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Remote sensing and census based assessment and scope for improvement of rice and wheat water productivity in the Indo-Gangetic Basin

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Understanding of crop water productivity (WP) over large scale, e.g., river basin, has significant implications for sustainable basin development planning. This paper presents a simplified approach to combine remote sensing, census and weather data to analyze basin rice and wheat WP in Indo-Gangetic River Basin, South Asia. A crop dominance map is synthesized from ground truth data and three existing LULC maps. National statistics on crop area and production information are collected and the yield is interpolated to pixel level using moderate resolution imaging spectroradiometer (MODIS) normalized difference vegetation index (NDVI). Crop evapotranspiration is mapped using simplified surface energy balance (SSEB) model with MODIS land surface temperature products and meteorological data collected from 56 weather stations. The average ET by rice and wheat is 368 mm and 210 mm respectively, accounting for only 69% and 65% of potential ET, and 67% and 338% of rainfall of the crop growth period measured from Tropical Rainfall Measurement Mission (TRMM). Average WP for rice and wheat is 0.84 and 1.36 kg/m^3 respectively. WP variability generally follows the same trend as shown by crop yield disregarding climate and topography changes. Sum of rice-wheat water productivity, however, exhibits different variability leading to better understanding of irrigation water management as wheat heavily relies on irrigation. Causes for variations and scope for improvement are also analyzed.

crop water productivity, remote sensing, census, Indo-Gangetic Basin

1 Introduction

Food security is a major concern in many developing countries. To meet the rising food demand by both the increasing population and the changing diet, the world needs to ensure sustainable land productivity improvement over coming decades[1]. Among the many constraining factors of land productivity, e.g., soil, seed, fertilizer, insects and diseases, water is one of the key constraints to be tackled. With the ever competitive demand from industry, domestic uses and eco-system, agricultural sector is seen to get less water allocation despite the increasing pressure for more food production[2]. Together, the increasing food demand and decreasing water allocation suggest that the agricultural sector has to produce more food with less water, that is, to increase the water productivity of agriculture.

Water is one of the most critical inputs to agriculture. However, the level of water use differs significantly across regions, farming systems, canal command areas, and even farm plots[3]. It is not clear how water is better used by crops hence contributing to productivity improvement with all aspects of efforts, especially in large river basin across countries. To measure the effectiveness of these interventions, water accounting and water

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productivity analysis are required to understand system, i.e. the relation between water input and agricultural output.

There are various sources providing water to meet crop requirement: precipitation, irrigation, ground flux, soil moisture, and air moisture, among which rainfall and irrigation are the two major inputs. These two inputs are somehow monitored at certain level, e.g., rainfall from single station, irrigation diversion from head canal. However, the actual use of these inputs is not clear. One example is irrigation return flow which is often difficult to measure despite its significance in many regions. As many efforts are made to study the fate of return flows on the ground, the remote sensing data interpreted actual crop water consumption provides another way to assess crop water input and the crop productivity which is a response of water input. This approach provides spatially explicit water productivity assessment while avoids going into complex ground processes.

Remote sensing (RS) is an innovative tool to observe land surface processes over large scale in a cost-effective approach[4]. Numerous studies have demonstrated the strength of RS in crop yield as reviewed by Yang et al.[5] and crop consumptive use of water (evapotranspiration) monitoring as reviewed by Courault et al.[6] which are key elements of crop water use and water productivity studies. These approaches require relatively less ground information while provide vital inputs to enable more comprehensive analysis. However, the relation between spectral reflectance and surface flux and crop conditions in different locations are highly variable hence always subject to modification and validation prior to new applications[7]. Another issue in the applications of RS is the often seen gap between RS interpretation and national census which further complicates the results, and effectively prevent stakeholders to make better use of RS techniques[8]. In many cases, statistical data is used to validate RS results at final stage[9,10]. Some researchers have tried to combine census data and remote sensing imagery in the interpretation processes. These efforts are frequently seen in population estimates[11,12], land use/ land cover mapping[8,13—15] and the drivers of change[16]. However, crop productivity estimates are often achieved through remote sensing interpretation and then validated with ground measurements.

This paper presents an innovative approach to combine meteorological data, ground survey, national census with remotely sensed imagery to assess water use, yield, and finally crop water productivity for the Indo-Gangetic rice-wheat cropping system in South Asia. The statistical data were synthesized to calculate district/state level land productivity, which was then further interpolated to pixel-wise using MODIS NDVI image based on a crop dominance map. With actual ET map produced, by taking meteorological data and MODIS land surface temperature (LST) products as inputs, water productivity maps are generated by dividing the crop productivity maps by ET maps. The spatial variation of rice-wheat water productivity is assessed, the causes for variation and scope for improvement is discussed.

2 Study area and materials

Indo-Gangetic Basin (IGB), also known separately as Indus and Ganges Basins, covers a huge area of 2.25×10^6 km^2 including Nepal, significant parts of India, Pakistan, Bangladesh and small parts of China and Afghanistan (Figure 1). Diverse climate, topography, and soil conditions exist in the basin. The climate is strongly characterized by monsoon with annual average precipitation varying from less than 100 mm to 4000 mm, most of which occurs during June to October. Three physiographic regions: mountain, plains and delta are found originating from southern slope of Himalayas and extending towards two directions: southwest till Arabian Sea and southeast till Bay of Bengal. IGB is the world's most populous basin inhabited by 747 million people (2001), around three-quarter of which live in the rural area. The four major countries, India, Pakistan, Bangladesh and Nepal, are all experiencing fast population growth which imposes high pressure on water and food security.

Out of the total drainage area, more than 50% (1.14×10^6 km^2) is cultivated. Rice-wheat rotation is the predominant cropping system in the region, mixed with cotton, sugarcane, pulses, millet, and jute etc. Extensive irrigation is practiced in the major food production zones for Kharif paddy rice and Rabi wheat along with other crops. Within the basin, although large quantity of water is diverted for irrigation, groundwater use is the most popular practice in India and Bangladesh[17], which makes it difficult to count the actual water uses and depletion. Crop sowing dates and growth length vary according to climate conditions, water availability, farmers' habits and crop varieties[18].

Datasets from various sources were collected in this study, including district-wise crop production statistics

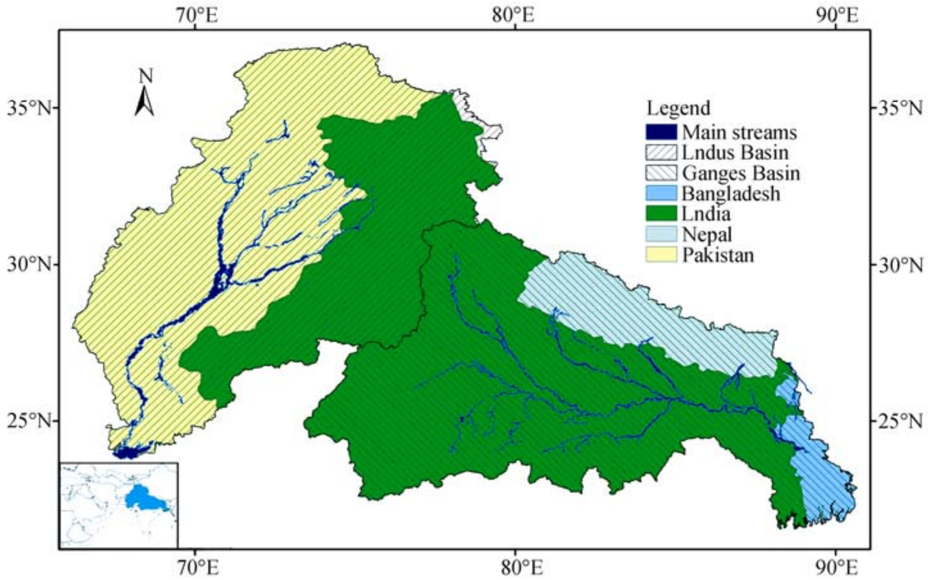

Figure 1 The Indo-Gangetic River Basin study area.

from national census, daily meteorological data of 56 weather stations across the basin, normalized difference vegetation index (NDVI) 16-day 250 m and land surface temperature (LST) 8-day 1 km products from MODIS satellite sensor onboard Terra, land use/ land cover maps and some other GIS layers, e.g., administrative boundaries from online open sources. Three existing LULC maps were collected for the basin. These maps were brought together and synthesized to a crop dominance map with GT data support.

A ground truth mission was conducted in October 2008 (rice harvest season) which collected information of 175 samples on LULC, watering sources, crop rotation, yield, and social-economic aspects. The cropping pattern was observed from each agricultural sample. Questionary survey was carried out to collect historical and background information including farm plot size, irrigation method and frequency, crop price, crop rotation, yield, water saving policies etc. Crop cut experiments (1 m^2) were also included to collect wet and dry biomass and grain yield information of 34 farms.

3 Methodology

The methodology adopted in this study involves three steps: crop dominance map to determine major rice-wheat cultivation extent; crop productivity map to map rice and wheat yield at pixel scale; ET map to calculate crop consumptive water use. The water productivity is finally produced by dividing crop productivity map by ET map.

3.1 Crop dominance map

Crop type map is essential to extrapolate yield to pixel-wise and estimate crop evapotranspiration. However, it is difficult to accurately map crop type over large domain. This study takes several maps which already exist from previous studies and synthesized them to a crop dominance map.

Three LULC maps were collected for the basin: the USGS Global Land Cover Characteristics Database (GLCCD) of 1992—1993[19], the International Water Management Institute (IWMI) global irrigated and rainfed area map (GIAM) of 2003[20], and the University of New Hampshire South Asia rice map of 2002[21]. These maps were produced from various sensors and have different interpretations. The GLCCD map has 24 classes out of which 5 classes cover agriculture. The GIAM map has 30 classes and all of them are dedicated to agriculture. The paddy rice map has only one class exclusively for rice.

The three maps were crossed with each other with weighing factors to extract agricultural and non-agricultural areas in common. The mixed areas were taken out and classified based on MODIS 500 m NDVI with Google Earth high resolution images and ground truth data. The major areas for the predominant crops, rice and sugarcane in Kharif and wheat in Rabbi season, were identified first based on rice map and GIAM map. Remaining rice, sugarcane and wheat areas, together with other crops, were assigned to the mixed agricultural classes. “Crop groups” were identified for each mixed class based on characteristics of NDVI magnitude and temporal changes. The proportion of each crop within the group was then determined based on statistical data. Spectral matching technique as proposed by Thenkabail et al.[22] is the major method adopted in the subsequent classification process. Detailed description is beyond the scope of this paper but could be found in ref. [23].

3.2 Productivity map

District yield map is straightforward to produce as crop production data are often reported/collected at administrative boundary level. However, the actual water use and crop performance are dependent on many factors, e.g., topography, soil, water, climate and on farm management practices, which do not necessarily correspond to administrative boundaries. Hence, there is a need to identify the actual extent of crop performance variations, which could be easily assessed from pixel based raster maps. In this study the district-wise rice and wheat productivity maps were further disaggregated to pixel-wise taking MODIS NDVI data at crop heading stage. The detailed procedure is given below by taking wheat as an example.

Average wheat growth period as extracted from MODIS NDVI imagery is shown in Figure 2 for different parts of the basin. The main wheat growth period in the IGB is from November to April. Wheat season in the downstream areas of Ganges Basin starts later than other areas, but harvested at around same time. This study takes the average dates of November 24 and April 14 as start and end of wheat season as adopted by Bastiaanssen[24]. Wheat heading stage is thus determined to be from February 18—26 corresponding to a MODIS NDVI 8-day period. The average growth period is rather arbitrary as the actual sowing and harvesting dates vary in the basin. However, as precise crop calendar for the basin is not available, the average dates are acceptable. This is because major body of areas is cultivated on or closely around these dates, and for the other areas, evaporation and transpiration around initial and harvest stages are relatively small compared with those of crop peak growing stage.

MODIS 250 m NDVI maximum value composition (MVC) image of this period was generated to ease the effects of clouds. Non-wheat areas were masked out using the crop dominance map. District average NDVI values for wheat were then calculated and related to district average wheat yield. In this way the linear regression equation was built up, as shown in

$$Y = Y_{\text{avg}} \times \text{NDVI}_{\text{p}} / \text{NDVI}_{\text{avg}}, \tag{1}$$

where Y_{avg} and NDVI_{avg} are district average yield and NDVI respectively, NDVI_{p} is NDVI of any given pixel. The equation was then applied to all wheat fields, leading to a 250 m by 250 m resolution yield map of wheat.

3.3 ET map

A number of models have been developed to estimate evapotranspiration using remotely sensed imagery, among which simplified surface energy balance (SSEB) model is one integrating remote sensing thermal imagery and meteorological data. SSEB extended the assumption that the temperature differences between land surface and near-surface air vary linearly with land surface temperature (LST) in SEBAL, by stating that latent heat flux (actual evapotranspiration) also varies linearly with LST[25]. Hot pixel and cold pixel represent “no ET” and “maximum ET” respectively. Therefore, the actual ET (ET_{a}) of other pixels is linearly distributed between the range of hot pixel (ET_{a} = 0) and cold pixel (ET_{a} = maximum ET), resulting in a proportional ET fraction value (ET_{f}) for each pixel as expressed:

$$\text{ET}_{\text{f}} = (T_{\text{H}} - T_{\text{X}})/(T_{\text{H}} - T), \tag{2}$$

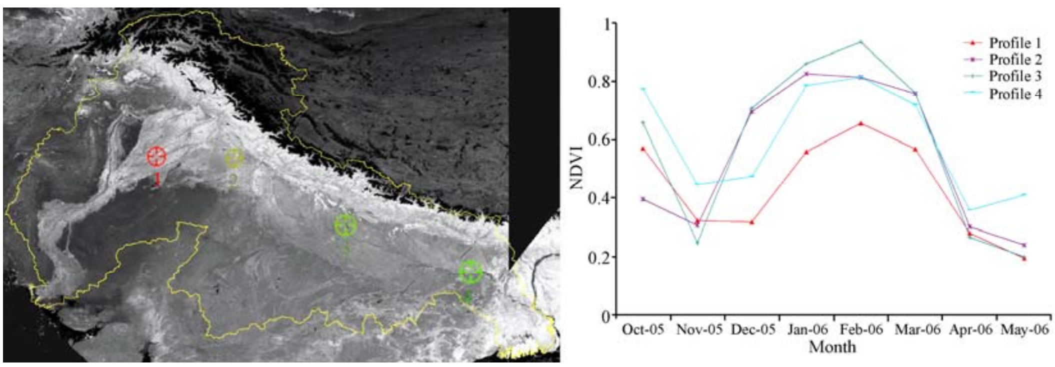

Figure 2 Wheat growth cycles in IGB as determined from MODIS 16-day NDVI products.

where ET_f is ET fraction ranging from 0 to 1, T_H and T_C are the temperature of hot and cold pixels respectively; T_X is the surface temperature of any given pixel on the image. This equation enables to generate an ET fraction map based on LST map from thermal imagery. However, apart from the hot pixels with no ET, another "anchor pixel" needs to be identified to determine the slope. Potential ET (ET_p) can be calculated through FAO approach from ET_0 and K_C. Hence ET_p can be taken as maximum ET corresponding to cold pixels. The Actual ET map of day *i* ($ET_{a,i}$) can be generated by multiplying ET_f with ET_p of day i as shown as

$$ET_{a,i} = ET_p \times ET_f . \tag{3}$$

In this study daily reference ET (ET_0) was calculated using Hargreaves equation with temperature data from 58 stations across the basin. K_C values of different wheat growth stages were adopted from Ullah et al.[18]. Daily ET_p raster map was interpolated from point ET_p of the 58 stations using tension spline algorithm. Daily $ET_{a,i}$ was then calculated and summed up to seasonal ET maps.

4 Results and discussions

4.1 Yield maps

Rice and wheat productivity maps are shown in Figure 3. The average rice yield for IGB Pakistan, India, Nepal and Bangladesh parts are 2.6, 2.53, 3.54 and 2.75 t/ha respectively. However, tremendous differences exist for different areas of the basin. The "bright spot" in Indian Punjab state with some adjacent areas from Haryana and Rajasthan states (red patch in Figure 3 rice yield map) has an average yield of 6.18 t/ha, which is significantly greater than most of other areas within the basin. The "hot spots" of low yield rice is found in Indian Madhya Pradesh, Rajasthan, Bihar States and Bangladesh Dhaka Division with average yield of 1.18, 1.49, 2.04 and 1.97 t/ha respectively. Furthermore, with the spatially explicit map of pixelwise rice yield map, significant variability is observed at local scale. For example, the bright spot with very high yield has around 1% area with less than 3 t/ha yield. And the very low performance of Bihar also has a "bright spot" in a 37 km-diameter cycle centered at 25.4°N, 84.44°E (southwest of Bhojpur District) with an average yield of 4 t/ha.

4.2 ET maps

Wheat and rice ET_a maps are shown in Figure 4. The seasonal average paddy rice ET_a from June 10— October 15, 2005 is 368 mm, ranging from 147 to 536 mm with standard deviation of 92.6 mm (1% points were sieved). The average ET for non-rice cropland of the same period is 305 mm, with a slightly higher standard deviation of 99.4 mm. The average rice ET is significantly less than reference ET (518 mm) and rice potential ET (534 mm). The reasons for low ET could be attributed to the following: 1) mixed land cover within pixel classified as "pure" rice field; 2) crop stress. The resolution of MODIS thermal bands used to produce ET map is 1 km×1 km. In such a big area rice only grows in a part of it. The rest could be field bunds, trees, barren land and other crops, which bring down the average ET rate. Crop stress is another important constraint. The rice yield in IGB is generally low compared with many other parts of the world. Low yield could be attributed to many constraining factors including variety, soil, water and climate which all lead to reduced transpiration. The fact that large area under rice in the eastern region remains rainfed is a significant factor directly contributing to water stress.

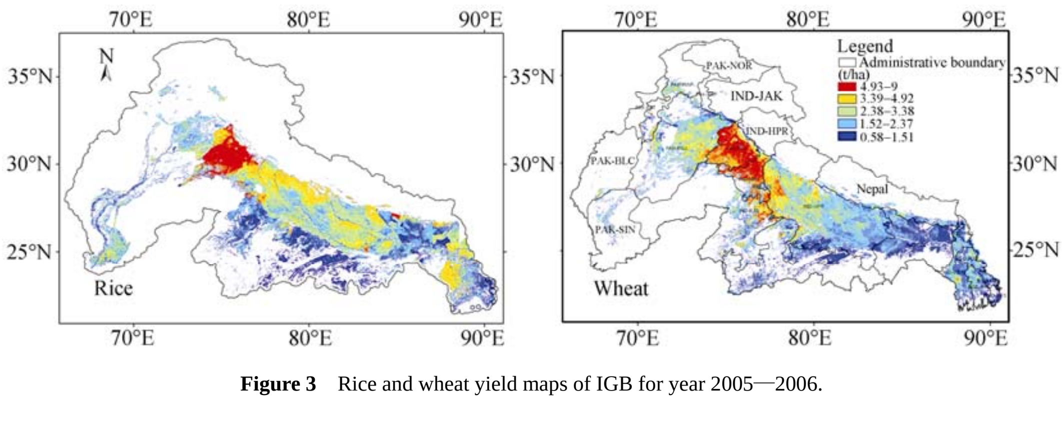

Figure 3 Rice and wheat yield maps of IGB for year 2005—2006.

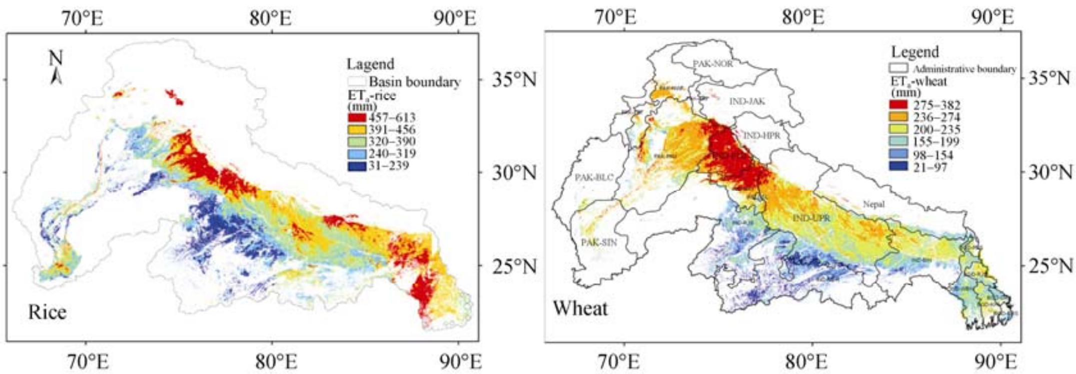

Figure 4 Actual evapotranspiration from rice and wheat cropland for year 2005—2006

The average wheat evapotranspiration over the averaged wheat growth period from November 24, 2005 to April 14, 2006 is 210 mm with standard deviation of 61 mm (Figure 3). Although highest values were also observed in the wheat yield bright spots, ET displayed different changing patterns. The ET values tend to be more uniform across the basin despite more variability in yield, which means similar water input against various output. This provides a great opportunity that either water could be saved under the same yield levels or productivity could be increased with same water input. This also highlights an important issue that in low productivity areas, it may not be the water deficiency but mainly low yielding varieties and input and management inadequacies that cause lower wheat yields.

4.3 Water productivity maps

Average rice water productivity in the basin is 0.84 kg/m^3, with minimum, maximum and standard deviation values of 0.2, 2.04, and 0.372 kg/m^3 respectively (1% extreme pixels sieved). The water productivity variation follows closely the pattern of yield variation. The Indian Punjab and adjoining areas, covering 6% of total rice area, have very high water productivity with an average value of 1.51 kg/m^3. However, as much as 19% of total rice areas have WP less than 0.5 kg/m^3, which occur mainly in Indian Madhya Pradesh, Bihar States and Bangladesh Dhaka Division.

Some areas show different trends in WP variation compared to yield and ET map. A high WP strip, around 10—70 km in width, starts from 75.5°N (longitude), 29°E (latitude) in southern Haryana State and goes towards the east till the Southern Bihar State, India (85.2°N (longitude), 24°E (latitude)). The yield for this area is relatively low with an average value of 3.2 t/ha. However, the average ET of the same area is as low as 277 mm, making the WP relatively high. The higher WP values here do not suggest satisfying performance in this case. Rather, it provides interesting clues to reveal the reasons for the differences, the potential for yield improvement, and the possible interventions by “scaling up” to other areas.

The average wheat WP is 1.36 kg/m^3 with standard variation of 0.66 kg/m^3. Due to the extremely low ET in the Indian Rajasthan and Madhya Pradesh states, water productivity in these areas showed higher values despite low yield (Figure 5). These states still cultivate low yielding traditional wheat varieties which incidentally have high cooking quality and fetch premium price in

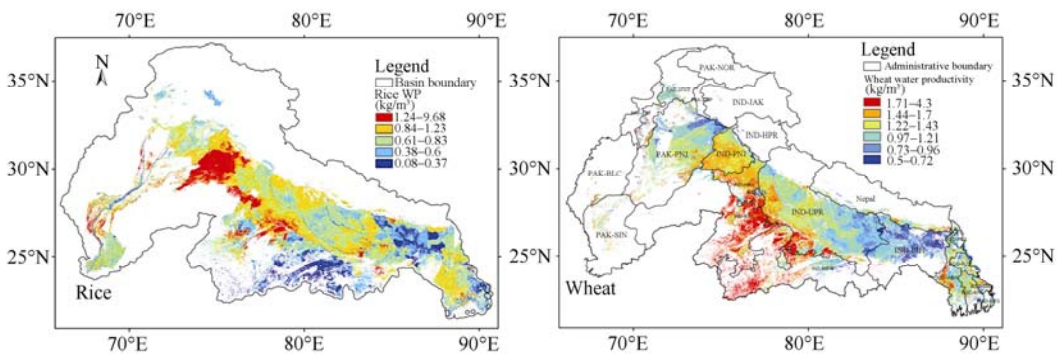

Figure 5 Water productivity of rice and wheat in IGB for year 2005—2006.

the market. The growing season in these states is also of shorter duration due to shorter winter period and early maturity of the crop. The high yield areas showed high water productivity values although they are not among the highest. The Bihar State in India has the largest areas with lowest WP, which means significant scope form improvement exists here. The downstream of Ganges shows relatively good performance despite high variability in yield.

The average rice WP expressed in US dollars in 2005 at local market price is 0.136 US$/m^3. , while for wheat it is 0.212 US$/m^3. The summed water productivity for rice and wheat as expressed in economic values (US$/m^3) is shown in Figure 6. The average WP for sum of rice and wheat is 0.302 US$/m^3. The spatial variation of WP is found to be different both from rice and wheat WP maps. The shared areas of rice and wheat cultivation are influenced by wheat more than rice. However, areas with low wheat WP but high rice WP and the other way around are found in many areas. The rice WP contri buted 50.7% to the total WP (Figure 6) due to larger cultivation area despite lower WP values.

4.4 Causes for variations and scope for improvement

Rice and wheat water use and water productivity are relatively low with tremendous variation in Indo-Gangetic River Basin, which indicates significant scope for improvement. Figure 7 shows the ratio of rice and wheat

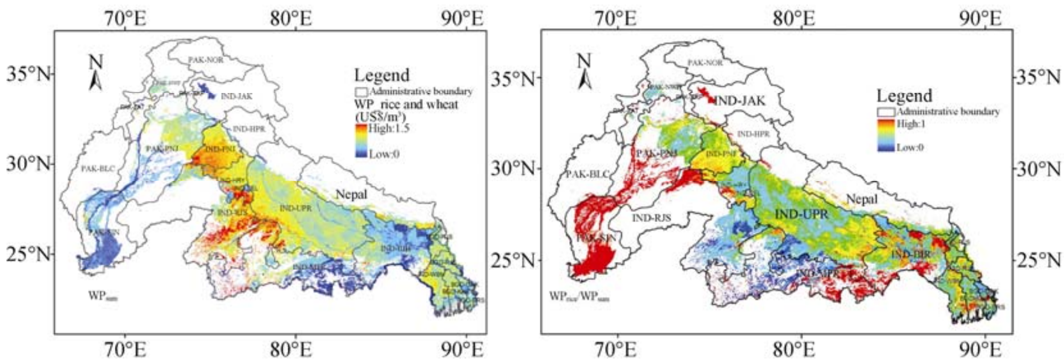

Figure 6 Summed water productivity of rice and wheat and the ratio of rice water productivity to summed water productivity in IGB.

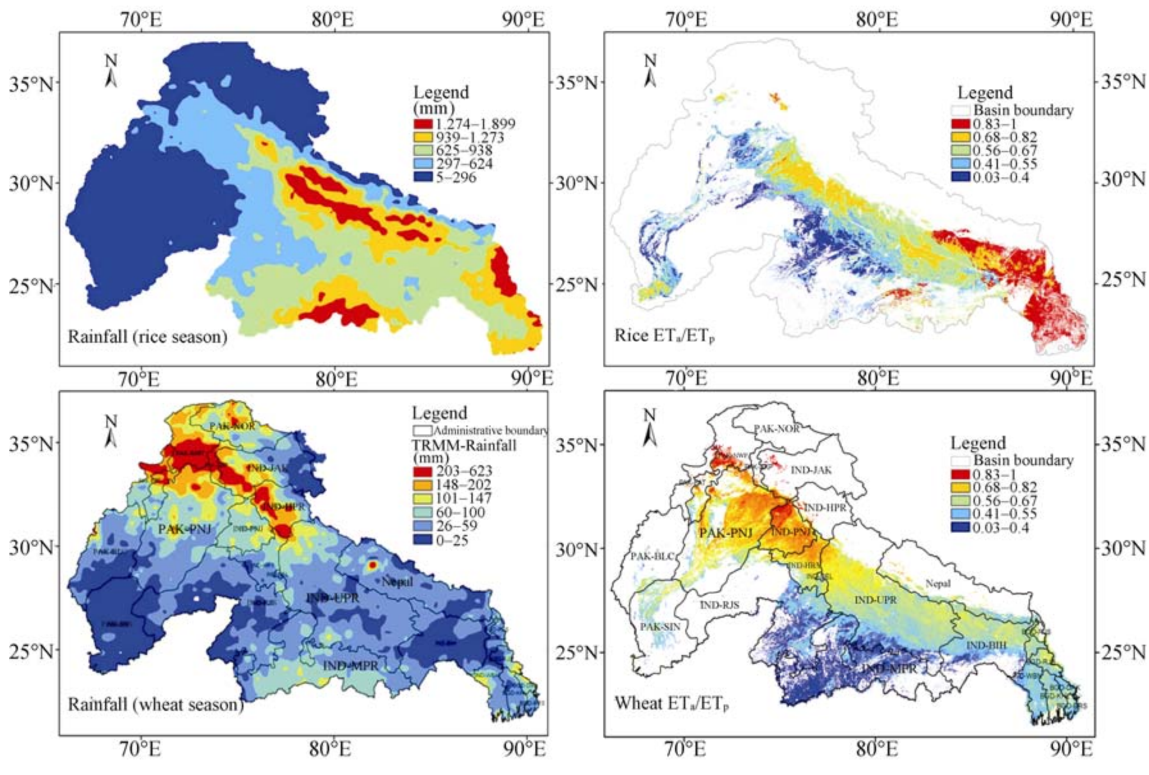

Figure 7 TRMM rainfall during rice and wheat growing seasons and the ratio of rice and wheat actual ET to potential ET in IGB.

actual ET to potential ET along with rainfall distribution of crop growing period measured from Tropical Rainfall Measuring Mission (TRMM). It is observed that the rainfall is much lower in Indus Basin in rice growing season while higher in Ganges Basin in wheat season. Both rice and wheat ET_a to ET_p ratio is higher in high rainfall areas. Higher rainfall means more water for evapotranspiration. However it does not necessarily lead to higher yield and water productivity, as shown in Figures 3 and 5. This could be attributed to poor local crop and water management practices; especially the low fertilizer use, traditional varieties and crop disease and pests. Rainfall may occur at anytime. Hence higher rainfall area has more water to evaporate but could still suffer from water stress during crop critical growth period (especially the terminal grain filling stage) which drastically affects the final grain yield accumulation. The inconsistent yield and WP distribution against rainfall shows that the main constraint is not water availability, but the timing of water supply and others on farm management. Well developed irrigation and drainage system together with matching management practices can help to maximize utilization of rainfall and achieve high yield and water productivity. Other land and crop interventions, e.g., leveling, insects and diseases control, fertilizer, variety, are also important factors to be considered along with water management.

Scope for improvement could be assessed from the “bright spots” in comparison to “hot spots”. For example, the bright spot in Indian Punjab State and adjacent areas, with 5% of basin rice and wheat cropping area, has high WP of 0.433 US$/m^3. If the basin average value of 0.302 US$/m^3 could be increased to the same as in bright spots. Then the basin could theoretically save 30% of agricultural water consumption with same quantity of production or increase 30% of production with same quantum of water input. Although this is limited by many constraining factors, a little bit increase in WP still has a lot of significance for regional food security.

5 Conclusions

Basin water productivity assessment is of huge significance for better regional water and land management. Proper understanding on the magnitude of WP, the variations, and the scope for improvement is essential in achieving sustainable development to ensure food security. The methods and results presented in this paper aimed to address this issue. The yield, consumptive use and water productivity of the predominant crops, rice and wheat, in IGB are determined in a simplified approach by combining census, remote sensing, weather, and filed survey data. The interpolation of yield data from districtwise statistical values to pixelwise through NDVI bridges publically accepted official figures and advanced remote sensing technology. The method avoided complex land surface processes and biophysical parameter estimations in remote sensing. It does not require field calibration prior to new applications and could be easily applied elsewhere. The accuracy is promising as long as census production data falls within acceptable range. An important input to this yield estimation method is crop map. Precise crop type map will make the result more accurate. A map that distinguishes crop varieties will even make it possible to map yield according to each crop variety, which could significantly improve model accuracy. The simplified surface energy balance model is another effort to bring simplicity to crop water use studies. It takes ET_0 calculated from conventional approach, e.g., P-M equation, Hargreaves, using easily accessible data, and multiplies with crop coefficient to calculate potential ET, which is then extrapolated to large area based on land surface temperature distribution. Although rigorous validation is still required for further application, SSEB is recommended for large area time series ET analysis in operational assessment.

1 Molden D, Frenken K, Barker R, et al. Trends in water and agricultural development. In: Molden D. Water for Food, Water for Life: A Comprehensive Assessment of Water Management in Agriculture. London: Earthscan, 2007. 57－89

2 Rosegrant M W, Ringler C, Gerpacio R V. Water and land resources and global food supply. In: 23rd International Conference of Agricultural Economists on Food Security, Diversification, and Resource Management: Refocusing the Role of Agriculture. Sacramento: Dartmouth Publishing Co. Ltd., 1999

3 Molden D, Murray-Rust H, Sakthivadivel R, et al. A water-productivity framework for understanding and action. In: Kijne J W, Barker R, Molden D. Water Productivity in Agriculture: Limits and Opportunities for Improvement. Wallingford: CAB International, 2003. 1－18

4 Schmugge T J, Kustas W P, Ritchie J C, et al. Remote sensing in hydrology. Adv Water Resour, 2002, 25(8-12): 1367－1385

5 Yang P, Wu W, Zhou Q, et al. Research progress in crop yield estimation models based on spectral reflectance data (in Chinese). Trans CSAE, 2008, 24(10): 262－268

6 Courault D, Seguin B, Olioso A. Review on estimation of evapotranspi-

ration from remote sensing data: From empirical to numerical modeling approaches. Irrig Drain Syst, 2005, 19(3): 223－249
7 Moulin S, Bondeau A, Delecolle R. Combining agricultural crop models and satellite observations: From field to regional scales. Int J Remote Sens, 1998, 19(6): 1021－1036
8 Frolking S, Qiu J, Boles S, et al. Combining remote sensing and ground census data to develop new maps of the distribution of rice agriculture in China. Glob biogeochem Cycles, 2002, 16(4): 1－10
9 Frolking S, Xiao X, Zhuang Y, et al. Agricultural land-use in China: A comparison of area estimates from ground-based census and satellite-borne remote sensing. Glob Ecol Biogeogr, 1994, 8(5): 407－416
10 McCoy R M. Field Methods in Remote Sensing. New York: Guilford Press, 2004. 159
11 Harvey J T. Estimating census district populations from satellite imagery: Some approaches and limitations. Int J Remote Sens, 2002, 23(10): 2071－2095
12 Sutton P, Roberts D, Elvidge C, et al. Census from heaven: An estimate of the global human population using nighttime satellite imagery. Int J Remote Sens, 2001, 22(16): 3061－3076
13 Hurtt G C, Rosentrater L, Frolking S, et al. Linking remote-sensing estimates of land cover and census statistics on land use to produce maps of land use of the conterminous United States. Glob Biogeochem Cycles, 2001, 15(3): 673－685
14 Mesev V. The use of census data in urban image classification. Photogramm Eng Remote Sens, 1998, 64(5): 431－438
15 Neto E R, Hamburger D S. Census data mining for land use classification. In: Cao L, Yu P S, Zhang C, et al. Data Mining for Business Applications. New York: Springer, 2009. 241－251
16 Rindfuss R R, Stern P C. Linking remote sensing and social science: The need and the challenges. In: Liverman D, Moran E F, Rindfuss R R, et al. People and Pixels: Linking Remote Sensing and Social Science. Washington: National Academy Press, 1998. 1－27
17 Shah T, Singh O P, Mukherji A. Groundwater irrigation and South Asian agriculture: Empirical analysis from a large scale survey of India, Pakistan, Nepal and Bangladesh. Hydrogeology J, 2006, 14(3): 286－309
18 Ullah M K, Habib Z, Muhammad S. Spatial Distribution of Reference and Potential Evapotranspiration across the Indus Basin Irrigation Systems. Technical Report, International Water Management Institute, Lahore, Pakistan, Working Paper 24. 2001
19 Loveland T R, Reed B C, Brown J F, et al. Development of a global land cover characteristics database and IGBP DISCover from 1 km AVHRR data. Int J Remote Sens, 2000, 21(6-7): 1303－1330
20 Thenkabail P S, Biradar C M, Turral H, et al. An Irrigated Area Map of the World (1999) Derived from Remote Sensing. Technical Report, International Water Management Institute, Colombo, Sri Lanka, Research Report 105. 2006
21 Xiao X, Boles S, Frolking S, et al. Mapping paddy rice agriculture in South and Southeast Asia using multi-temporal MODIS images. Remote Sens Environ 2006, 100(1): 95－113
22 Thenkabail P S, Gangadhararao P, Biggs T, et al. Spectral matching techniques to determine historical land use/land cover (LULC) and irrigated areas using time-series AVHRR pathfinder datasets in the Krishna River Basin, India. Photogramm Eng Remote Sens, 2007, 73(9): 1029－1040
23 Cai X L, Sharma B. A regional crop dominance map based on remote sensing, census and groundtruth data. In: International Conference on Food Security and Environmental Sustainability. Kharagpur: Indian Institute of Technology, 2009
24 Bastiaanssen W G M, Thiruvengadachari T, Sakthivadivel R, et al. Satellite remote sensing for estimating productivities of land and water. Int J Water Resour Dev, 1999, 15(1-2): 181－196
25 Senay B G, Budde M, Verdin J P, et al. A coupled remote sensing and simplified surface energy balance approach to estimate actual evapotranspiration from irrigated fields. Sensors, 2007, 7(6): 979－1000