41% of variations in observed ΔY (n = 719, $p < 0.001$, root mean squared error [RMSE] = 12%) and ΔIRR (n = 233, $p < 0.001$, RMSE = 14%). We also conducted 50 times of five-fold cross validation to verify model robustness (Fig. S9). The multi-model inference procedure was conducted using the 'glmulti' package in R [38]. Combing predicted AWD effects on rice yield and irrigation water use, we further calculated AWD-induced changes in water productivity (Equation 3).

$$\ln R^{Y} = SWP \times f_1(CWA, sand, altitude) + f_2(T, pH, U_{AWD}) + C_1 \tag{1}$$

$$\ln R^{IRR} = SWP \times f_3(CWA, T, U_{AWD}) + U_{AWD} \times f_4(CWA, T, sand) + CWA + C_2 \tag{2}$$

$$\Delta WP = \left(\frac{R^{Y}}{R^{IRR}} - 1 \right) \times 100 \tag{3}$$

where

$$\begin{cases} f_1(CWA, sand, DEM) = a_1 \times CWA + a_2 \times sand + a_3 \times altitude + a_4 \\ f_2(T, pH, U_{AWD}) = a_5 \times T + a_6 \times pH + a_7 \times U_{AWD} \\ f_3(CWA, T, U_{AWD}) = b_1 \times CWA + b_2 \times T + b_3 \times U_{AWD} + b_4 \\ f_4(CWA, T, sand) = b_5 \times CWA + b_6 \times T + b_7 \times sand + b_8 \end{cases} \tag{4}$$

lnR^{Y} and lnR^{IRR} represent effect size of AWD on rice yield and irrigation water use. ΔWP represents AWD-induced changes in water productivity. *SWP* represents soil water potential, *T* is mean daily air temperature, *CWA* is climatological water availability, calculated as cumulative precipitation minus crop evapotranspiration during the growing season, *altitude* represents altitude of experimental sites, *sand* is soil sand content, *pH* is soil pH, and U_{AWD} is upper AWD threshold. C_1, C_2, a_1–a_7 and b_1–b_8 are model parameters calibrated using a least-squares error technique.

Mapping the lowest AWD threshold of soil water potential

We provided a spatially explicit map of the lowest threshold of soil water potential at 15-20-cm depth without yield penalty for AWD compared to continuous flooding (See Fig. S15 for methodology flowchart). To do so, we combined the best-fitting models of

ΔY and ΔIRR (Equation 1 and 2) and global gridded datasets of predictors. In addition to the global gridded datasets of environmental predictors for rice fields (i.e., mean daily air temperature, cumulative precipitation and crop evapotranspiration during rice growing season, soil pH, soil sand content and altitude), model input data also included the upper AWD threshold, which is unknown across the global rice fields. Therefore, we set four levels of upper AWD threshold, ranging from 2 to 5 cm by 1 cm step (the interquartile range of our dataset). For each grid with a given upper AWD threshold, we first calculated the threshold of soil water potential without yield losses by setting $\ln R^Y$ as zero in Equation 1 (Equation 5). The optimal lowest AWD threshold of soil water potential was then determined by maximizing water productivity without yield losses (Equation 6). Input data for all variables were standardized using mean and standard deviation that were derived from observation dataset (Equation 5). Predictions of the lowest threshold of soil water potential were finally converted to the original scale in the unit of kpa.

$$SWP_{threshold,i,s} = -\frac{C_1 + a_5 \times T_i + a_6 \times pH_i + a_7 \times U_{AWD,i,s}}{a_1 \times CWA_i + a_2 \times sand_i + a_3 \times altitute_i + a_4} \quad (5)$$

$$z_i = \max\left\{\Delta WP_i \left(SWP_i, U_{AWD,i,s}\right)\right\}, \text{ subject to } SWP_i \geq SWP_{threshold,i,s} \quad (6)$$

where $SWP_{threshold,i,s}$ denotes the threshold of soil water potential without yield losses for grid cell i with upper AWD threshold at $U_{AWD,i,s}$ (i.e., 2, 3, 4, or 5 cm), ΔWP_i represents water productivity for grid cell i with lower and upper irrigation threshold at SWP_i and $U_{AWD,i,s}$, z_i represents the maximal water productivity for grid cell i, C_1 and a_1–a_7 are calibrated model parameters.

We acknowledge the critical role of process-based models in predicting AWD effects, provided they incorporate critical crop hydraulic related processes (e.g., carbon assimilation and allocations) and are appropriately parameterized. However, a majority of mainstream models still rely on empirical relationships with volumetric soil water content to simulate AWD impacts (e.g., CERES-RICE)[39], with only a few using the concept of soil water potential (e.g., ORYZA v3, WHCNS)[40, 41, 42]. Despite the latter's advantages, model parameters crucial for simulating AWD effects on crop growth vary significantly depending on environmental and management-related conditions (e.g., fertilizer application, depth of plough soil layer)[43], making them difficult to determine at regional to global scales. Moreover, gathering detailed gridded model input data, especially those related to management practices (e.g, timing and amount of irrigation and fertilization, bund height, tilling depth), is notoriously difficult. These challenges significantly impede the application of process-based models in this context. Given these challenges, an empirical approach emerges as a practical solution for estimating global-scale soil water potential thresholds, while avoiding the complexities associated with process-based modeling.

To compare the spatially explicit soil water potential thresholds with the field water depth threshold of −15cm, we converted field water depth into soil water potential using two empirical nonlinear statistical models (in the form of power and exponential function) and one process-based model (Fig.2 and S25, See Supplementary Text 2 for details). We collected 836 simultaneous observations of field water depth and soil water potential to calibrate statistical model parameters for the empirical models and soil hydraulic parameters for the process-based model (Table S9). After parameter calibration, more than 70% of variations in soil water potential could be reproduced (R^2 = 0.76, 0.81 and 0.72 based on the power, exponential function and process-based model, $p < 0.001$, Fig. S25). For global prediction of soil water potential corresponding to the −15cm field water depth ,we combined the well-calibrated statistical models and global gridded dataset of growing season precipitation and sand content at 5-arc-minute spatial resolution. We also run the process-based model for each grid at 0.5-degree spatial resolution forced by daily meteorological variables and soil properties by depth (Supplementary Text 2) and the prediction was then resampled to 5-arc-minute resolution. We used the median predictions of the three approaches in the main text (Fig. 2).

Global predictions of AWD effects

We assessed AWD effects on rice yield, irrigation water use and water productivity from applying the soil water potential-based and field water depth-based AWD schemes, respectively. In the assessment, we assumed irrigation was available and reliable for the application of AWD over the entire growing season. To do so, we first predicted the gridded AWD effects on rice yield and irrigation water use respective for the major and the second rice-growing seasons using ΔY and ΔIRR models (Equation 1-2). In addition to the threshold of soil water potential, model input data included the global gridded data set of climate, soil and altitude variables. The extent of global harvested areas of irrigated rice was obtained from GEAZ+ 2015 Data (5-arc-minute resolution)[44]. Climate data (including precipitation, temperature and potential evapotranspiration) over both rice-growing seasons was acquired from the ERA5 at 0.25-degree resolution (resampled to 5 arc-minute)[34]. Soil data (including sand content and pH) was acquired from the Global Soil Dataset (5-arc-minute resolution)[36]. Soil data from the Harmonized World Soil Database was also used to prove the robustness of results (Fig. S26 and Table S12). Altitude data was acquired from the NOAA ETOPO dataset at 15-arc-second resolution (resampled to 5-arc-minute resolution)[35]. AWD effects on water productivity were calculated from predicted AWD effects on rice yield and irrigation water use (Equation 3).

AWD effects at the global and regional scales were calculated by weighing gridded AWD effects of the major and the second rice-growing seasons using their respective baseline under continuous flooding irrigation and corresponding area fractions from the crop calendar data of GGCMI Phase 3 [45]. The baselines of rice yield and irrigation water use for the two rice-growing seasons were estimated from the ensemble mean of nine process-based crop models participating GGCMI phase 3 (i.e., AWWA, GYGMA1p74, EPIC-IIASA, ISAM, LandscapeDNDC, LPJmL, pDSSAT, PEPIC, PROMET) [45], following the approach by ref. [32]. To account for year-to-year variations, all the results were calculated for 2001-2015 and presented as average values (Fig. 2 and 3, Table S12).

Uncertainty estimation

A Monte Carlo simulation was used to estimate the overall uncertainty for calculating the lowest soil water potential threshold and AWD effects on yield, irrigation water use and water productivity. To generate a proper prediction interval, our estimates accounted for two sources of uncertainty: the model coefficients and the input data (Table S10). The models of ΔY, ΔIRR and Field water depth-Soil water potential conversion were run by randomly generating model coefficients from their fitted multivariate normal distributions and the climate and soil variables following independent normal distributions with the same mean as our dataset and a standard deviation of the absolute difference between the dataset used in this study and other global datasets (Table S10). We then calculated the predicted values from the models through 1,000 iterations so that the mean and 2.5% and 97.5% quantiles could be constructed with the 95% prediction interval.

Data Availability

The observation data set compiled for this study are available in Supplementary Data. Global harvested area of irrigated rice is available from https://doi.org/10.7910/DVN/KAGRFI. Climatic zone classification is available from http://webarchive.iiasa.ac.at/Research/LUC/GAEZ/index.htm. Climate data is available from https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels?tab=download. Soil data are available from http://globalchange.bnu.edu.cn/research/data (Global Soil Dataset) and https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v12/en/ (Harmonized World Soil Database). Altitude data are available from https://www.ncei.noaa.gov/products/etopo-global-relief-model. Crop calendar data are available from https://zenodo.org/record/5062513. Global nitrogen application rate data is available from https://doi.org/10.6084/m9.figshare.14842965. Base map of the country boundaries was obtained from Resource and Environmental Science Data Platform of China (https://www.resdc.cn/data.aspx?DATAID=205). All other data that support the findings of this study are available in the main text or the Supplementary Information.

Code Availability

This study used MATLAB R2020a and the 'glmulti' package in R (version 4.0.4) for data analyses. Source codes are available from https://doi.org/10.6084/m9.figshare.27249210.v1 (ref. [46]).

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Author Contributions

F.Z. and X.H.W. designed the study. Y.B. performed all computational analyses. Y.B., X.H.W., and F.Z. drafted the paper. All co-authors reviewed and commented on the manuscript.

Competing Interests

The authors declare no competing interests.

Figure Legends/Captions

Figure 1 AWD effects on rice yield (ΔY) and its drivers. (a) Frequency distribution of ΔY (%) from soil water potential-based (green bars, n = 744) or field water depth-based (orange bars, n = 523) AWD experiments. The dashed vertical lines indicate the 5th, mean and 95th percentile range. **(b-c)** Relationships between ΔY (%) and the lowest soil water potential at 15-20-cm soil depth (kpa) **(b)** or field water depth below soil surface (cm) **(c)**. The lines are regression lines with dashed lines indicating non-significant relationship ($p > 0.05$) based on two-sided t-test. Shaded area around the solid line shows the 95% confidence interval of the estimations. Relationships between ΔY and the other drivers could be found in Fig. S3.

Figure 2 Spatial patterns of the lowest threshold of soil water potential. (a) Soil water potential-based AWD threshold that maximizes water productivity and maintains rice yield at the level of continuous flooding (kpa). The dots indicate thresholds of soil water potential derived by interpolating the relations between soil water potential and ΔY based on experiments with at least two AWD gradients. **(c)** Field water depth-based AWD threshold (kpa, converted to soil water potential for comparison and median estimate of two empirical nonlinear statistical models and one process-based model was used, see Methods and Supplementary Text 2). **(e)** Soil water potential-based threshold minus field water depth-based threshold (kpa). The inset bar plots represent the ratio (%) of irrigated harvested rice areas for which the threshold is within the classification. Base map of the country boundaries was obtained from Resource and Environmental Science Data Platform of China (https://www.resdc.cn/data.aspx?DATAID=205). The right panels **(b, d, f)** represent the distribution of soil water potential-based and field water depth-based threshold and their differences across sub-regions classified by climate zones and soil textures (kpa). Results are shown for gridded irrigated rice areas globally (n = 176,307) and in sub-regions: Tropical (sandy: n = 5,839, loam: n = 38,897, clay-loam: n = 17,329, clay: n = 30,909), Subtropical (sandy: n = 1,554, loam: n = 34,724, clay-loam: n = 6,983, clay: n = 14,204), and Temperate (sandy: n = 1,746, loam: n = 18,620, clay-loam: n = 2,454, clay: n = 3,048). The boxes and whiskers show the 5th, 25th, median, 75th and 95th percentiles and the red dots show the mean value of the data. Enlarged maps for Asia are present here and see Fig. S12 for global view.

Figure 3 Priority areas for the soil water potential-based AWD scheme. (a) Spatial pattern of differences in AWD-induced water productivity between soil water potential-based and field water depth-based AWD scheme (ΔWP, %). The inset bar plot represents the percentage (%) of irrigated harvested rice areas that fall within the specified classification categories. **(b)** Priority areas for the soil water potential-based

AWD scheme. Priority areas are identified as water-stressed areas (water stress index ≥ 25% defined by United Nations) with larger water productivity under the soil water potential-based AWD than the field water depth-based AWD scheme. Enlarged maps for Asia are presented here, see Fig. S16-S17 for global maps. Base map of the country boundaries was obtained from Resource and Environmental Science Data Platform of China (https://www.resdc.cn/data.aspx?DATAID=205).

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