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A pixel-based indicator of upland crop waterlogging using remote sensing soil moisture data

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Abstract: The waterlogging hazard is a serious agricultural disaster for upland crops in agricultural cultivation regions of humid climate over the world, such as in South China, South-east Asia and South Asia. Traditional waterlogging monitoring and risk assessment are usually carried out with a limited number of in-situ meteorological-based observations by using certain kinds of hazard evaluation indicators, and the effectiveness could be easily hampered by unsatisfied spatial coverage, high expense, and more importantly, the neglect of soil texture heterogeneity. In this study, we proposed a novel method for quantifying the occurrence threshold of waterlogging at upland croplands based on AMSR-E/AMSR-2 remote sensing soil moisture dataset and constant spatial information of soil texture. The method was applied to the croplands in the middle and lower reaches of the Yangtze and Huaihe Rivers in China. The method used local crop phenology pattern of the "paddy-upland rotation", mainly the soil water demand discrepancies of different crops in different seasons within the study area. Then we conducted pixel by pixel analysis to extract four different soil moisture values, namely $Rht_{0.2}$, $Rht_{0.4}$, $Rht_{0.6}$, and $Rht_{0.8}$, from the soil moisture temporal dynamics during the paddy rice growth season. The values were taken as waterlogging thresholds to simulate waterlogging disasters. The simulations were validated against historical waterlogging records from 14 counties located in the study area. Validation showed that $Rht_{0.6}$ achieved the best performance in capturing the actual waterlogging days, with 7 of the 14 counties having monitoring accuracies higher than 70%. In the subsequent step, a multiple linear regression model was developed to express $Thr_{0.6}$ as a function of soil texture parameters (i.e. soil sandy fraction and soil clay fraction), which results in a determination coefficient (R^2) of 0.77. This suggests the feasibility of a remote-sensing-pixel-based indicator for modelling the soil moisture threshold to evaluate the occurrence of waterlogging at upland croplands (e.g., winter wheat and oilseed rape). The indicator is advantageous for considering the heterogeneous underlying soil characteristics of different pixels, and also at its independency of a complicated and expensive network of in-situ meteorological-based observations. Our following studies will take more environmental factors into account apart from soil texture parameters, in order to further enhance the indicator for better estimation of the waterlogging threshold. Also, this pixel-based indicator will be applied for the development of an integral framework for monitoring upland crop waterlogging in a near-real-time manner at regional scale, with remote sensing soil moisture datasets at finer resolutions.

Keywords: *Soil moisture, passive microwave remote sensing, AMSR, waterlogging disaster, upland crop*

1. INTRODUCTION

Waterlogging is an agricultural disaster caused by excessive soil water over the normal physiological needs of a specific crop at certain phenological stages. Generally, it leads to free standing water on soil surface when soil water content of surface layer exceeds at least 20% higher than the field capacity (Aggarwal et al. 2006), and then there is a high possibility that waterlogging would occur. Waterlogging could impose severe constraints on crop growth and production (Jackson and Colmer 2005), especially for the upland crops cultivated in areas characterized by humid climate and excessive precipitation, such as South China, South-east Asia, and South Asia. Therefore, the monitoring and early warning of waterlogging hazards are of great importance for ensuring the agricultural production and food security.

Traditionally, the monitoring and early warning of waterlogging hazard are usually issued by the local meteorological department based on measurements of climatological factors (e.g., precipitation and sunlight hours), land surface properties (e.g., topography and soil texture), and surface soil moisture values. Effective metrics from in-situ observed soil moisture or other meteorological variables have been proposed, including the Palm Drought Severity Index (Weber and Nkemdirim 1998), Surface Water Supply Index (Shafer and Dezman 1982) and Standard Precipitation Index (Guttman 1998; Shafer and Dezman 1982). Surface soil moisture (hereafter referred as soil moisture) as specifically defined as the water content within the reach of plant roots (generally refers to the water contained in the upper 1-2 m of soil) is one of the most important and widely used indicators of soil water status (Verstraeten et al. 2006). Since soil moisture serves as an early warning indicator which contains the "memory" of previous precipitation events (Koster and Suarez 2001), it is therefore a preferable indictor for waterlogging and drought as widely used in the literatures (Champagne et al. 2011; Hassan et al. 2019; Zhang et al. 2014).

However, *in-situ* soil moisture observations are limited by their unsatisfactory performance in spatial coverage and high expense. Therefore, the *in-situ* waterlogging monitoring practice can only be used at limited number of locations. On the contrary, remote sensing techniques, especially the microwave remote sensing with advantages of all-weather observations and excellent penetration into vegetation canopy (Song et al. 2014), have been proven as an effective approach in retrieving large scale soil moisture. However, the reliability of the widely used in-situ based meteorological metrics (e.g. those mentioned in last paragraph) relies heavily on the length (30 years or longer) of the supporting dataset, yet hardly can a microwave radiometer or radar meet this requirement currently.

From the plant physiological point of view, waterlogging means excessive water stress lasting for a certain period hence causing irreversible negative impact to plant growth. Numerous studies about water stress have been carried out for various plant types under lab conditions, such as wheat and rapeseed (Boem et al. 1996; Hu et al. 2004; Yavas et al. 2012). However, at field or regional scales, there is currently no practical method available for determining the waterlogging threshold of soil moisture content for croplands to our knowledge. Hence, it is necessary to explore alternative methods to determine the waterlogging thresholds. Remotely-sensed soil moisture can be used to develop metrics of waterlogging threshold to meet such purpose.

On this premise, this study proposed a novel method for developing the remote-sensing-pixel-based waterlogging indicator based on surface soil moisture content and soil texture information. Middle and lower reaches of the Yangtze and Huaihe Rivers were selected as study areas, where large proportion of the area has regular paddy-upland crop rotation, i.e., paddy rice and overwintering upland crops. Soil moisture data in the study area was extracted through the microwave soil moisture time series. Soil moisture thresholds of waterlogging hazard in the study area was determined by analyzing the water demand difference between paddy rice and upland crops at each pixel. The optimum soil moisture threshold was deduced and determined through a trial and error process against historically real waterlogging records at county level. And then a model for retrieving the optimum soil moisture threshold of waterlogging as a function of soil texture parameters was established. Details of the data and methods are described in the following sections.

2. METHODS AND MATERIALS

2.1 Study Area

Our study area, including Jiangsu, Hubei and Anhui Provinces, locates in the middle and lower reaches of the Yangtze and Huaihe Rivers in China (Figure 1). This region is vulnerable to waterlogging due to the prevailing monsoon climate in the spring. The overwintering upland crops, mainly winter wheat and rapeseed in this region, have been the targets of waterlogging research for decades. It covers an area of 430,000 km^2, spanning from 108°E to 120°E in longitude and 29°N to 35°N in latitude. The climate in this region is dominated by subtropical monsoon and featured by continuous cloudy days and abundant precipitation, especially during the spring and early summer, with annual precipitation of 750-1,800 mm. The crop plantation systems in this region is featured by the “paddy-upland rotation”, i.e., the upland crops (mainly winter wheat and rapeseed) in the spring and early summer followed by the paddy rice after the harvest of the upland crops (Figure 1).

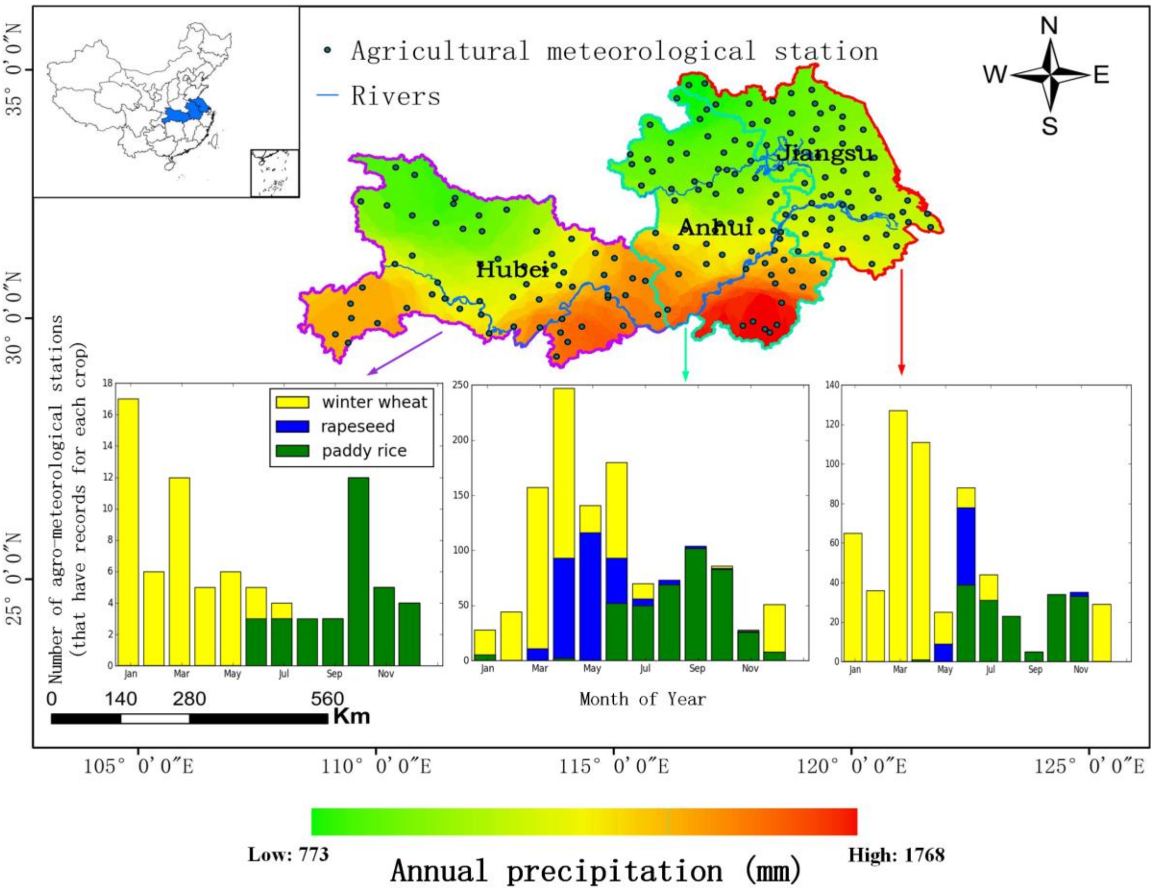

Figure 1. Location map of the study area which is composed of three administrative provinces, i.e., Hubei, Anhui, and Jiangsu, of China. The map of precipitation was produced through Kriging interpolation by using the average precipitation records of the meteorological stations in the study area from 1980-2010. The below part of the figure depicted the dominant crop planting composition per month of each province. The data sources were obtained from different national-level agro-meteorological stations located within each province, which are available at the China Meteorological Data Service Center (http://data.cma.gov.cn).

2.2 Data and methods

The primary remote sensing soil moisture data used for quantifying the waterlogging occurrence threshold of upland crops in this study are the 25-km resolution AMSR-E/AMSR-2 passive microwave soil moisture products of the descending overpasses. The dataset was produced and released by the University of Montana which is now publicly available at the National Snow and Ice Data Center (Du et al. 2017). Figure 2 presents the daily soil moisture time series for a randomly selected 25-km resolution pixel (centered at about: 118.7°E and 34.1°N), where 82% fraction of the pixel was recognized as croplands that was located in Anhui Province. This time series trajectory is produced by applying the Whittaker-Smoother (WS) filtering technique (Atzberger and Eilers 2011) to the multi-year average of AMSR-E soil moisture retrievals from 2003-2010 as well as AMSR-2 soil moisture from 2013-2016. The general start and end time of the overwintering (upland) crop season and that for the paddy rice season, which have been extracted from the China Meteorological Data Service Center, are illustrated using vertical dot line in this figure. It can be seen that the growth period of paddy rice is accompanied by generally higher levels of surface soil moisture, as opposed to that of the overwintering upland crops. In fact, many previous studies (Dong et al. 2006; Liang 1983; Yang et al. 2015) have inferred that the minimum soil water demand, or the lower soil moisture threshold of paddy rice field during the entire growth period should be between 80-85% of the local saturated soil moisture capacity (SSMC), while for most of the phenological stages, the optimum relative soil humidities for wintering wheat and oilseed rape are no more than 80% of the local SSMC under normal conditions (Hu 2000; Zhu and Su 2013).

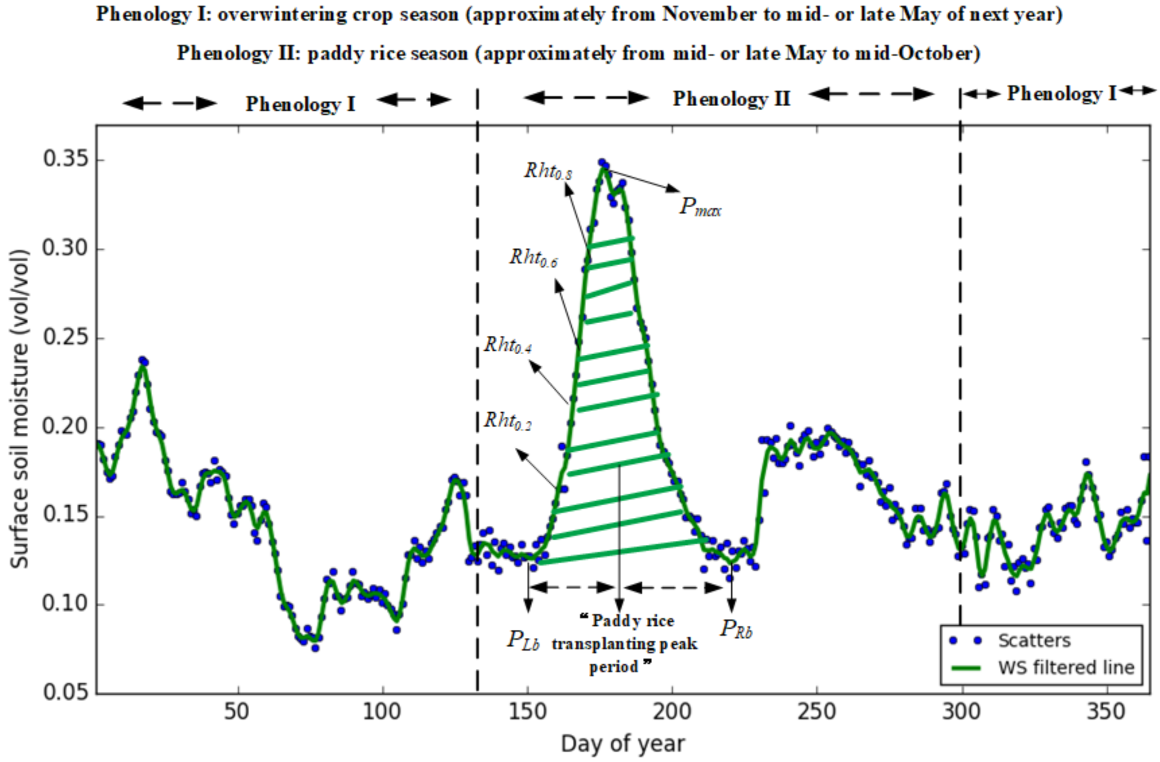

Figure 2. The AMSR-E/AMSR-2 soil moisture temporal data (multi-year average) of an AMSR-E pixel that is randomly selected from the study area and used to explain the paddy-upland crop rotation. The pixel is located in Muyang County, Anhui Province, with centroid about 118.7 °E and 34.1 °N. "vol/vol" denotes the volumetric ratio.

Heuristically speaking, the lower soil moisture threshold of paddy rice could be recognized as the waterlogging threshold for the upland crops in our study area. This might not be always objective at the passive-microwave-pixel scale due to the limitations from inevitable retrieval errors of the microwave soil moisture products, soil texture variations, ground water table difference, etc. However, we argued that it is generally reasonable to employ certain characteristics from the soil moisture trajectory during rice growth period as a benchmark to retrieve the waterlogging threshold of upland crops, since in such a manner, the relative soil moisture demands between paddy rice and upland crops could be generally fixed regardless of the abovementioned limitation factors. Therefore, the logic is that we should explore the specific phenology features of paddy rice growth period which can be deemed as the waterlogging threshold of upland crops at that specific pixel. In this study, our exploration was focused on the paddy rice growth sub-period with relatively higher soil moisture level. This sub-period is actually the "paddy rice transplanting period" (see the green slash areas in Figure 2) reflected at the passive-microwave-pixel scale, as has been investigated by Song et al. (2018). In Figure 2, the left and right boundary points are represented using P_{Lb} (DOY_{Lb}, SM_{Lb}) and P_{Rb} (DOY_{Rb}, SM_{Rb}), whereas the point with maximum soil moisture value is marked as P_{max} (DOY_{max}, SM_{max}). The mathematical symbols of *DOY* and *SM* herein respectively denote variables of time (day of year) and soil moisture content. The details on the searching processes of P_{Lb} and P_{Rb} for each pixel can be found in Song et al. (2018). In the next step, four candidate values for the waterlogging threshold of the upland crops are selected, i.e. $Rht_{0.2}$, $Rht_{0.4}$, $Rht_{0.6}$, $Rht_{0.8}$. Their definitions are expressed as:

$$Rth_k = SM_{max} - k \times (SM_{max} - SM_{min}), k = 0.2, 0.4, 0.6, 0.8 \tag{1}$$

$$SM_{min} = 0.5 \times (SM_{Lb} + SM_{Rb}) \tag{2}$$

To determine the optimum waterlogging threshold per pixel, the historical waterlogging event records at county level in the study area were used. There were in total 14 counties with historical waterlogging records. In each county, there were one or two valid AMSR-E pixels (Figure 4). We only selected the pixel that has the largest overlapping fraction against each county to simulate the occurrences of historical waterlogging. And the four candidate waterlogging threshold values were tested independently by trial and error in these simulation procedures. During the simulations, any day that has its soil moisture content higher than the tested threshold value was characterized as a "waterlogging day". Validations were then conducted using the real waterlogging records (real dates). The results were shown in the next section.

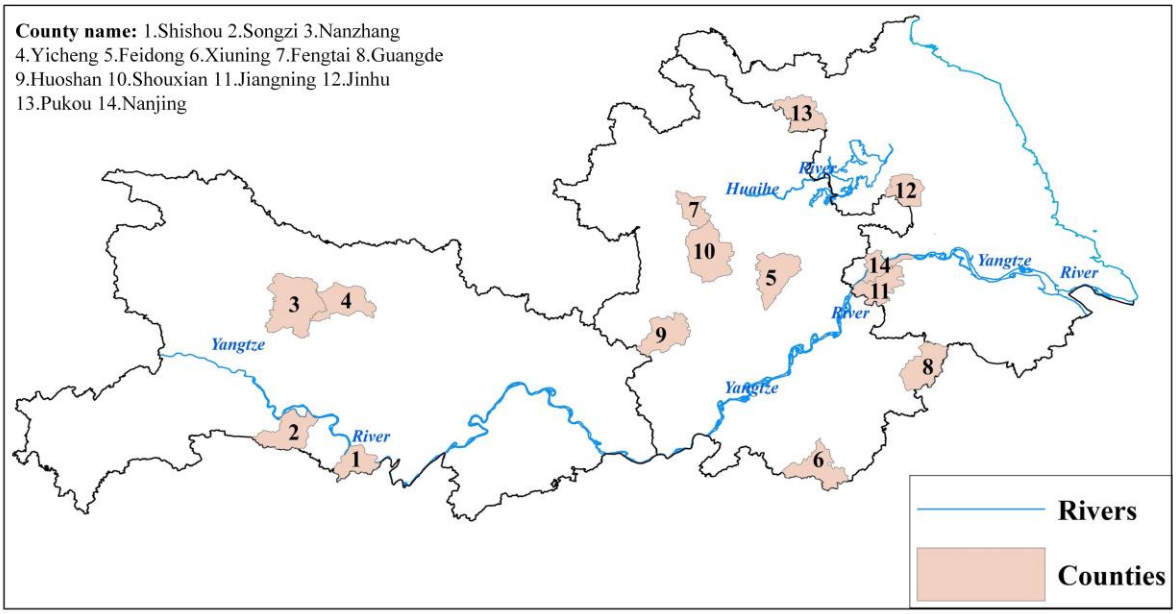

Figure 3. Counties with historical waterlogging records for test and validation purpose.

3. RESULTS

The monitoring accuracy for each candidate threshold value was defined as the percentage of the number of days that is correctly simulated as waterlogging dates based on that threshold. Results for the 14 validating counties are plotted in Figure 4. $Rth_{0.6}$ achieved the best performance when compared to the other three thresholds ($Rth_{x,\ x=0.2,\ 0.4,\ 0.8}$), with 12 out of 14 counties having monitoring accuracy higher than 50%, among which 7 counties have an accuracy higher than 70%. Therefore, we suggest $Rth_{0.6}$ can be taken as the optimum waterlogging threshold based on remotely-sensed soil moisture.

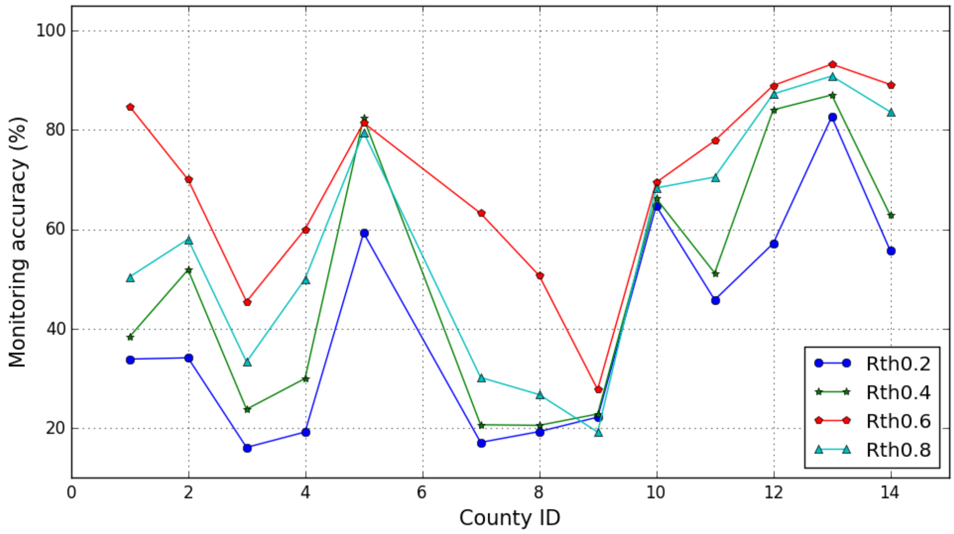

Figure 4. Monitoring accuracies against historical waterlogging records for the 14 validation counties in Figure 3, based on different waterlogging threshold values.

Figure 5 shows the spatial distribution of the parameter $Rth_{0.6}$ for all 25-km pixels that have cropland fraction higher than 65% in our study area (identified by the MODIS MCD12Q1 land cover dataset in 2013). Figure 5 also shows the maps of soil clay and sandy fractions, which were spatially averaged into the 25-km resolution using the 0-5cm soil sandy/clay fraction images from the "Soil Grid 1km" global dataset (Mendes de Jesus et al. 2014). The north and the northeastern part of the study area has relatively higher $Rth_{0.6}$ values. Since this area is also featured with obviously lower soil sandy fraction (SSF) and higher soil clay fraction (SCF), it is reasonable to model $Rth_{0.6}$ as a function of SSF and SCF. We thereby correlated the soil sandy/clay fraction data with AMSR-E/AMSR-2 soil moisture, and a multiple linear regression model with a substantially high determination coefficient (R^2) is demonstrated using Equation (3) as follow:

$$Rth_{0.6} = -0.416 \times SSF + 0.574 \times SCF + 0.297, R^2 = 0.77 (p = 0.05) \quad (3)$$

The model revealed that the soil texture of sandy/clay fractions can explain about 77% of the waterlogging threshold value for upland crops like winter wheat and oilseed rape. Such high R^2 value suggests that Equation (3) can be regarded as an appropriate indicator for calculating the waterlogging threshold of upland crops based on the remote-sensing pixels.

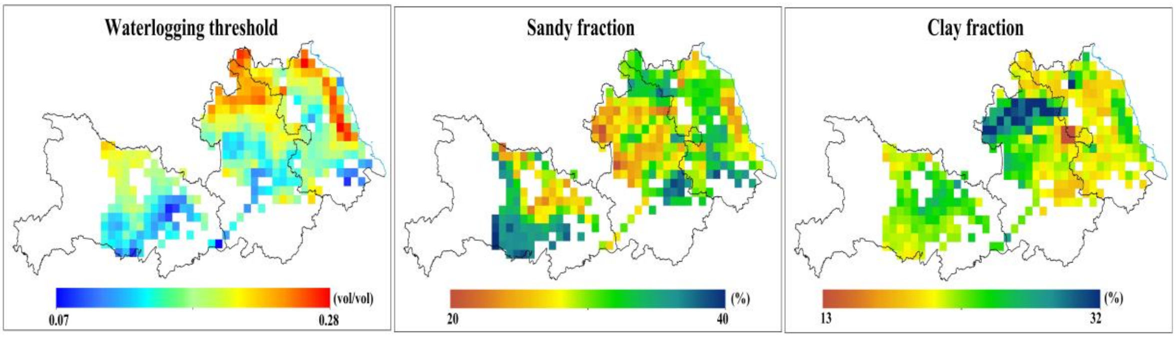

Figure 5 Spatial distribution of the optimum waterlogging threshold ($Rth_{0.6}$) for all 25-km pixels with cropland fraction higher than 65% (left), and the corresponding maps of sandy fraction (middle) and clay fraction (right) within the top soil layer (0-5 cm).

4. CONCLUSION

Waterlogging is an important agricultural disaster and could cause severe reduction of upland crop production in areas with humid climate and excessive precipitation, where effective manners for monitoring and early warning of upland crop waterlogging is crucial for food security. However, current waterlogging methods mainly rely on in situ observations from meteorological measurements, which have very limited spatial representativeness in reflecting the heterogeneity of the underlying soil texture at a continuous regional scale. Passive microwave remote sensing soil moisture data are competent in compensating the shortcomings of in situ measurements, while physically reasonable waterlogging monitoring indicators or waterlogging threshold determination methods at remote-sensing-pixel levels are still needed in the current time before the data can be applied for large-scale agricultural use.

In this study, we proposed a method for determining the soil moisture threshold of waterlogging occurrence for upland crops of winter wheat and oilseed rape using the 25-km AMSR-E/AMSR-2 datasets. The study site was selected in a region characterized by regular “rice-upland” crop rotation pattern. And based on the multi-year average soil moisture time series per pixel, the exploration process of the optimum waterlogging threshold for the upland crops made full use of the water demand difference between paddy rice and upland crops. The optimum waterlogging threshold was finally determined by testing and validating against historical waterlogging records. A multiple linear regression model was established between the optimum waterlogging threshold and two soil texture parameters, i.e. SSF and SCF, with an R^2 as high as 0.77. This indicates that the optimum waterlogging threshold can be modelled through soil texture information by using this remote-sensing-pixel-based indicator. To further enhance the modeling performance for the waterlogging threshold, more potential factors should be considered, including the soil moisture levels and vegetation density during some specific and sensitive growth stages of the upland crops. In summary, the pixel-based indicator developed in this study could be applied for the development of an integral framework for monitoring upland crop waterlogging in a near-real-time manner at regional scale, with remote sensing soil moisture datasets at finer resolutions.

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