sustainability

MDPI

Article

Remote Sensing and Modelling Based Framework for Valuing Irrigation System Efficiency and Steering Indicators of Consumptive Water Use in an Irrigated Region

Muhammad Usman [1,2,*], Talha Mahmood [1], Christopher Conrad [1] and Habib Ullah Bodla [3]

1. Department of Geoecology, Institute of Geosciences and Geography, University of Halle-Wittenberg, 06120 Halle, Germany; talha2647@gmail.com (T.M.); christopher.conrad@geo.uni-halle.de (C.C.)
2. Department of Remote Sensing, Institute of Geography and Geology, University of Würzburg, 97074 Würzburg, Germany
3. Program Monitoring and Implementation Unit (PMIU), Irrigation Department Punjab, Old Anarkali, Lahore 54000, Pakistan; dgpmiu_bodla@yahoo.com

* Correspondence: Muhammad.usman@geo.uni-halle.de

Received: 20 September 2020; Accepted: 10 November 2020; Published: 16 November 2020

check for updates

Abstract: Water crises are becoming severe in recent times, further fueled by population increase and climate change. They result in complex and unsustainable water management. Spatial estimation of consumptive water use is vital for performance assessment of the irrigation system using Remote Sensing (RS). For this study, its estimation is done using the Soil Energy Balance Algorithm for Land (SEBAL) approach. Performance indicators including equity, adequacy, and reliability were worked out at various spatiotemporal scales. Moreover, optimization and sustainable use of water resources are not possible without knowing the factors mainly influencing consumptive water use of major crops. For that purpose, random forest regression modelling was employed using various sets of factors for site-specific, proximity, and cropping system. The results show that the system is underperforming both for Kharif (i.e., summer) and Rabi (i.e., winter) seasons. Performance indicators highlight poor water distribution in the system, a shortage of water supply, and unreliability. The results are relatively good for Rabi as compared to Kharif, with an overall poor situation for both seasons. Factors importance varies for different crops. Overall, distance from canal, road density, canal density, and farm approachability are the most important factors for explaining consumptive water use. Auditing of consumptive water use shows the potential for resource optimization through on-farm water management by the targeted approach. The results are based on the present situation without considering future changes in canal water supply and consumptive water use under climate change.

Keywords: consumptive water use; performance assessment; indicator importance assessment; water management; Pakistan

1. Introduction

According to the Global Risk Report published by the World Economic Forum in 2019, water crises are becoming a grave concern in recent times, along with climate change, natural disasters, and biodiversity loss and ecosystem collapses [1]. The greatest burden on freshwater availability and utilization is rapid human development that causes the management of water resources to be very complex and environmentally unsustainable [2]. The world population is expected to be 9 billion by the end of 2050, which means humans of the entire world would need more food than that was required during the last 8000 years of mankind [3]. This situation forecasts exponential demands and a rift between water for energy and water for agriculture, thus making a very complex situation for achieving Sustainable Development Goals (SDG) 2, 6, and 7 by the United Nations.

Agriculture is a major consumer of the world's freshwater resources that is central to any food and water security policy. An increase in either land or water resources could be potential solutions to address agricultural water scarcity [4], however, 93% of the land suitable for agricultural production has already been utilized in the South Asian countries [5]. Moreover, the scope for further extension of water resources is very limited in the region including Pakistan [4,6]. Many recently published literatures identify irrigation efficiency improvement as an alternative potential solution to water shortage [7,8], however, critics of this approach argue that it is only possible if the freed water is not wasted in boosting current crop water consumptions, expanding irrigated areas, switching from deficit to flood irrigation, and growing of high delta crops [9–11]. Moreover, the irrigation efficiency improvements at a local scale (i.e., on-farm) usually result in shifting water use patterns, as this saved water could be used at some other part of the same watershed [12].

The aforementioned concerns pose a greater challenge for water and food security achievement through irrigation efficiency improvement at a local scale. Nevertheless, nowadays, all water policies incentivize farmers to restrict water withdrawals for crop water consumption, which could improve the performance of irrigation systems at various scales. This point could only be justified by evaluating irrigation system performance at multiple spatial scales that would gauge the success or failure of any water-saving policy [13]. However, such analysis usually demands the estimation of spatial crop water consumption [4,14]. Despite many successes for retrieval of this data in recent years, its spatial calculation is still a major limiting factor for many regions of the world [15]. Reference [16] has shown how large scale studies could benefit from the availability of such data. Additionally, such data are of utmost importance considering the variabilities of biophysical parameters for a particular watershed in evaluating external indicators of irrigation system performance. These performance indicators are necessary for policymaking and long-term strategic decision making [17]. Furthermore, such assessments would ensure the implementation of water rights and policies [15] at various levels.

Many agricultural, social, economic, and environmental performance indicators have been developed during the last decade of the previous century [17], but their application was suppressed until the end of the last few years due to a lack of approaches available to estimate consumptive water use at wider spatial scales [18]. Using Remote Sensing (RS) data in conjunction with point information for water accounting and productivity made it possible to explore irrigation systems from field to basin scales [19,20]. Now it has become a reality to assess equity, adequacy, and reliability of irrigation schemes using energy balance (EB) approaches [4,18,20–22]. These EB approaches can be classified into single-source models including the surface energy balance algorithm for land (SEBAL), the surface energy balance index (SEBI), the simplified surface energy balance index (S-SEBI), the surface energy balance system (SEBS), and the internalized calibration (METRIC) [23–26] and dual-source models, including Atmospheric Land Exchange Inverse Model (ALEXI) and two source model (TSM) [27–29]. The SEBAL model was developed for the heterogeneous surfaces based on surface energy balance for actual evapotranspiration estimation on a daily basis, which decreases the dependencies on point-based weather data, crop information, and application of efficiency assessment indicators to small areas [30].

Estimation of consumptive water use is vital for water resources planning, management, and regulations [31] through irrigation efficiency assessments [18]. Strategies to increase in irrigation efficiencies are therefore the prime focus of numerous efforts to water scarcity. Nevertheless, its achievement solely depends on the understanding of factors affecting patterns of water use across a river basin. These factors could be site-specific, proximal, and cropping system related (i.e., crop diversity) [32–34]. The effects of these driving factors (i.e., indicators) could be different for various seasons and different land covers due to various anthropogenic activities, which need to be explored. In the best knowledge of the authors, no study is reported in the published literature, particularly for the study region, where effects of such indicators that could influence the water availability and utilization by agriculture, are being investigated. The current manuscript presents the novel approaches where RS data were utilized in conjunction with modelling approaches for profiling of consumptive water use, assessing its driving factors, for improved decision making. The rest of this article is organized as follows. Section 2 describes the study site, whereas Section 3 reveals the datasets. Section 4 reports the methods, and Sections 5 and 6 present the results and discussion from our findings, respectively.

2. Study Region

2.1. Irrigation System

A century old Indus Basin Irrigation System (IBIS) of Pakistan is the largest contiguous irrigation system in the world, which is serving an area of 16 million hectares (Mha) with some 172 billion m^3 of river water flowing per year [35]. Originally, the IBIS was designed for an annual cropping intensity of about 75%, but that has grown up to 200% [36]. The major reason is rising food demands due to accelerated population growth and better nutrition requirements. This has put tremendous pressure on the irrigation demands and resultantly serious consequences to the ecosystem balance. However, the canal supplies have either remained stagnant or decreased over time, and many canals have lost their design capacity due to siltation and erosion of their banks [37]. The result is over-dependence on groundwater resources.

Rechna Doab, one of the largest irrigation schemes of the IBIS, that lies between Ravi and Chenab rivers, has been selected for the current study (Figure 1). The gross command area of this irrigation system is about 2.98 Mha, out of which 2.3 Mha is cultivated and irrigated land. Rechna Doab is categorized on various spatial scales including irrigation circles (i.e., 4 in total), irrigation divisions (i.e., 11 in total), and irrigation subdivisions (i.e., 28 in total). Irrigation subdivisions are considered to be the smallest irrigation management units whose structuring is performed for equitable distribution of canal water among various users.

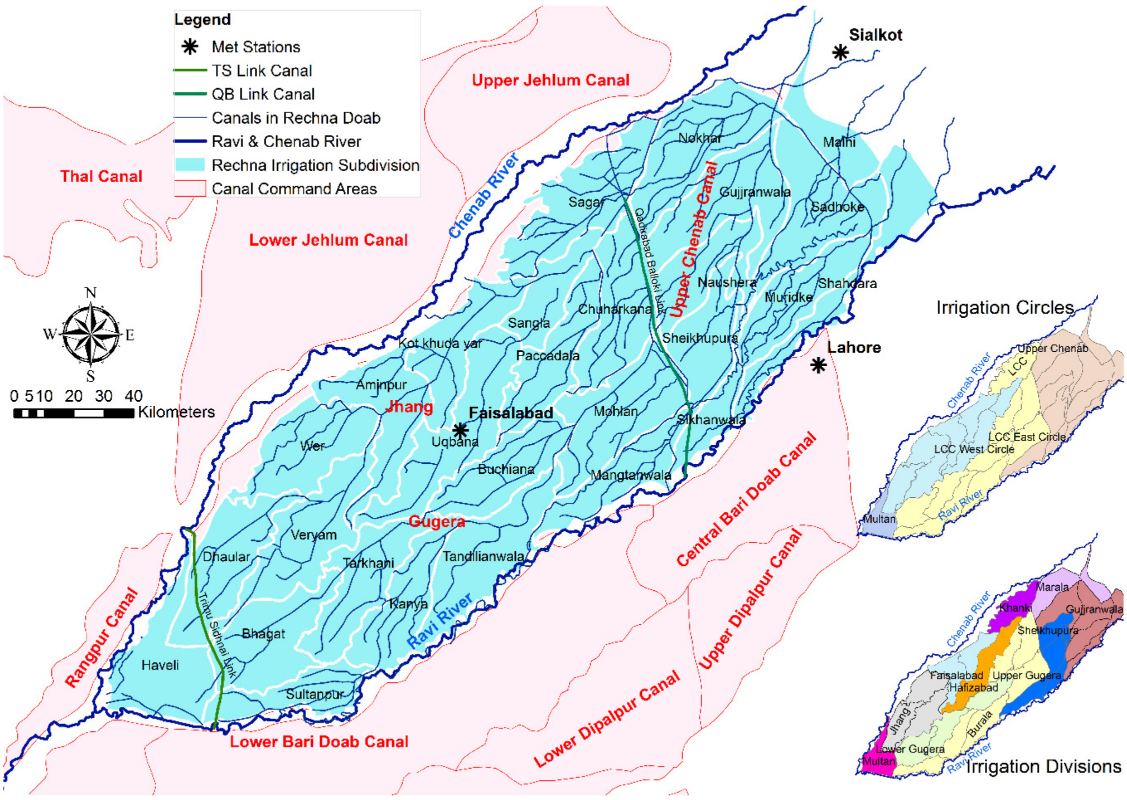


Figure 1. A detailed description of the irrigation system at various spatial scales in Rechna Doab.

2.2. Agriculture and Climate

The study area is categorized as agricultural land where various crops are grown throughout the cropping year including rice, wheat, sugarcane, fodder, cotton, and vegetables, etc. The cropping year can be sub-divided into two seasons, namely Kharif and Rabi, where the Kharif season generally starts from May and ends in October, whereas the Rabi season extends from November to April. Rice and wheat are the two major crops during the Kharif and Rabi seasons, respectively. The other major crops cultivated during the Rabi season are Rabi fodders (mainly berseem and oat), while cotton and Kharif fodders (mainly sorghum, maize, and millet) are grown in the Kharif season. Sugarcane is another major crop in the region that is an annual crop, which is cultivated in September and February [38].

The climate of the area is arid to semi-arid. The climate conditions fluctuate in terms of temperature and rainfall. Four types of weather seasons prevail that include summer, winter, spring, and autumn. The summers are hot and long-lasting, with temperatures ranging between 21 and 50 °C. Daytime temperature ranges between 10 and 27 °C during winter, whereas it may drop to zero at night. The average annual rainfall in Rechna Doab varies from 290 mm in the southwest to 1046 mm in the northeast. The highest rainfalls occur during monsoon months from July to September, and that accounts for about 60% of total annual rainfall [38].

3. Datasets

3.1. Remote Sensing Data

The use of various types of RS data is central to achieve various objectives of this study. Such data were used for land use land cover mapping and estimation of consumptive water use. For land-use-land-cover mapping, MODIS Normalized Difference Vegetation Index (NDVI) data, both from Aqua and Terra sensors at a spatial resolution of 250 m, were downloaded that correspond to 8 days' temporal resolution for a period from 2005 to 2016. Estimation of consumptive water use using SEBAL involves multiple processing steps that utilize various RS data including Digital Elevation Model (DEM), Land Surface Temperature (LST), Emissivity, Albedo, and NDVI. DEM data are used to incorporate the elevation effects on LST, which are available cost-free with global coverage of 30 arc-seconds (i.e., GTOPO30) from https://earthexplorer.usgs.gov/, whereas other RS data were downloaded from MODIS at a spatial resolution of 1km cost-free from https://modis.gsfc.nasa.gov/. All MODIS products were downloaded on daily temporal resolutions, except NDVI, which were downloaded at 8 days' temporal scale.

3.2. Geographical Information System (GIS) Data

Various types of GIS data were utilized for the exploration of irrigation system performance and estimating indicator/variable importance for consumptive water use. For instance, the percentage of the land slope was worked out using DEM data, and canal densities were estimated from the canal shape files taken from the Punjab Irrigation Department (PID), Pakistan. Similarly, vector data of water bodies, canal outlets (i.e., moghas), and soil texture were also gathered from PID. Information on road distances, road densities, and city distances was processed from the Open Street Maps. Population density data were collected from https://sedac.ciesin.columbia.edu/data/set/gpw-v3-population-density/data-download.

3.3. Field Data

Field data is mandatory for checking the quality of results from the RS techniques and also for performing various geographical analyses. Field data collection campaigns were conducted in 2012, 2017, and 2018 for ensuring the quality of results from land use land cover mapping. During the campaigns, GPS data of various major crops including wheat, cotton, sugarcane, rice, fodders, etc., were collected from more than 800 locations per each year. During summer 2018, field equipment including net radiation sensor (NR Lite2), soil heat flux plate (HFP01SC), and soil moisture and heat sensors

(CS655) were installed to track the data on net radiation, soil heat, and sensible heat fluxes. Such data are very useful for validating the results of consumptive water use estimated from RS techniques.

3.4. Secondary Data

These data include crop inventory taken from Directorate of Agriculture Punjab, Pakistan http://www.amis.pk/Agristatistics/Statistics.aspx. Daily data of canal flows were gathered from PID and rainfall information at three locations (i.e., Sialkot, Lahore, and Faisalabad) inside/near Rechna Doab from Pakistan Meteorological Department (PMD). Daily data of other climatic parameters including maximum and minimum temperatures, wind speed, relative humidity, and sunshine hours were collected from the meteorological site located at the University of Agriculture Faisalabad, Pakistan (UAF).

4. Methods

4.1. Land Use Land Cover Mapping

The steps of pre-processing and geo-referencing of NDVI data were followed by temporal linear interpolation of bad quality pixels based on their pre and post time corresponding pixels. Once reliable NDVI data were attained, then mosaicking, subsetting, and stacking functions were run, followed by unsupervised classification for a period from 2005 to 2018, employing k-means clustering algorithm [39] in the R environment. Followed by clustering, the refinement of results was done by expert opinion (i.e., agronomists' opinion) considering the cropping calendar of the study area. For this purpose, temporal profiles of NDVI data were utilized to identify crop growth stages and for the merging of some classes. A significant increase in NDVI was represented as the initial crop growth stages, while declining trends were identified as the end of a cropping season. Separate land use land cover classes were attained for Rabi and Kharif cropping seasons [4]. The quality of results was evaluated using a well-known confusion matrix approach using ground-truthing data [39], and also comparing results with the crop inventory maintained by the government for each administrative district of Punjab.

4.2. SEBAL for Estimating Consumptive Water Use

Actual evapotranspiration (ET_a)/consumptive water use was estimated using MODIS data products employing the SEBAL algorithm [24]. The application of SEBAL is well tested in various agroecosystems of the world, including Pakistan [4,22,40].

The estimation of consumptive water use using SEBAL involves several modelling steps to work out the energy exchanges between the land surface and atmosphere (Figure 2). The algorithm works on the assumption that if the energy needed for photosynthesis and heat stored in vegetation is neglected, then the land surface energy balance can be expressed as:

$$R_n = G_o + H + LE \quad (1)$$

where R_n is absorbed net radiation ($W{\cdot}m^{-2}$), Go is soil heat flux ($W{\cdot}m^{-2}$), H is sensible heat flux to warm or cool the atmosphere ($W{\cdot}m^{-2}$), and LE is the latent heat of vaporization of water from the soil, water, and vegetation ($W{\cdot}m^{-2}$). The explanation of each component of Equation (1) can be found from [24,40] in more detail.

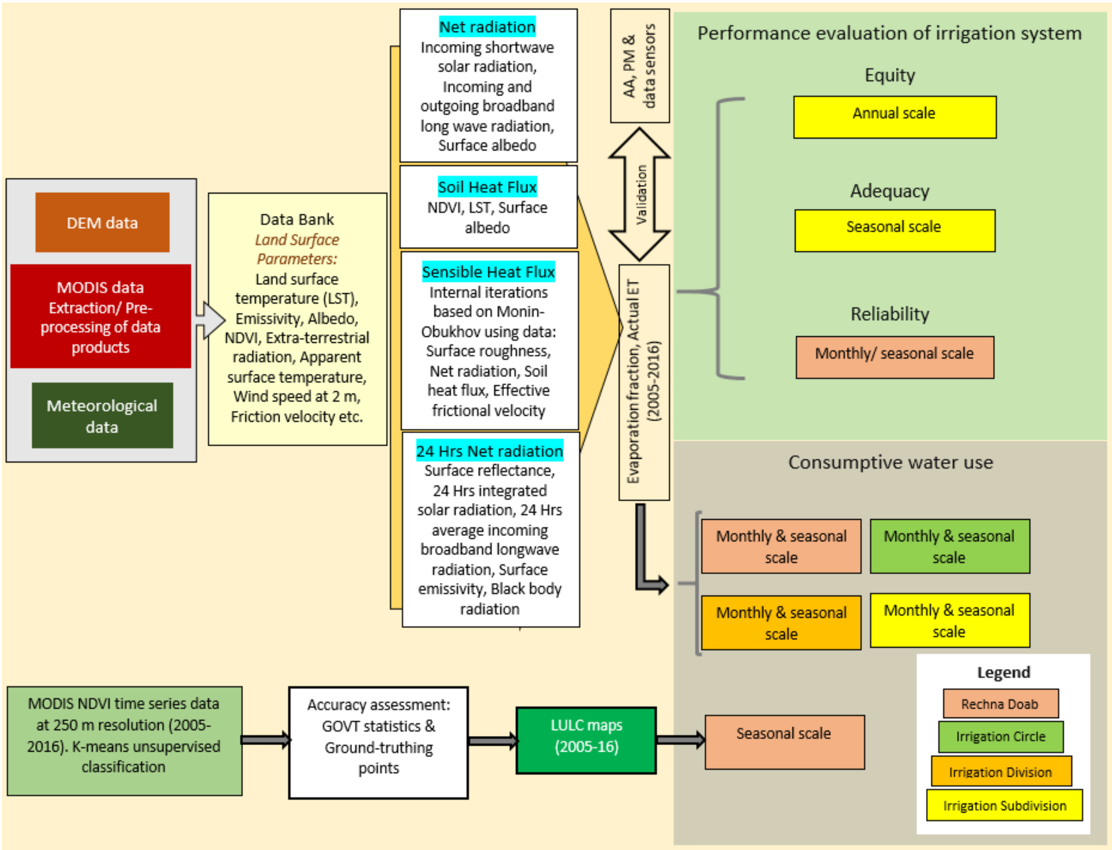


Figure 2. Workflow diagram depicting Soil Energy Balance Algorithm (SEBAL) methodology, irrigation system performance assessment mechanisms, and spatial–temporal scales of processing.

4.3. *Validation/Plausibility Analysis of SEBAL ET_a Results*

SEBAL based ET_a results were compared and validated with actual ET from the advective-aridity (AA) method [4,41] and with data from field sensors installed at the experimental site of UAF. The AA based ET_a was calculated using the meteorological data from the weather station of UAF. Additionally, Penman–Monteith based ET_o was calculated, which serves as an upper boundary for SEBAL ET_a for the water-limited irrigated region Rechna Doab. Moreover, the results of net radiation and soil heat flux from the SEBAL algorithm were compared with the sensor data.

4.4. *Calculation of Performance Indicators*

The performance of the irrigation system was explored, using various indicators, for equity, sufficiency (i.e., adequacy), and reliability of irrigation water delivery [21] under actual field conditions [22]. Such indicators are mainly estimated using parameters of ET_o and spatially distributed ET_a for water distribution improvement, and the description of each performance indicator utilized in this study can be found below:

4.4.1. Equity of Irrigation Distribution

Equity of irrigation systems is generally measured from the irrigation supply side of the system. In the current study, it was worked out, on irrigation subdivision spatial scales, from the farmer's side (i.e., water utilization for crops) considering the fact of canal water shortage for agriculture in Rechna Doab [4,22]. The estimation of equity does not only give the impression about the status of water distribution in different parts of the system, but also its distribution within an individual irrigation subdivision. It was calculated from the data on the depth of water utilized by agriculture by relating the annual consumptive water use maps with irrigation subdivision polygons. The results were evaluated using standard deviation (SD) and coefficient of variation (CV) for the duration from 2005 to 2016.

4.4.2. Adequacy of Irrigation System

Adequacy is the most explored parameter for any irrigation scheme to check whether sufficient water was delivered or not to a command area. It assesses the reduction in consumptive water use and for evaluating the irrigation water delivery sufficiency [42]. In the current study, it is estimated by three different ways, described below:

Overall Consumed Ratio (e_p)

It quantifies the degree to which crop irrigation requirements are met by irrigation water supply in the irrigated area [43]. The ratio is defined as below:

$$e_p = \frac{ET_o - P_e}{V_c} \tag{2}$$

where ET_o is potential evapotranspiration, P_e is effective rainfall, and V_c is the volume of irrigation water diverted from resources and/or groundwater.

A target ep value should be set within an existing irrigated area and compared to the actual ratio on a monthly and seasonal basis [21]. Assuming the values of irrigation water application efficiency (0.60–0.70) and conveyance efficiency (0.85) in Rechna Doab, the acceptable value should be between ≤0.51–0.59.

Relative Water Supply (RWS)

It is an indicator of the adequacy of irrigation water delivery from the irrigation supply side. It compares supplied irrigation water with that of irrigation demanded [42]. A target RWS value of ≥2.0 is recommended by [17] as a benchmark. The ratio can be depicted as follows:

$$RWS = \frac{V_c + P_g}{ET_o} \tag{3}$$

where ET_o is potential evapotranspiration, P_g is total rainfall, and V_c is the volume of irrigation water diverted from resources and/or groundwater.

Relative Evapotranspiration

Ref. [21] documented different approaches based on relative evapotranspiration (also known as evaporation fraction, EF), which mainly cover the key aspects of equity, adequacy, and reliability. Adequacy of irrigation systems was explored based on average seasonal evaporation fraction (EF) that was measured for a particular cropping season based on series of EF maps, which was then plotted for assessing the irrigation water availability [44]. According to [44], a relative evapotranspiration value ≥0.75 is considered acceptable for agriculture, although they never remain constant over time. For the current study, the Kharif and Rabi seasons are considered separately for assessing the availability of water using relative evapotranspiration.

4.4.3. Reliability of Irrigation System

Reliability is a measure of sufficiency of water for the entire cropping season (i.e., time dimension), which can be assessed using seasonal EF values. For the current study, irrigation system reliability was assessed in two ways, (i) temporal coefficient of variation of EF, as suggested by [45], and (ii) by using a crop water deficit (CWD) indicator [46]. Concerning relative evapotranspiration, a higher coefficient of variation values represents less reliable water supplies and vice versa. CWD is defined as the difference between potential and actual evapotranspiration (CWD = $ET_o - ET_a$) of the cropping pattern. A common period of one month is considered for CWD analysis and, according to [46], an average CWD value of ≤30 mm· month^{-1} is considered acceptable.

4.5. Spatio-Temporal Scales for Assessment

Estimation of consumptive water use and irrigation system performance was performed on various spatiotemporal scales, the details of which can be found in Figure 2. Both Kharif and Rabi cropping seasons from 2005 to 2016 were considered for the majority of the analyses. Moreover, the reliability was also explored on monthly time scales, and equity was explored yearly.

4.6. Factors/Variables Importance Analysis

4.6.1. Set of Factors

The utilization of crop water (i.e., consumptive water use) is influenced by natural and anthropogenic factors. They can be divided into various classes including site-specific conditions (i.e., physical factors), proximity to irrigation infrastructure, and factors based on characteristics of the cropping system. The following set of variables are screened to see their relationships with water use in the Rechna Doab (Table 1).

i. Physical factors influence the cropping system in various ways that drive the water utilization and its supply [47–50]. The major variables include slope, canal density, road density, soil texture, elevation, and population density. Land slope influences consumptive water use, as some slopes create hindrance in reachability and flow of water, and therefore result in increased efforts for irrigation [51]. Higher canal densities would enable easy access to irrigation water and resultantly higher cropping intensities. Moreover, better soil moisture can be maintained in such regions due to low soil temperatures [51]. Road density does not have a direct impact, but could influence crop water use indirectly by facilitating better extension services. This could help in adopting better technologies and informed decision making, in time [51]. Moreover, crop husbandry could be improved due to easy and frequent access to the field by the farmers. Soil texture is a variable that influences water demands directly due to varying crop rotations, crop inputs, and due to different water holding capacities [52]. The elevation is another vital variable, which influences consumptive water use in multiple ways. Higher elevation usually results in fewer irrigation demands due to lower temperatures and higher precipitation, however, it increases the energy demands for pumping irrigation water and land leveling efforts. Population density could affect crop water utilization as better technical services for irrigation could be available in the vicinity of larger cities. However, it could influence adversely because of the lowering of farming interest due to fragmented and small landholdings among larger populations. Additionally, increased population leads to tough competition for water availability among various sectors competing for water, for instance, water diversion for agriculture, industry, and domestic needs [53].
ii. Proximity factors are another class of variables influencing crop water use/availability. Such variables include distances of farms from water bodies, from irrigation canals, from roads, from cities, and from canal outlets (i.e., mogha) [54]. Distances from water bodies help to maintain ecosystem balance, ground surface cooling, and a better supply of irrigation water, however, there are very few water bodies located in the Rechna Doab. Distances from canal infrastructures could be very vital, as longer distances result in more loss of canal water through seepage and resultantly less flows in the remote regions [55]. Distances from road and cities could affect better access to fields to adopt diversified cropping practices and to perform various advanced cropping activities. It influences the farmer's interest in diversified agriculture and therefore making adjustments within their irrigation resources for resource optimization [33,56]. Canal outlets are the exit points of irrigation canals from where water is distributed among various farms. Farms near to canal outlet receive generally more water, as longer distances could lead to more

water loss during the channel flow. This might not always be true, considering soil texture and lining of water distribution channels [48,57,58].

iii. The third set of variables are related to the cropping system, as it includes Simpson cropping diversity that takes care of spatial heterogeneity, and rotation diversity that caters to the multi-temporal pattern of cropping practices. According to [59], cropping and rotation diversity could influence crop conditions and water utilization due to improved soil conditions. Healthier soils result in better soil moisture-holding and improved irrigation water delivery at farms. The Simpson Diversity Index (SDI; [60]) reflects the probability of the next crop species being another species, thus indicates the spatial pattern of cropping diversity in a certain region [52,61]. It can be measured as below:

$$\mathrm{SDI} = 1 - \frac{\sum_{m=1}^{M} n(n-1)}{N(N-1)} \tag{4}$$

where n is the number of fields in a particular class m (i.e., covered area of a class). M is the total number of crop classes, and N is the total amount of fields under consideration.

Circular buffer zones of 5 km were developed around each field to investigate crop diversity locally [52]. The SDI value near 1 indicates a more diversified cropping system and vice versa. SDI was estimated for each land use land cover map from 2010 to 2016 and aggregated at local scales before adding a temporal dimension by estimating rotation diversity [59].

Table 1. Factors (predictor variables) including their description and preparation steps used in the random forest (RF) regression modelling.

Predictor Variable Name	Type	Description	Unit/Source
Slope (X_1)	Site specific	Land suitability for irrigation: Higher slopes increase the irrigation efforts.	Percent slope as derived from Digital Elevation Model (DEM).
Canal density (X_2)	Site specific	Better access and availability to canal water. Short distances enable more crop diversity and facilitate the growth of higher delta crops (e.g., Rice, Cotton).	Km/km^2, waterway layers were analyzed using the density function of the spatial analyst tool (ArcGIS).
Road density (X_3)	Site specific	Strong connectivity means better extension services from research and academia about the latest technologies.	Km/km^2, polylines of open street map were analyzed using the density function of the spatial analyst tool (ArcGIS).
Soil texture (X_4)	Site specific	Categorical information about soil distribution: A variable that influences water demand, varying crop rotation, and other crop inputs.	Zones of major soil types were extracted from spatial data collected from IWMI, Pakistan
Elevation (X_5)	Site specific	Terrain elevation from GTOPO at 1km resolution. A higher elevation means higher energy demands for pumping irrigation water and decreased irrigation demands due to more precipitation.	GTOPO30 global Digital Elevation Model (DEM), https://earthexplorer.usgs.gov/.
Water bodies distance (X_6)	Proximity	Fewer distances mean better environmental conditions and better irrigation water availability in the vicinity regions.	Meter, Euclidean distance measured with geospatial data collected from Punjab Irrigation Department, GOVT of Punjab, Pakistan.
Canal distance (X_7)	Proximity	Long distances imply a reduced amount of irrigation water availability and vice versa due to decrease flow and higher transmission losses.	Meter, Euclidean distance measured with geospatial data collected from Punjab Irrigation Department, GOVT of Punjab, Pakistan.
Road distance (X_8)	Proximity	Better access to field and irrigation systems for improved management of the agricultural system.	Meter, Euclidean distance measured with open street map.
City distance (X_9)	Proximity	Near infrastructure is assumed to increase management skills due to advisory services, and also easy and economical access to the latest technologies, along with more demand for water for human needs, etc.	Meters, Euclidean distance measured with open street map.
Population density (X_{10})	Site specific	Better services availability with bigger cities. Adversely affecting agricultural inputs due to small landholdings, resulting in lower farming interest. More population density leads to more demand for domestic human consumption.	Density/arc-second, https://sedac.ciesin.columbia.edu/data/set/gpw-v3-population-density/data-download.
Mogha (outlet) distance (X_{11})	Proximity	Similar to canal distances, but at a higher level. Lower distances mean better availability of irrigation water to crops	Meter, Euclidean distance measured with geospatial data collected from Punjab Irrigation Department, GOVT of Punjab, Pakistan.
Cropping diversity (Simpson) (X_{12})	Cropping system	Simpson index of cropping diversity.	Dimensionless.
Rotation diversity (multi-temporal) (x_{13})	Cropping system	Simpson index of the diversity of crop types from 2010–2015.	Dimensionless.

4.6.2. Implementation of Random Forest Regression modelling

A Random Forest (RF) regression model was used to explore the relationships between consumptive water use with the above-described variables/factors. Non-linear interactions between variables cannot be handled by linear regression modelling [62], therefore a non-parametric regression tree RF model was employed, developed by [63]. RF approaches result in better regression accuracies in comparison to linear regression approaches [64]. However, it may result in less reliable variable importance if variables have high mutual correlations [65]. Moreover, if variables are of different types, then using the "cforest" function in the "party" package of R with the default option "controls = cforest_unbiased" would be helpful, as it measures variable importance conditionally that preserves the correlation structure between variables [66,67]. Otherwise, the use of the "randomForest" package of R would also be fine, nevertheless, don't fall for z-score (i.e., set scale = FALSE) of Gini importance.

For the current case, as variables of different types are used, therefore, to avoid mutual correlation among variables, the "cforest" package was utilized with conditional importance, and stabilized results were reached by setting the number of trees equal to 500. The number of samples was selected separately for each crop type considering its acreage, and about 65% of pixels under each major crop class (i.e., rice, cotton, wheat, and sugarcane) were considered for processing. Simulations were performed for agriculture as a class and also for each major crop independently from 2010 to 2015 (i.e., separately for Kharif and Rabi seasons). Each model was run 10 times, resulting in a total of 360 model simulations. An average conditional variable importance was calculated for the ranking of each variable to explain its association with consumptive water use (i.e., crop water utilization). The spatial representation of variables that are utilized for the importance assessment can be seen from Figure 3.

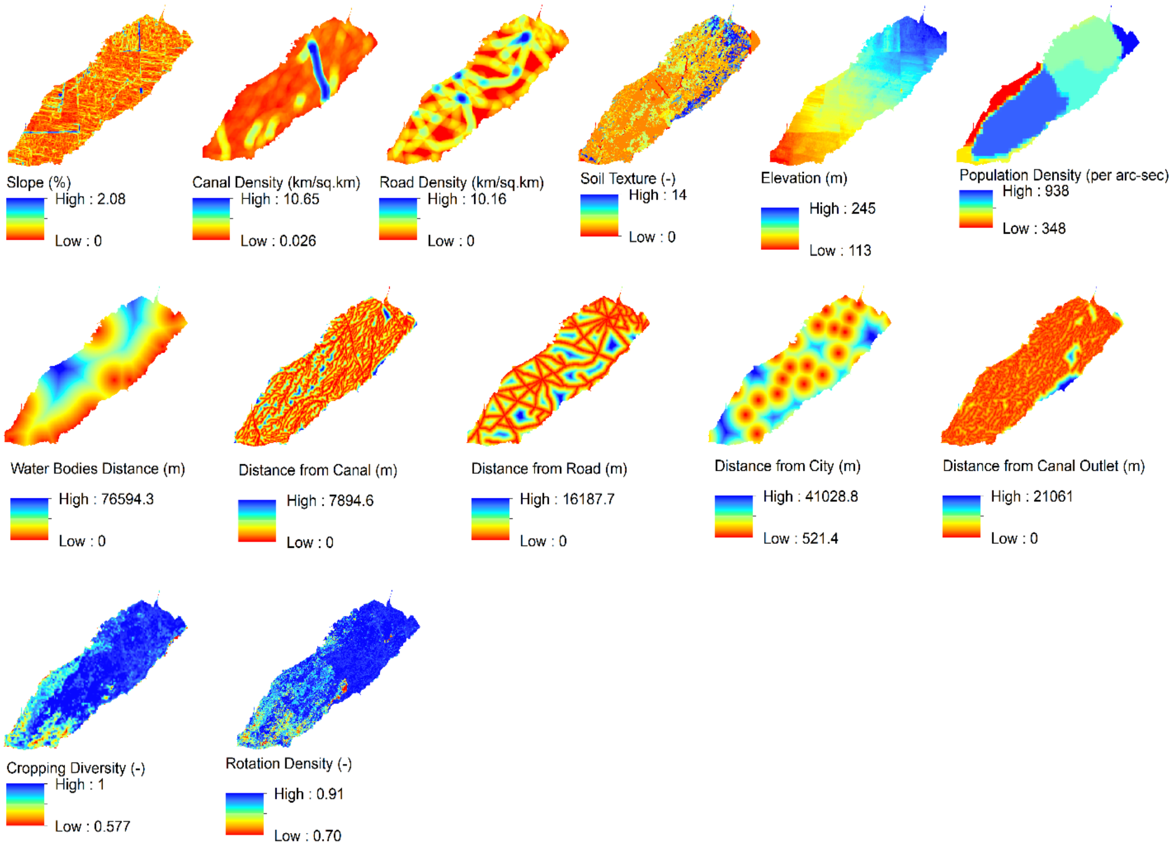


Figure 3. Maps of the independent variables used for the Random Forest regression modelling. (1st row) = Site-specific variables; (2nd row) = Proximity variables; (3rd row) = Cropping system variables.

4.7. Statistical Analyses

The Theissen Polygon method was used for the spatial distribution of point rainfall data collected at three meteorological stations located in/near Rechna Doab. This is achieved by drawing perpendicular bisectors to the lines joining each station with those immediately in its surrounding. These bisectors form a network of polygons, and each polygon houses one station (Figure 4).

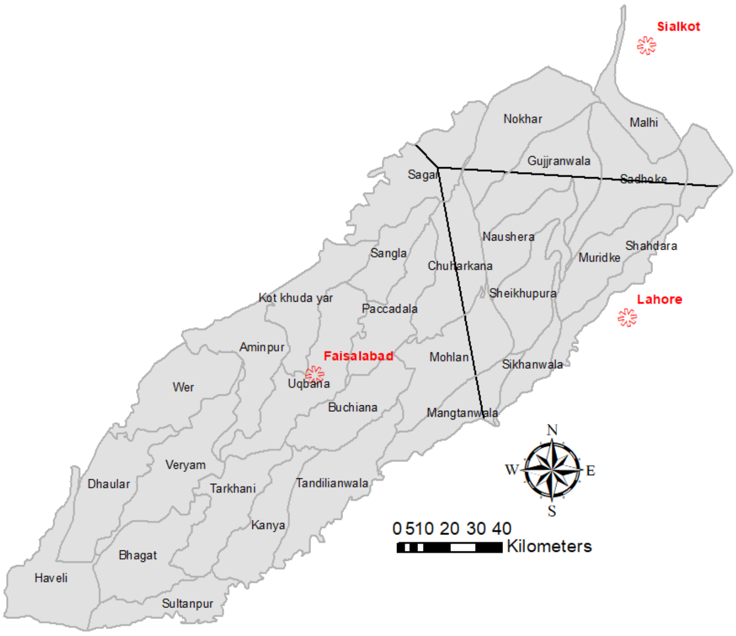


Figure 4. Theissen Polygons for estimating average rainfall in various irrigation subdivisions.

In the final step, the precipitation depth measured at a particular station, was assigned to the whole polygon. The following formula can be used to estimate the average rainfall of the entire region:

$$\overline{P} = \frac{P_1A_1 + P_2A_2 + P_3A_3 + \ldots + P_nA_n}{A_1 + A_2 + A_3 + \ldots + A_n} \quad (5)$$

where P_1, P_1, P_1, $\ldots P_n$ are rainfall values of each meteorological stations, and A_1, A_2, $A_3, \ldots,$ A_n are the areas of each respective polygons. $\overline{P}$ is average rainfall over the entire region.

Effective rainfall is considered to be a direct portion of total rainfall for consumptive water use that was estimated using USDA Soil Conservation Services (SCS) method.

The time-series analyses were performed using the Mann-Kendall (M-K) test to check the seasonal trends [68–70] in precipitation and canal flow datasets. The other statistical tests employed for this study include the Welch *t*-test for comparing two datasets (*t*-test), coefficient of variation (CV), standard deviation (SD), and coefficient of determination (R^2) [4,71,72].

5. Results

5.1. The Status of Canal Water Supply and Rainfall

Analysis of canal flow data shows that an average of 311,040 ha m volume of water is delivered to Rechna Doab during the whole cropping year from the river Chenab that irrigates an area of about 2,464,891 ha. An average irrigation depth of 201.2 mm takes place during the Rabi seasons, and 303.6 mm during the Kharif seasons. The M-K test results of canal water supply for the period from 2005 to 2013 showed significantly decreasing seasonal flow (i.e., tau-value of −0.101 and *p*-value of $7.78e^{-12}$). In Faisalabad, average rainfall depth is much higher during the Kharif seasons (i.e., 312 mm) as compared to the Rabi seasons (i.e., 73 mm). This is mainly attributed to monsoon during the summer months from mid-July to mid-September [4]. M-K trend analysis of rainfall data showed invariable differences at various stations including Sialkot, Lahore, and Faisalabad. Nevertheless, the results are significantly variable for Faisalabad during Kharif seasons as rainfall depths have significantly decreased here (i.e., tau value of −0.582 and *p*-value of 0.0044). For Rabi, the results are insignificantly variable, with positive trends for the whole period. Results of Lahore station are insignificant both for the Kharif and Rabi seasons (i.e., *p*-values of 0.2284 and 0.1272, respectively). For Sialkot, rainfall trends are positive both for Kharif and Rabi seasons, however, changes are insignificant for the entire duration as p-values of 0.1253 and 0.2001 are observed, respectively.

5.2. Land Use Land Cover Mapping

Accuracy assessment was performed by comparing the crop acreage results from RS and state-owned statistics that can be seen from Figure 5 for all major crops including wheat, rice, cotton, and sugarcane. The comparisons for other classes are not made due to the unavailability of statistics data. Moreover, only the agricultural classes are dominant and therefore should need to be taken care of in Rechna Doab. The results are quite good for rice and cotton being cropped in their specific regions during the Kharif seasons. Wheat also showed very good results because of its cultivation in vast areas during Rabi seasons (i.e., winter wheat), so it's mapping at 250 m spatial resolution is quite good (Figure 5). Sugarcane is a perennial crop that showed overall poor results. Nevertheless, its results are also satisfactory in the majority of districts of Punjab, but the overall results are poor due to its poor performance in remote southern Punjab. This unanticipated outcome could either be due to poor results from RS or the poor quality of state-owned crop statistics data. Another reason could be the mixing of sugarcane with cotton and fodders, particularly in the mixed cropping zone of Punjab.

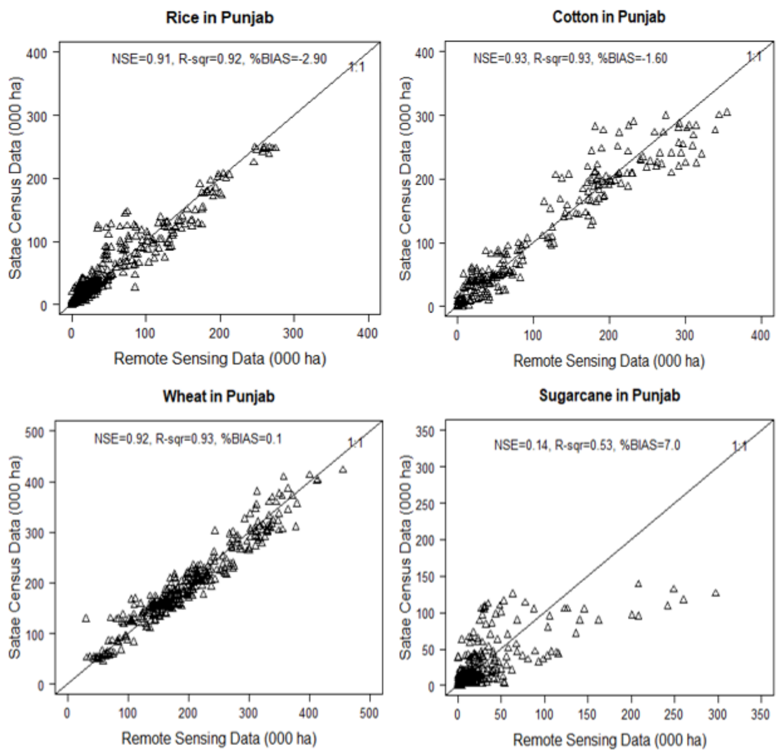


Figure 5. Comparison of results between RS based crop acreage and state-owned statistics data.

The user's and producer's accuracies for all classes were recorded between 60–80% (Figure 6). Wheat showed overall the highest accuracies for the entire study period. The values of rice are also very consistent throughout the study period; however, the accuracies of cotton are relatively unstable as compared to rice and wheat. Sugarcane showed comparatively lower accuracies than other crops, as stated earlier.

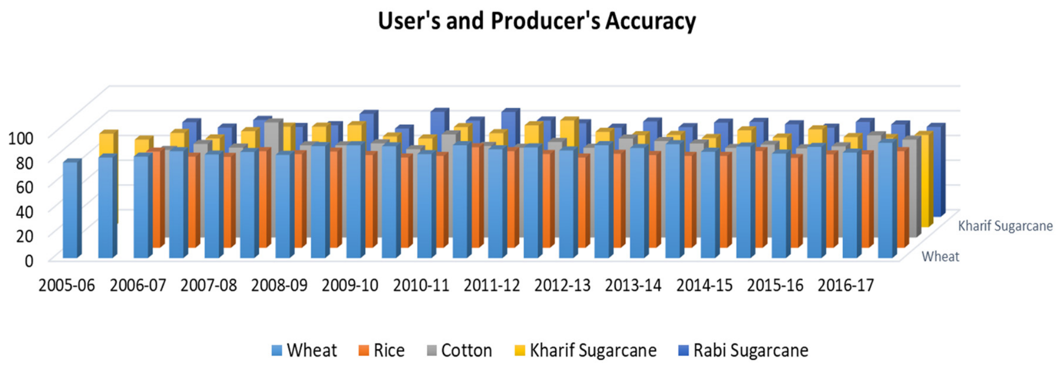


Figure 6. Percentage values of user's (odd bars) and producer's accuracies (even bars) for major crops of Rechna Doab.

5.3. Plausibility Analysis of SEBAL Results

Figure 7 shows the comparison of SEBAL based ET_a with advective aridity (AA) based ET_a and Penman-Monteith (PM) based ET_o for Faisalabad. The correspondence between SEBAL and AA could be considered strong during winter as compared to spring and summer. Normally, the data scatter ability increases with the rising temperature (i.e., Kharif). A few previous studies on such a comparison by [4,41] report similar trends.

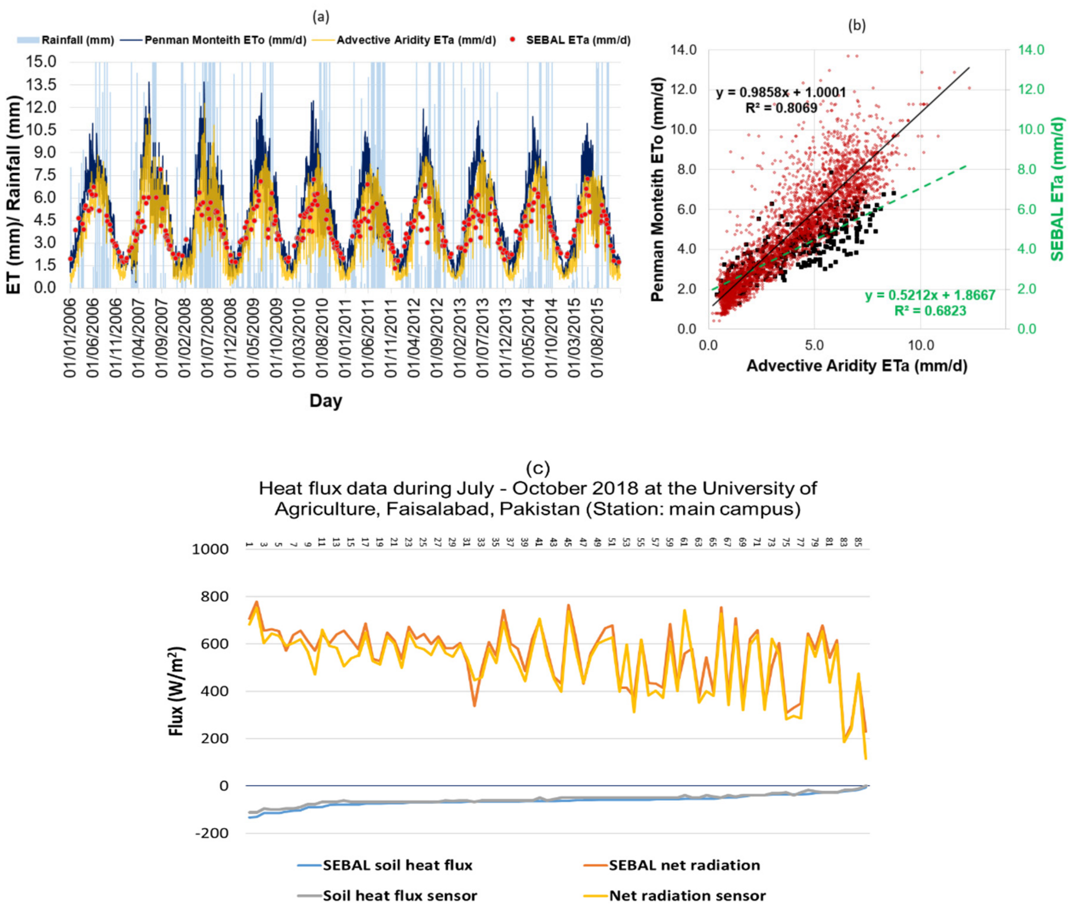


Figure 7. Plausibility analysis and validation of SEBAL based ET_a and energy fluxes. (**a**) Evapotranspiration and rainfall over the study years (**b**) relationship between Penman Monteith and SEBAL ET with Advective Aridity ET and (**c**) variation of different fluxes throughout the season at experimental site of the University of Agriculture, Faisalabad, Pakistan.

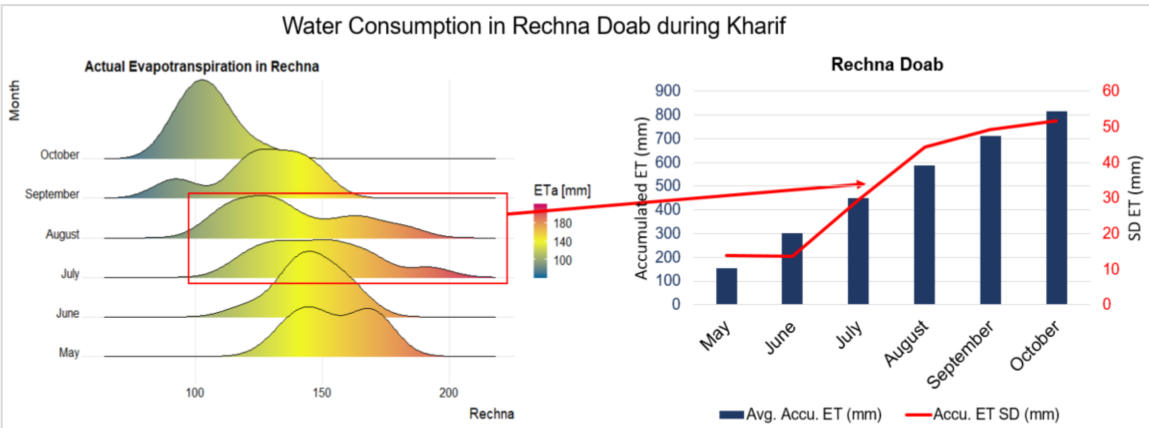
For a more robust comparison of SEBAL based heat fluxes, the results are compared with sensors data (i.e., net radiations and soil heat fluxes) (Figure 7c). The results of both net radiation and soil heat flux are very relating and consistent as R^2 is 0.86, NSE is 0.82, RMSE is 55.28, with only an over-estimation of 4.8% in the case of SEBAL net radiations. For soil heat flux, the value of R^2 is 0.96, NSE is 0.81, and RMSE is 9.21, with an over-estimation of 13.8% for SEBAL soil heat flux.

5.4. Analysis of Consumptive Water Use

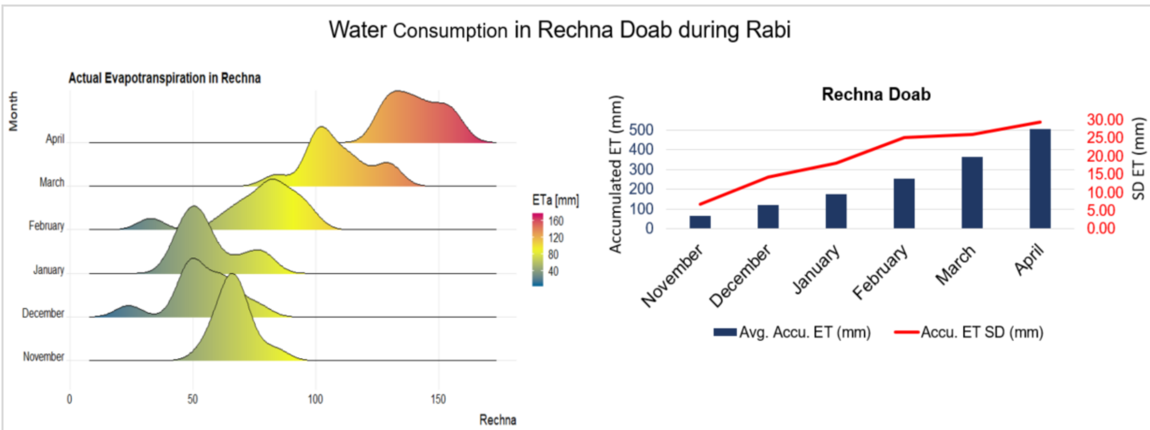
Assessment of crop water consumption was done both for Kharif and Rabi seasons on various spatial scales i.e., over Rechna Doab, irrigation circles, irrigation divisions, and irrigation subdivisions.

5.4.1. Crop Water Consumption in Rechna Doab

Figure 8 shows the monthly and cumulative consumptive water use in Rechna Doab. The total amount of water consumption during the Kharif seasons is about 2.01 million hectares meter (M ha-m). Monthly values increase from October to May, with the highest crop water consumption in May with an average volume of 0.38 M ha-m (i.e., 18.94%). October shows the least water consumption in the Kharif seasons, with an average amount of 0.26 M ha-m (i.e., 12.82%). The water consumptions from June to September are 0.36 M ha-m (i.e., 17.81%), 0.37 M ha-m (i.e., 18.19%), 0.34 M ha-m (i.e.,16.88%), and 0.31 M ha-m (i.e., 15.35%), respectively. For Kharif cropping seasons, little more than 800 mm of water is utilized by the crops. The standard deviation (i.e., ET SD) is relatively higher for the months from July to September due to monsoon rainfalls. Variable rainfalls during monsoon make crop water availability and its utilization heterogeneous in Rechna Doab.



(**a**)



(**b**)

Figure 8. Crop water consumption in Rechna Doab during the Kharif (**a**) and Rabi (**b**)seasons.

An individual month water consumption is highest in April with an average value of 0.35 M ha-m (i.e.,27.96%), followed by March with 0.27 M ha-m (i.e., 21.49%), February with 0.19 M ha-m (i.e., 15.26%), November with 0.16 M ha-m (i.e., 13.27%), January with 0.14 M ha-m (i.e., 11.27%), and December with 0.13 M ha-m (i.e., 10.75%) for the Rabi cropping seasons (Figure 8). The crop water consumption is higher in November as compared to December and January mainly due to the comparatively warm weather and due to high irrigation demands for the first irrigation of the wheat crop. The average total crop water consumption for the Rabi seasons is about 1.24 M ha-m, which is about 60% of the Kharif seasons. Higher ET SD is observed for February and March, mainly attributed to winter rainfalls and also due to temperature hike, especially in March. The average cumulative depth of crop water consumption for the Rabi seasons is about 500 mm.

5.4.2. Crop Water Consumption in Irrigation Circles

For the Kharif seasons, the results of the *t*-test indicate a significant difference of consumptive water use between the upper Chenab irrigation circle and the remaining irrigation circles i.e., Lower Chenab Canal (LCC) east, LCC west, and Multan circles at a significance level of 95%. The highest crop water consumption was found in the upper Chenab circle, amounting to nearly equal to 775 mm for the entire season. For the rest of the irrigation circles, the values are near to 700 mm. The patterns of monthly crop water consumption and SD are similar, as earlier explained for the entire Rechna Doab. For Rabi seasons, the comparative results are non-significant as per the *t*-test at a significant level of 95%. The crop water consumption in all regions is varying between 360 to 375 mm.

5.4.3. Crop Water Consumption in Irrigation Divisions

The results of the *t*-test show that upper irrigation divisions show significantly different behaviors of consumptive water use than middle and lower ones at a confidence level of 95%. The upper irrigation divisions including Murala, Khanki, Gujranwala, and one middle irrigation division named Sheikhupura show comparable results. The possible reason could be more availability of canal water in the upper regions due to better canal networking and rice cultivation. The remaining middle irrigation divisions including upper Gugera, Hafizabad, and Faisalabad resemble. The lower irrigation divisions including lower Gugera, Burala, and Jhang perform similarly, except Multan, which shows significantly different behavior from other lower regions. The water consumption in Multan is similar to some middle irrigation divisions, for instance, Faisalabad and Hafizabad, etc. The probable reason could be its vicinity to both of the rivers surrounding Rechna Doab. Additionally, the Trimu-Sidhnai link canal passes from this region that could greatly influence the ecosystem of the region. The crop water consumption is highest in the upper irrigation divisions, amounting to nearly equal to 900 mm. This amount is nearly 800 mm in the middle irrigation divisions and about 750 mm in the lower irrigation divisions of Rechna Doab. For the Rabi seasons, not surprisingly, the results are fairly similar in all irrigation divisions (i.e., crop water consumption range between 495 to 525 mm) that are mainly attributed to extensive wheat cultivation in the Rabi seasons. It is also due to similarities in canal water supplies everywhere in Rechna.

5.4.4. Crop Water Consumption in Irrigation Subdivisions

Investigating the patterns of crop water consumption was extended to the smallest irrigation administrative unit of Rechna Doab (i.e., irrigation subdivisions). The upper irrigation subdivisions show very consistent results even at this scale as patterns of crop water consumption are insignificantly different at 95% confidence level (i.e., *t*-test). Increased heterogeneity is observed in the middle and lower irrigation subdivisions of Rechna Doab. The middle irrigation subdivisions including Sangla, Kot Khuda Yar, and Mohlan show similar results, while Paccadala and Uqbana show analogous crop water consumption patterns. Three middle irrigation subdivisions including Sheikhupura, Sikhanwala, and Magtanwala react similarly to upper irrigation subdivisions. The possible reason for higher crop water consumption in these middle irrigation subdivisions could be their proximity to river Ravi.

Wer, Tandlianwala, Aminpur, and Buchiana are among lower middle irrigation subdivisions that show similar patterns, which are completely different than other middle irrigation subdivisions. The results for lower irrigation subdivisions are more heterogeneous, for instance, Veryam and Bhagat irrigation subdivisions show similar trends. Similarly, Tarkhani and Kanya behave in similar ways. Daular and Sultanpur are the lower irrigation subdivisions that resemble the middle irrigation subdivisions of Uqbana, Paccadala, and Sangla, etc., respectively. The behavior of the Haveli irrigation subdivision matches with some irrigation subdivisions in the middle of Rechna Doab (i.e., Aminpur, etc.). From the crop water consumption perspective, the irrigation subdivisions of Malhi, Nokhar, Sagar, Sadhoke, Gujranwala, Shahdara, Chuharkana, Naushera, Muridke, Sheikhupura, Sikhanwala, and Mangtanwala could be grouped together (i.e., value around 900 mm). The irrigation subdivisions of Sangla, Kot Khuda Yar, Mohlan, and Sultanpur could be grouped into a separate class with values ranging between 715–730 mm. The Paccadala, Uqbana, and Dhaular irrigation subdivisions could be placed into one group with crop water consumption range between 735–745 mm. The Aminpur, Wer, Buchiana, Tandlianwala, and Haveli irrigation subdivisions could be another group, having values around 700 mm. Veryam and Bhagat could sort together with values around 755 mm. The Tarkhani and Kanya irrigation subdivisions could be the last group, with values around 800 mm. For the Rabi seasons, the results are simple and quite straightforward to explain due to non-significant differences in crop water consumption, with a few exceptions of some upper and lower irrigation subdivisions. The highest and lowest crop water consumption rates range between ~410 mm to ~530 mm for some upper and lower irrigation subdivisions.

5.4.5. Water Consumption by Major Crops of Rechna Doab

Crop-specific water consumption analyses were performed for all major crops including rice, cotton, fodder, wheat, and sugarcane. The multi-seasonal data analysis shows that rice is the major water consumer in the Kharif seasons with a value of 857 (±64.3) mm, followed by sugarcane with a value of 821.1 (±59.3) mm, Kharif fodder with a value of 777.4 (±45.3) mm, and cotton with a value of 768.3 (±51.4) mm. For the Rabi seasons, the difference is very small among various crops, as sugarcane consumes 520.0 (±36.0) mm, followed by wheat and Rabi fodder with values of about 512.3 (±32.0) mm and 503.1 (±29.9) mm, respectively. As cultivation areas for each crop are largely variable, thus the consumed volume of crop water is enormously different, for instance, during the Kharif seasons, the highest volume of water is consumed by the Kharif fodder with an amount of 0.94 (±0.12) M ha-m, followed by rice with an amount equal to 0.74 (±0.06) M ha-m, sugarcane with a value of 0.11 (±0.05) M.ha-m, and cotton with a value of 0.07 (±0.02) M ha-m. For Rabi, wheat is predominantly the largest water consumer amounting equal to 0.74 (±0.04) M ha-m, followed by Rabi fodder with a value of 0.36 (±0.07) M.ha-m, and sugarcane with a value of 0.07 (±0.03) M ha-m. Results of the *t*-test for the Kharif seasons show that the crop water consumption between rice and cotton and between rice and Kharif fodder is significantly different, whereas the rest of the crop combinations show non-significant results. For the Rabi seasons, all crops show non-significant results at a significant level of 95%.

5.5. Performance Assessment Results

5.5.1. Equity

The equity of irrigation systems was calculated from intra-irrigation subdivision consumptive water use, and the results are presented in the form of CV values (Figure 9). There is a mixed trend of results from upper to lower Rechna Doab. However, relatively lower CV values in the upper irrigation subdivisions indicate equitable water distribution there. The relatively cooler climate and better availability of canal water could be influencing factors to keep CV values lower in the upper regions (i.e., also mono-cropping, rice cultivation). According to [22], the groundwater quality in most of the upper Rechna Doab regions is very good, and that could also cause equitable water distribution in these areas. For Rechna Doab, generally, the irrigation subdivisions located near rivers have more heterogonous crop water utilization (i.e., variable CV) that make some areas more favorable for canal water supply than others. The lower and middle regions show more inconsistent CV values that are an indication of variable canal water supplies. Additionally, the groundwater quality deteriorates from the upper to lower Rechna regions that suppress the groundwater usage in some lower regions compared to upper regions. Shahdara, Muridke, and Sagar irrigation subdivisions are located in the upper Rechna Doab that shows a higher CV, which could be attributed to variable water supply due to their proximity to rivers Ravi and Chenab. Some regions of these irrigation subdivisions could receive less water than others, and thus influence the cultivation of crops other than rice. The middle irrigation subdivisions including Sangla and Paccadala also show relatively higher CV values that could be due to their transition from rice–wheat zone to mix cropping zone. Moreover, the availability of canal water could be variable in certain regions due to their increased distances from the LCC canal feeder. The explanation of higher CV values for Uqbana and Veryam despite their inner locations inside Rechna Doab could be due to the cultivation of sugarcane. Moreover, the groundwater quality in both of the irrigation subdivisions is poor to marginal, and that also restricts its usage in fragmented parts [22]. Among the lower irrigation subdivisions, comparatively higher CV values were observed for Dhaular, Bhagat, and Haveli irrigation subdivisions. The possible reason for the higher CV in the case of Dhaular and Haveli is their proximity to the river and the flowing of a link canal in Haveli irrigation subdivisions. These geographical features influence canal water availability for certain parts of each irrigation subdivision, which promotes diverse cropping in these regions. Bhagat irrigation subdivision is located in an inner-location of Rechna Doab, yet exhibits higher CV values that could be attributed to poor soil and water quality. Additionally, the irrigation network is not dense in this part of Rechna Doab.

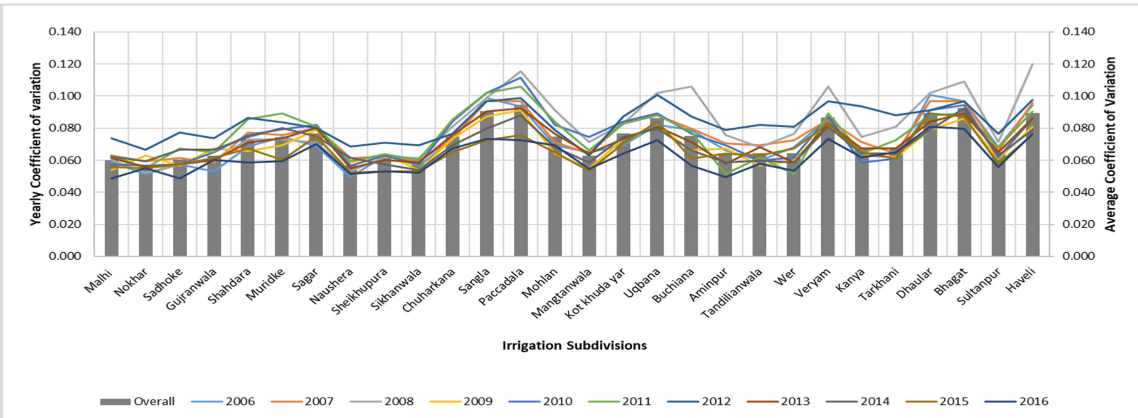


Figure 9. Irrigation subdivision level variabilities of crop water consumption (i.e., equity).

5.5.2. Adequacy

Overall Consumed Ratio (ep)

e_p would be the first indicator of any irrigation system due to the availability of data on water supply [73]. Stacked area charts (Figure 10a,b) depict ep variations both on seasonal and monthly time scales for Kharif and Rabi seasons. The average monthly values of ep for Kharif seasons show that overall crop water requirements are not met in any irrigation subdivision. The bandwidths of each month are greater than the benchmark value (i.e., average value of ≤0.54) and are growing from upper to lower irrigation subdivisions. This shows that water shortage is more pronounced in the lower regions as compared to upper regions. Individual monthly average consumptive water use indicates relatively larger insufficiency for July and August as compared to other months of the season. Similarly, from the seasonal ep values, it is clear that water supply is insufficient for the entire region, and the magnitude increases from the upper to lower irrigation subdivisions. The results are in agreement with findings from [4,22], who have reported relatively better water supply in the upper Rechna Doab.

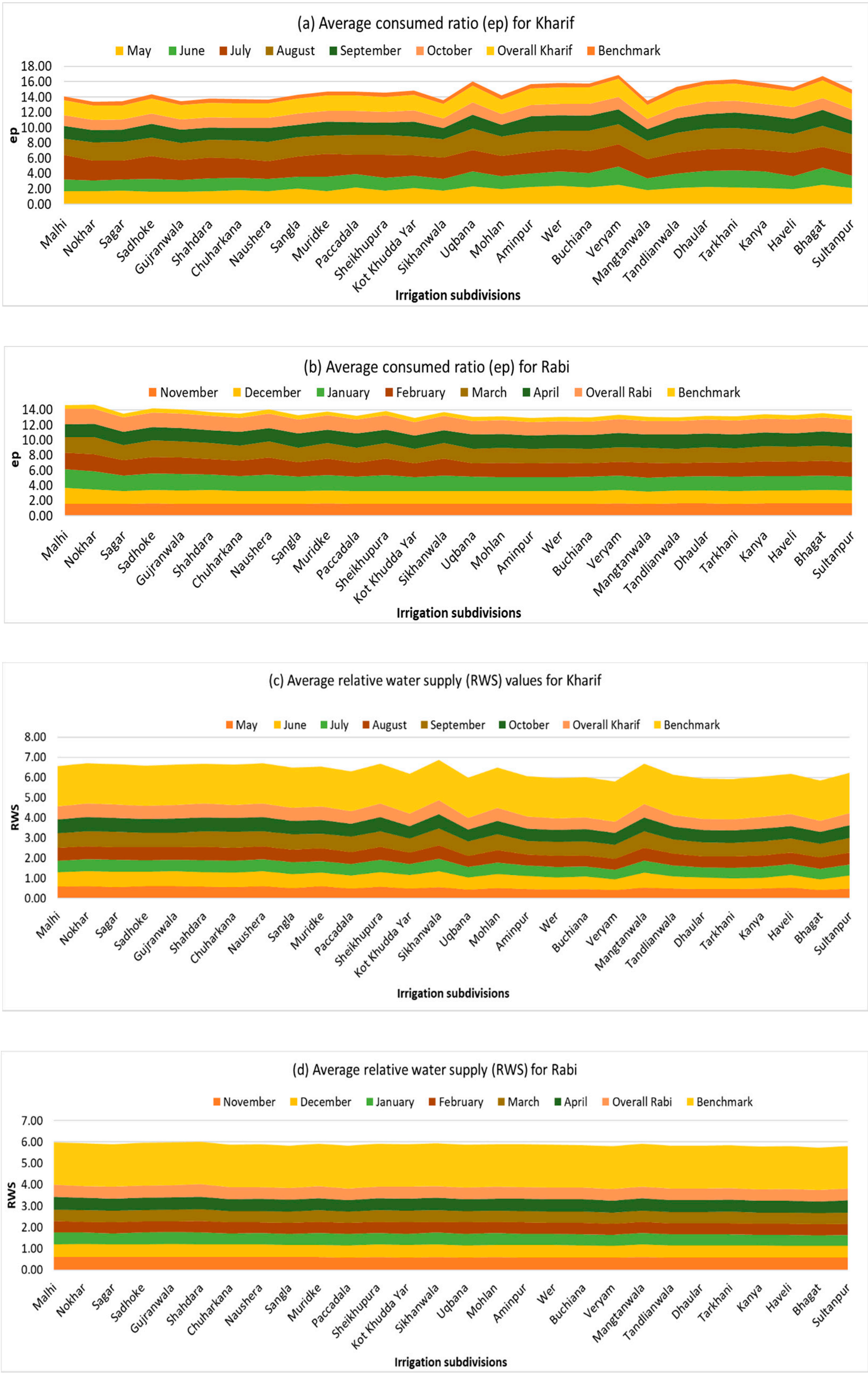


Figure 10. (**a**,**b**) Monthly and seasonal average values of the consumed ratio, (**c**,**d**) monthly and seasonal average values of relative water supply for different irrigation subdivisions. Please note down the different scale of the y-axis for different graphs.

Figure 10b shows the ep values for Rabi seasons, according to which water supply is not sufficient in any month of the season. Contrary to Kharif seasons, no increasing differences were observed for the lower irrigation subdivisions. Instead, slightly higher ep values were found in some upper irrigation subdivisions. Nevertheless, for the entire Rechna Doab, the ep values were not significantly different. It is also observed that slightly higher insufficiency was observed for January, which could be attributed to canal closures during these times. Overall, the sufficiency of water supply is better for Rabi as compared to the Kharif seasons.

Relative Water Supply (RWS)

From Figure 10c, it is evident that the water supply is never sufficient for any month of the Kharif seasons (i.e., optimal value ≥2.0). Relatively smaller values of RWS during May, July, and August were observed that are in agreement with results calculated from ep values. Higher values were observed for June and September, which is an indication of a relatively better water supply. Additionally, from the trend lines, it is clear that overall insufficiency is relatively higher in the lower Rechna regions as compared to upper regions.

For Rabi seasons, the difference among various monthly values is smaller than in Kharif seasons. Relatively smaller values of RWS were observed for February and March, whereas for the rest of the season, RWS values are nearly similar. Overall, the irrigation water supply is insufficient for the entire Rabi season, and this insufficiency is virtually analogous for the entire Rechna Doab.

Relative ET

Adequacy of an irrigation system using relative ET was explored at three spatial scales, i.e., irrigation circle, irrigation division, and irrigation subdivision. According to the findings, all irrigation circles exhibit a shortage of water availability, i.e., inadequacy. Inadequacy is relatively higher during Kharif as compared to the Rabi seasons. An EF value of 0.80 or above indicates adequate or sufficient water for agriculture [45]. The results of the *t*-test show that during the Kharif seasons, there is a significant difference between the upper Chenab irrigation circle and the rest of the regions. For the Rabi seasons, the upper Chenab and LCC west irrigation circles show analogous patterns, which are significantly different than other irrigation circles of Rechna Doab.

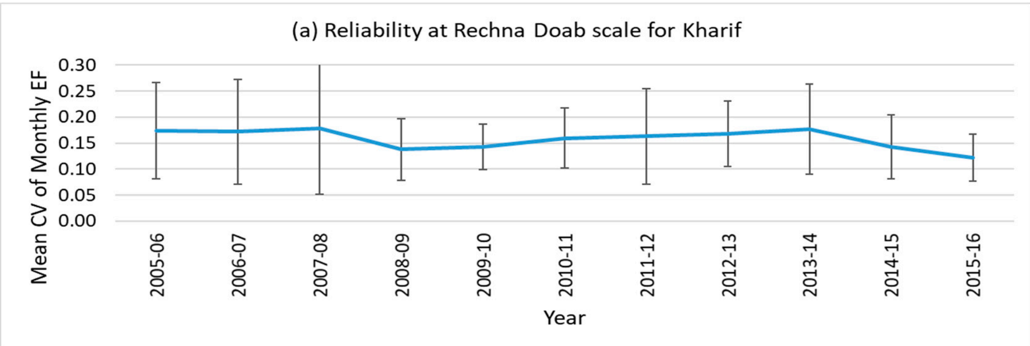
At the scale of irrigation division, all areas show water shortage (i.e., inadequacy) as average EF is smaller than 0.80. The inadequacy is relatively higher in the lower divisions as compared to upper ones, as EF values decrease from the upper to lower regions. Inadequacy is higher in Kharif compared to Rabi. Additionally, from year to year, variation is higher in Kharif as compared to Rabi seasons. There is a significant difference between upper irrigation divisions and middle and lower divisions during Kharif. The significance test results show that the difference is substantial between upper and various middle irrigation divisions, and between upper and lower irrigation divisions. For Rabi, there is still a significant difference between some upper and lower divisions (i.e., Gujranwala and Marala with lower irrigation divisions), however, results are insignificant, most of the time, for different regions.

Comparison results at the irrigation subdivision scales show a significant difference between upper and middle irrigation subdivisions, and between upper and lower irrigation subdivisions, especially for Kharif seasons. Although the canal water availability is relatively higher in the upper regions as compared to middle and lower regions, the major difference is because of rice and mix cropping between the two regions. This means additional water is supplied from groundwater sources, causing more pumping in the upper regions during the Kharif seasons [55,74]. The difference is heterogeneous and complex between middle and lower irrigation subdivisions. For the Rabi seasons, regional variation both at the middle and lower irrigation subdivisions was less.

5.5.3. Reliability

Temporal Variation of EF

For the current study, the temporal CV of EF was used to describe reliability [4,20,45] both for the Kharif and Rabi seasons (Figure 11). Apart from seasonal analysis, reliability was also explored for the Kharif and Rabi months by plotting the CV of monthly EF. Higher CV values represent less reliable irrigation water supplies and vice versa. The results for the entire Rechna Doab show that reliability is low for Kharif (i.e., CV is higher) as compared to the Rabi seasons. Within the season, less reliability is observed for Kharif that is mainly associated with higher temperatures and more scattered rainfall (i.e., July–September) in Rechna Doab. The trend line is generally flat in various Rabi seasons. Similarly, for irrigation circles, higher CV values were observed for the Kharif seasons as compared to the Rabi seasons, which represents the low reliability of water supplies. For both seasons, the CV is relatively less in the upper regions, showing relatively higher reliability as compared to lower regions. The significance test (i.e., *t*-test) results for Kharif show that the upper Chenab was significantly different than the LCC west and Multan regions. For Rabi, the Multan irrigation circle is showing significantly different results than all other irrigation circles. However, the rest of the regions show comparable outcomes in terms of reliability. At the irrigation division scales, the results are alike irrigation circles where the upper regions show comparatively lower CV values and resultantly higher reliability than the lower regions. The variability among various irrigation divisions is also higher for Kharif as compared to the Rabi seasons, which shows a more heterogeneous water supply during the season. At the smallest spatial scale (i.e., irrigation subdivision), mixed results of reliability were observed. Specifically, there is a significant difference between some upper and lower irrigation subdivisions (Figure 11g,h). Nevertheless, there are various regions in the middle and lower reaches of Rechna Doab that show non-significant results. The results for both Kharif and Rabi seasons are similar and completely random, overall showing less reliability of the irrigation system.



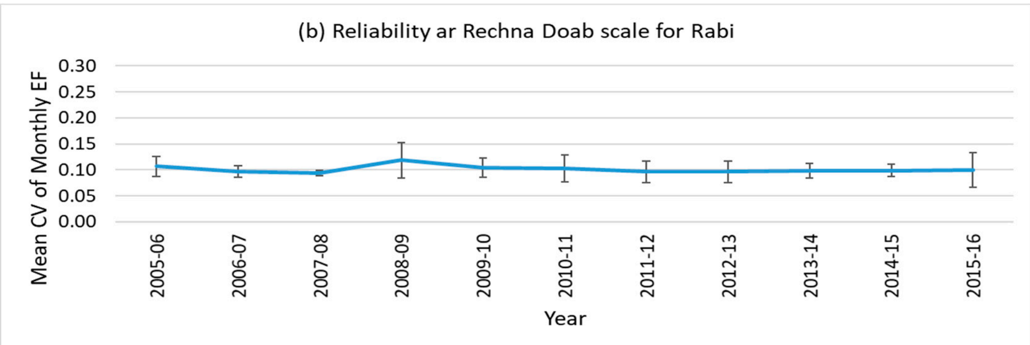


Figure 11. *Cont.*

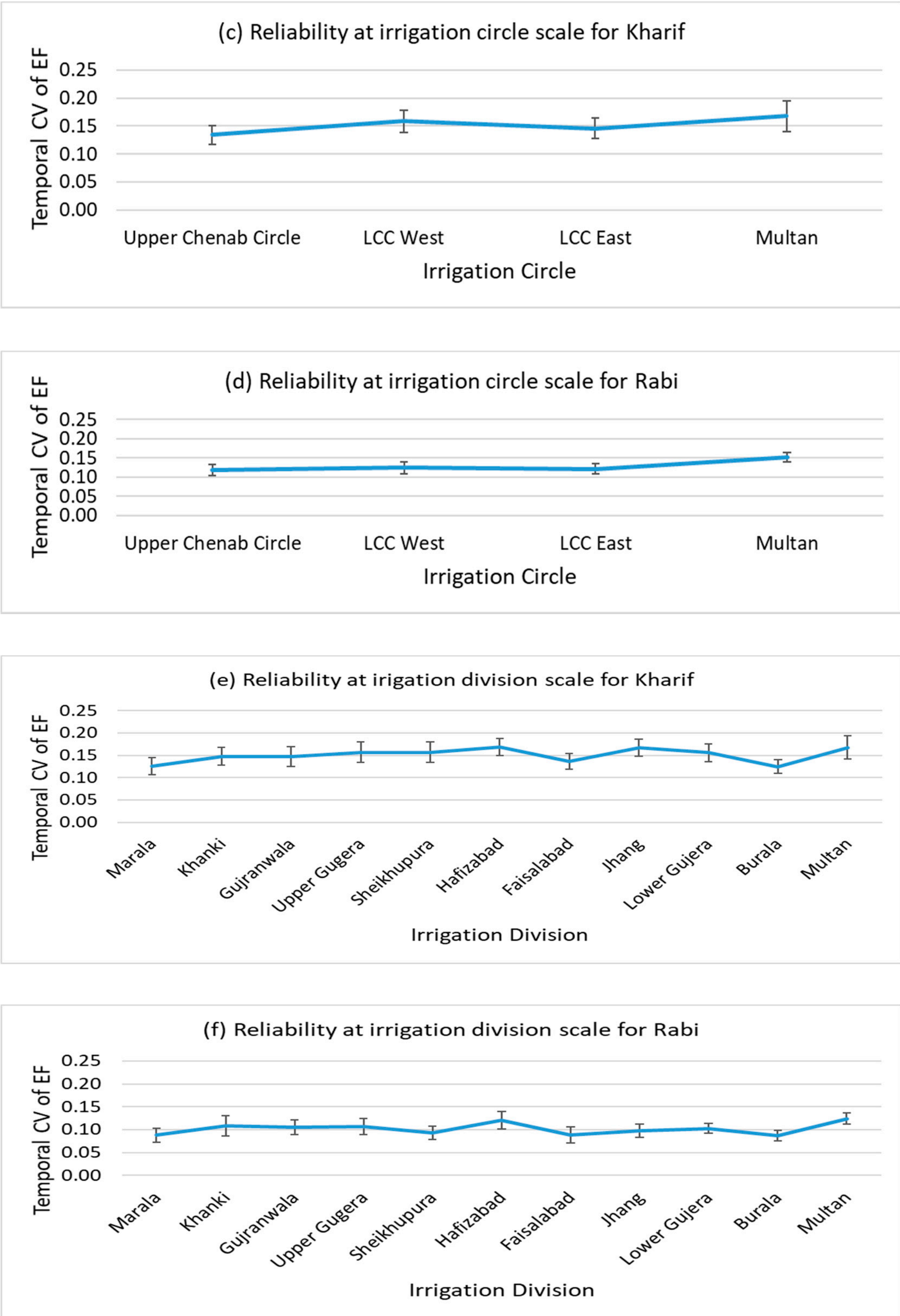
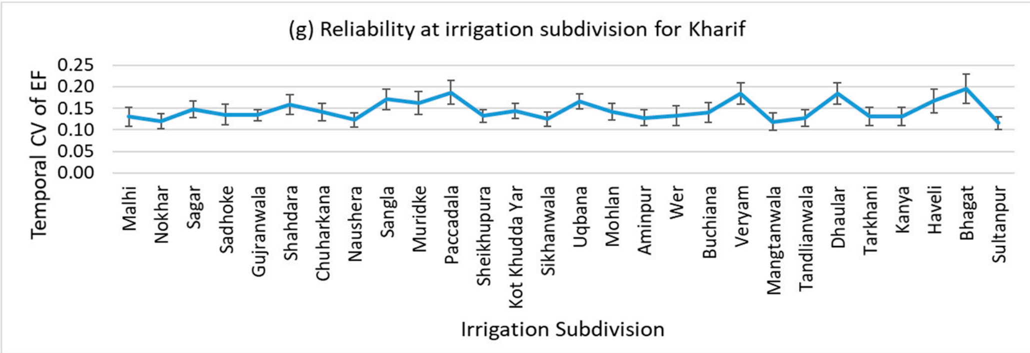


Figure 11. *Cont.*



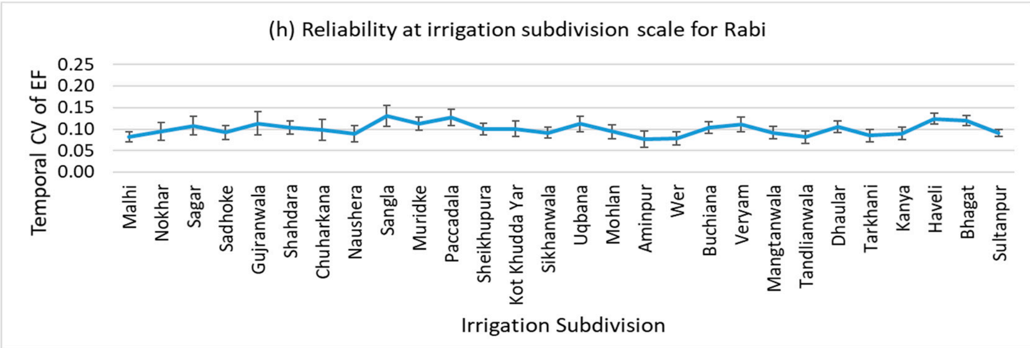


Figure 11. Reliability results for (**a**,**b**) Rechna Doab (**c**,**d**) irrigation circle (**e**,**f**) irrigation division and (**g**,**h**) irrigation subdivision spatial scales for the Kharif and Rabi seasons.

Crop Water Deficit (CWD)

The average monthly CWD values were found higher than the targeted value of ≤30 mm. month^{-1} both for the Kharif and Rabi seasons (Figure 12). For the Kharif seasons, the period from May to June is observed with the largest CWD values, whereas October is a month with the lowest CWD values. This indicates that the reliability of the irrigation system is lowest during May and June, and highest in October. For a particular irrigation subdivision, lack of month-to-month homogeneity is observed that is also an indication of poor reliability of the irrigation system. The overall seasonal values of CWD are fluctuating between 80–90 mm month^{-1}, which is certainly on a higher side. For the Rabi seasons, April and March showed the highest CWD values, whereas November, December, and January resulted in CWD values around 40 mm month^{-1}, which are quite close to the benchmark value. Overall, the system reliability is poor both for the Kharif and Rabi seasons. The spatial analysis results of CWD showed the unreliability of the irrigation system for the entire Rechna Doab.

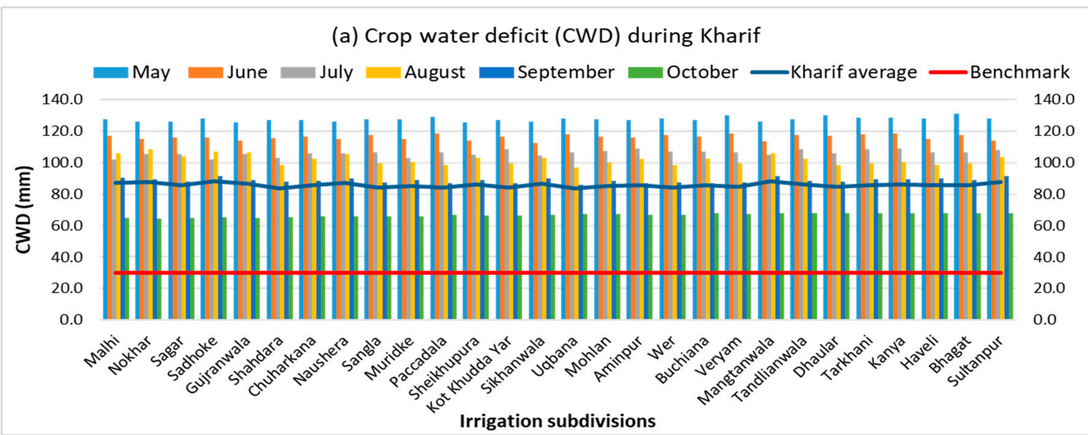


Figure 12. *Cont.*

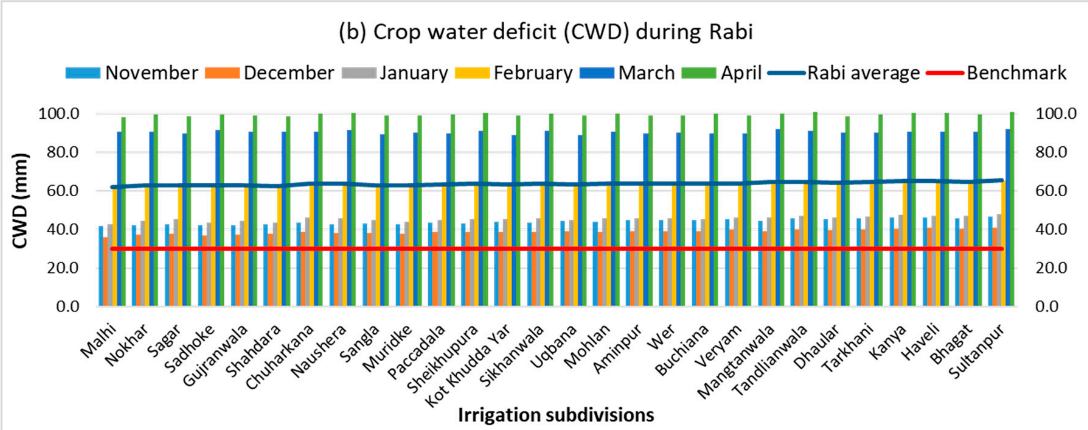


Figure 12. Monthly and seasonal average crop water deficit values for different irrigation subdivisions during the (**a**) Kharif and (**b**) Rabi seasons.

5.6. Indicators/Variables Importance Assessment

5.6.1. Importance Assessment by Different Seasons

Figure 13 shows the indicator assessment results of consumptive water use for the Kharif and Rabi seasons. Three different sets of indicators are represented i.e., site-specific variables, proximity variables, and cropping system indicators. Multi-seasonal crop data (i.e., agriculture) analyses show that for the Kharif seasons, consumptive water use was majorly influenced by the site-specific indicators followed by proximity and cropping system indicators. Overall, canal distance is the most influential variable that explains consumptive water use in Rechna Doab. From the list of site-specific indicators, the slope was found to be the most important indicator, followed by soil texture, road density, and canal density. However, the uncertainty was highest in the case of soil texture. From proximity indicators, road distance was placed at a second-place, followed by water area distances and distances from the settlements (i.e., city). However, the uncertainties were highest for distances from roads and cities. Most definite results were observed for distances from the water areas, as the least uncertainty was found in this case. Cropping system indicators influence consumptive water usage least, which could be attributed to an analogous diversity for the entire Rechna Doab. For the Rabi seasons, canal distances are no more the most influential indicator for consumptive water use. Various indicators show similar patterns with comparable higher uncertainties. The potential reason could be the lower water demand by crops in winter, and also wheat and Rabi fodders are cultivated on extensive lands in Rechna Doab. Overall, the site-specific and cropping system indicators better explain the patterns of consumptive water usage.

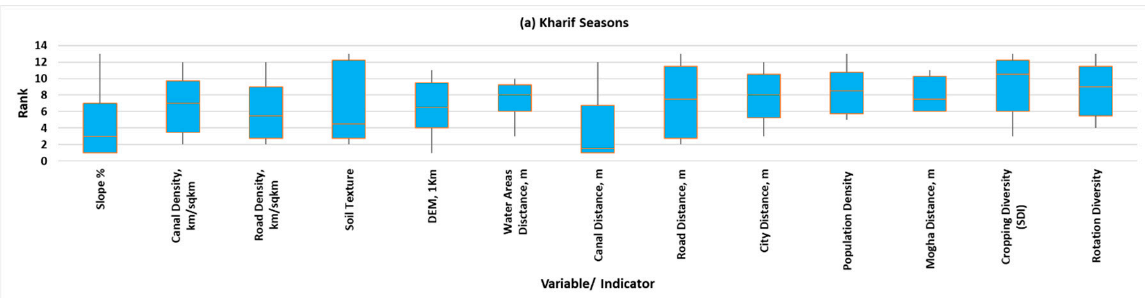


Figure 13. *Cont.*

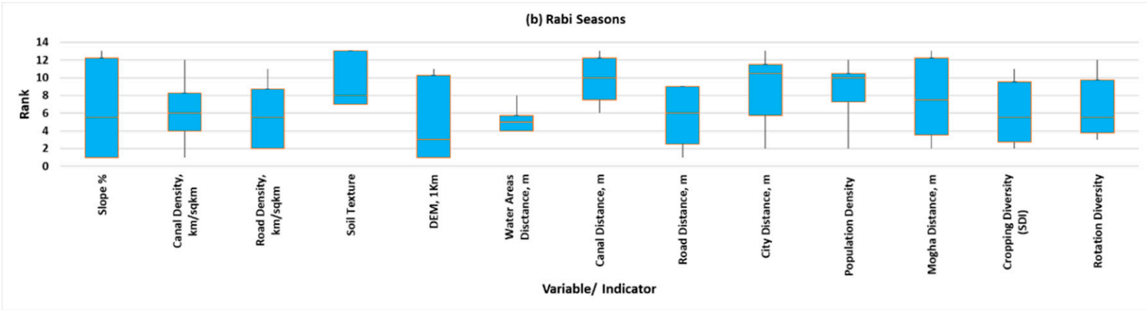


Figure 13. Indicators/variables importance ranking for consumptive water use during the (**a**) Kharif and (**b**) Rabi seasons.

5.6.2. Importance Assessment by Crop Types

The crop-wise indicator importance assessment results are shown in Figure 14. According to that, elevation was the most influential variable for rice. The other important indicators are canal density and canal distances from the fields. Since rice is a heavily irrigated crop, therefore its proximity to the irrigation system would be advantageous. Nevertheless, the results of mogha distances show that rice cultivation was not entirely influenced by canal irrigation, and also heavily dependent on groundwater (i.e., low rank and higher deviations). This could also be realized by the distances from the settlements (i.e., cities). Short distances from settlements are advantageous for easy farm access in performing various irrigation and farming related practices. For cotton, the population density was found to be the most influential variable because it is an extensively labor-intensive crop, right from cultivation to harvesting, for spraying, fertilizing, and cotton picking. The elevation is also influential for cotton due to its cultivation in specific agro-ecological conditions. Cotton is mainly cultivated in the lower reaches of Rechna Doab and cannot be grown in the upper regions due to more rainfall and humid conditions compared to the lower regions. Canal density and field distances from canals are not influential for cotton due to its less intensified irrigation demands. Results of sugarcane bear a resemblance to rice. Sugarcane cultivation is mainly influenced by elevation (i.e., majorly cultivated in the middle regions of the Rechna Doab). Moreover, distances from the cities and road density were also important due to the fact of its transportation to sugar mills after harvesting. Most of the sugar mills are constructed near to cities due to better infrastructure. Mogha distances, canal density, and canal distances are also vital due to its higher water requirements. Sugarcane is a perennial crop, so the maximum utility of canal water is advantageous for optimal utilization of resources. For wheat, elevation and canal density were considered the most influential variables. This does not prove its higher dependence on canal irrigation, but the fact is that in the upper Rechna regions, farmers practice mainly rice–wheat rotation. Wheat is cultivated extensively throughout the Rechna Doab during the Rabi seasons.

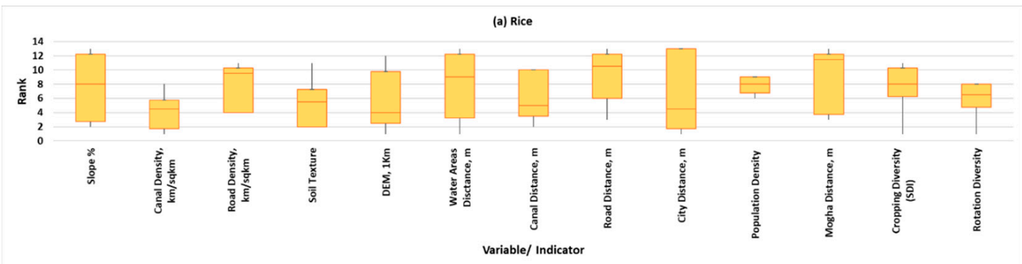


Figure 14. *Cont.*

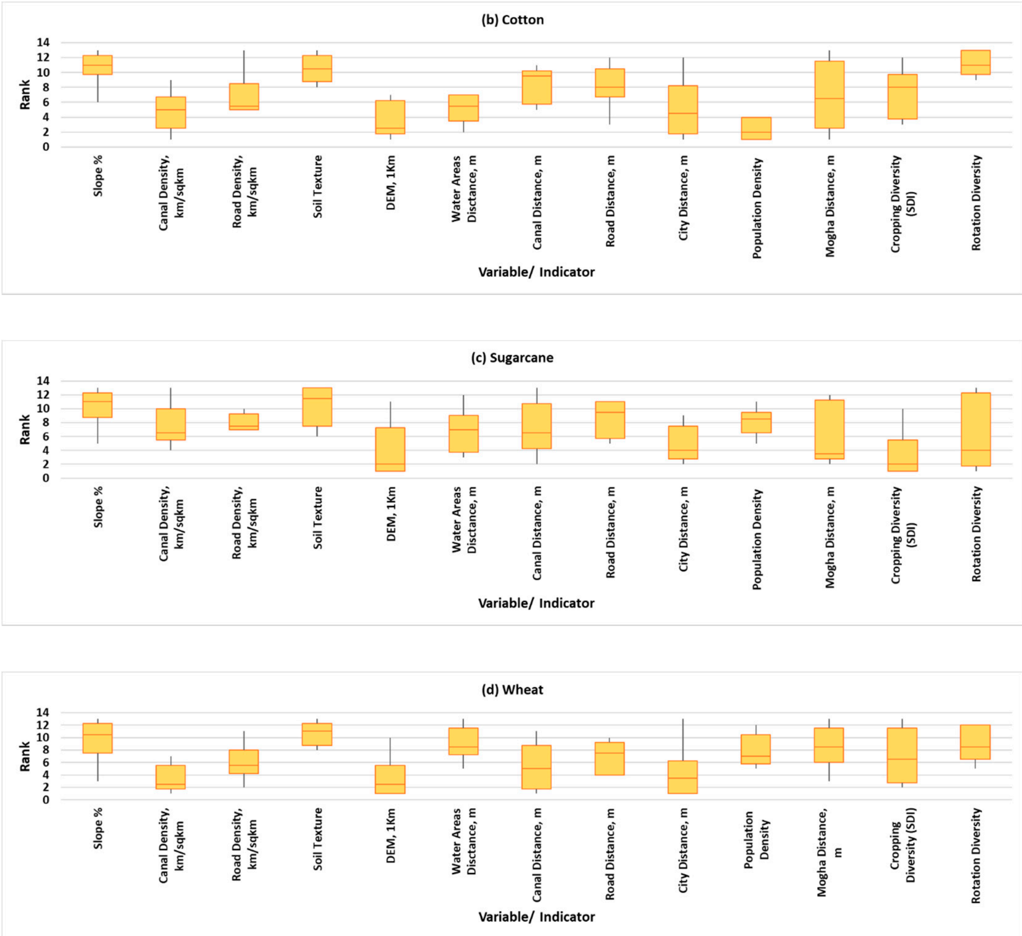


Figure 14. Indicators/variables importance ranking for (**a**) rice (**b**) cotton (**c**) sugarcane and (**d**) wheat crops in Rechna Doab.

5.6.3. Importance Assessment by Overall Consumptive Water Use

The top two indicators could be identified for each crop that belongs to either indicator class "proximity" or "site-specific". These indicators are the distance from canal, distance from canal outlet, elevation, and canal density. It is obvious that consumptive water use is highest for rice and sugarcane crops, and with the increase in distance from the canal, the water consumption decreases. Regarding the effects of site-specific variables, rice was planted under a wide range of canal densities ranging up to 10 km·km^{-2} in comparison to 4–5 km·km^{-2} for sugarcane. One explanation of this phenomenon could be its vast cultivation in upper Rechna Doab and equivalent dependency on canal and groundwater (i.e., intensive irrigations are required for rice throughout the season).

Sugarcane is mainly cultivated near riversides of the middle Rechna regions. Though water demand for sugarcane is high especially during the Kharif seasons, however, it does not require frequent irrigations like rice, so flexible irrigation planning using both canal and groundwater is possible. Cotton is cultivated mainly in the lower to middle reaches of Rechna (i.e., 130–180 m above MSL) whereas wheat is cultivated in the entire Rechna Doab (i.e., elevation from 130–240 m above MSL). From the results, it is clear that the scatter ability of pixels for cotton consumptive water use is similar for near and far distances, which is an indication of its low dependency on canal irrigation. For wheat, water consumption is fairly uniform (i.e., less variability of values along the y-axis compared to rice or sugarcane) along with the distances from the canal, which could be explained by the limited canal water availability due to canal closures and decreased flows in the upper Rechna Doab regions.

6. Discussion

6.1. Validation & Plausibility Assessment

Overall, SEBAL under-estimates ET_a as compared to AA, which could be because actual irrigation conditions cannot fully be reflected by the AA approach. Water-limited conditions indeed prevail in Rechna Doab, and the overall crop water demands are not fully met. This could also be reflected from the difference between ET_o (i.e., PM method) and actual ET_a (i.e., SEBAL).

Overall, the results are very acceptable considering the difference of scale on which both data were compared. In the case of SEBAL, there is a fair chance of mixing of pure agricultural regions with urban regions within a spatial scale of 1 km^2 that could result in the overestimation of fluxes (i.e., positive BIAS values).

6.2. Irrigation Source and Consumptive Water Usage

From the historical data analyses, it is clear that canal water supply is on the decline in Rechna Doab, along with significantly decreasing rainfall, especially in the middle and lower regions. On the other hand, according to [75], crop irrigation requirements would significantly increase in the coming years. The major reasons are elevated temperatures and decreasing air humidity. Moreover, the rainfall would also significantly decrease in Rechna Doab in the future. This sets back in two ways; first it cuts canal water supply share of rainfall and increasing crop water demands, and secondly it increases the load on groundwater resources. According to the study findings of [4,55], monthly potential evapotranspiration is much higher throughout the year as compared to monthly average rainfall, particularly in the middle and lower regions of Rechna Doab. Reference [76] confirmed that groundwater utilization is already on the rise in Punjab, including Rechna Doab. The consequences include lower crop yields, increasing energy costs, and land abandonment due to increasing secondary soil salinity [77,78].

6.3. Canal Water Supplies and Irrigation System Performance

Canal water supply is larger during Kharif, however, the canal water shortage is also higher mainly due to more crop water demands in the hot summer months. Like rainfall in the Rechna Doab, the canal water availability is heterogeneous in various regions that can be observed at closer canal distances through more variation of consumptive water use. This could be attributed to more flexible irrigation plans there. As we move farther from the canals, the distribution limb of consumptive water use values becomes narrow, which indicates more dependence on groundwater and alike irrigation practices. For the Rabi seasons, consumptive water use is about 60% of the Kharif seasons. Irrigation water availability in November is vital for the vast irrigation of the wheat crop. Any shortage during this time could delay the cultivation of wheat and thus adversely affect its yields [79]. According to [80], water availability for wheat in the country is about 26 MAF (million-acre feet), which is 28.6% lower than the requirement. Nevertheless, soil moisture storage in rice cultivated regions along with some early season rainfall could safeguard against early-season water stress and resultantly yield losses [81,82]. Comparatively higher consumptive water use in the upper Rechna Doab is an indication of this phenomenon.

The natural imbalance of irrigation demand and supply is further extravagated due to the poor performance of the irrigation system in the region. Differences in water distribution can be observed between upper and lower irrigation subdivisions. The major reasons are comparably more canal water availability in the upper irrigation subdivisions [4] and good groundwater quality [22]. Higher water availability encourages mono-cropping (i.e., Rice) in the upper regions. However, for lower regions, marginal to poor groundwater quality and limited canal water availability is a hindrance in accomplishing irrigation equity. It would further result in elevated differences in energy demands between the two regions.

Likewise, both spatial and temporal inequalities are observed for the irrigation system adequacy. It is more pronounced for Kharif as compared to the Rabi seasons, profoundly not due to less canal water supply, but due to elevated crop water demands as a result of harsh climatic conditions.

Adequacy is highest in July–August and January during the Kharif and Rabi seasons, respectively. During Kharif, canal closures due to river flooding could be a major reason, which puts an extra burden on groundwater during these times. Similarly, canal closure in January is the major reason. Rainfalls during January and February are very beneficial for avoiding early water and heat stresses to wheat.

The irrigation system reliability is another challenge in the region, as it is low both for the Kharif and Rabi seasons. Comparatively, reliability is better in the upper Rechna regions due to better canal water availability and higher rainfall. For Kharif seasons, reliability could not be achieved in any month and it is highest in May and June. The reasons are higher competition for irrigation of various newly cultivated crops, low rainfall, and decreased river flows. For the Rabi seasons, reliability is maximum from November to January, mainly due to the low demand for water by crops due to the cool environment. Reliability is lowest in March and April due to dry and hot weather at the end of the wheat cropping season. However, such climatic conditions, particularly in April, are advantageous to avoid lodging of wheat.

6.4. The Current Balance of Crop Water Usage and Required Actions

The audit results of water usage for various crops can be seen from Figure 15. The results are based on data analysis from the last five cropping seasons for all major crops including rice, sugarcane, cotton, and wheat. These results are based on the number of cumulative years ranging from one year to a maximum of five years of consumptive water use data. The pixels of each crop are selected based on the crop map for a particular season and the histogram analysis was performed. The data follows the normal distribution, so average (~median) consumptive water use value was selected as a benchmark to estimate its difference from the 5th and 95th percentile values that would represent the so-called under and over irrigated pixels of a particular crop.

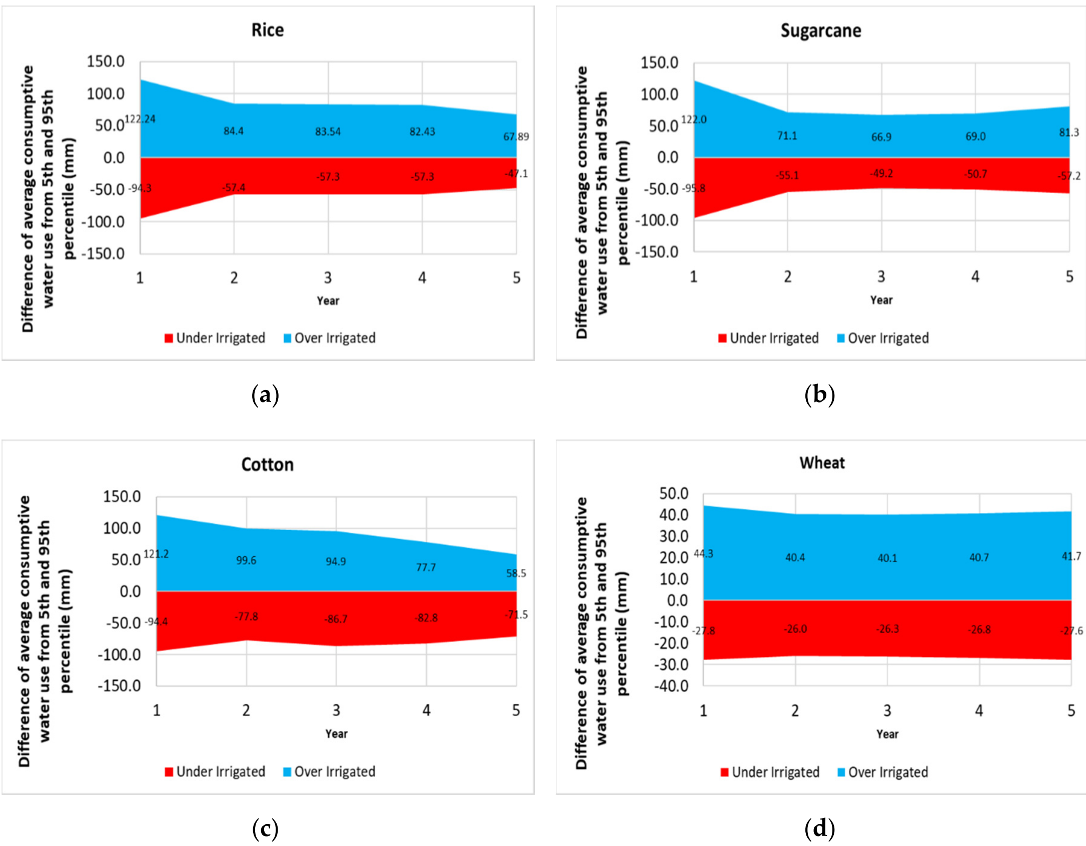


Figure 15. Crop specific consumptive water use difference of average value with 5th and 95th percentile for (**a**) rice (**b**) sugarcane (**c**) cotton and (**d**) wheat. The blue color shows a positive deviation from the average value and the red color shows the negative deviation from the average value.

The outcome indicates a considerably positive equilibrium for all crops. The reason could be its strong perseverance against water and salinity stress [83] in comparison to the other crops. These results are an indication of the optimization of resources through on-farm management practices. In recent years, a lot of efforts have been put on the lining of irrigation channels and laser land leveling in Rechna Doab [84,85]. On-farm water management is a continuous process and cannot be halted. Moreover, further actions are required through a targeted and well-thought policy formulation. For example, the consumptive water use (i.e., water availability) of all crops is greatly influenced by the distance from the canals that give a clue to revise the water allowance for near and remote canal regions. Similarly, the canal lining at its secondary or tertiary levels could save considerable water by cutting seepage losses that would improve water availability in far regions.

7. Conclusions

Satellite remote sensing has played a major role in estimating consumptive water use and its workability for resource optimization in recent years. The results of the present study indicate that remote sensing successfully helps to overcome issues of inherent spatial and temporal scaling associated with field-based approaches. The barriers of availability of remote sensing data for capturing field-scale heterogeneity and high temporal coverage are diminishing quickly. The rapid improvement in the algorithms for estimating spatial consumptive water use has increased its utility and confidence for the successful evaluation of the irrigation systems all around the world. The current study has successfully employed remote sensing data and techniques to estimate consumptive water use for demand–supply gaps and performance assessment of irrigation system efficiencies at various spatiotemporal scales. Various indicators utilized to assess efficiencies show that the system is underperforming in all aspects including equity, adequacy, and reliability. The situation is relatively intense during the Kharif seasons mainly due to harsh weather conditions and thus higher competition for canal water. Additionally, the result disparities exist between some upper and lower regions of Rechna Doab, according to which the lower regions are relatively bad performing. The modelling results indicate that specific consumptive water use is affected by various indicators comprised of distance from canal, elevation, canal density, and distances from cities. These results emphasize the importance of crop specifically targeted on-farm water management policies. The net crop-specific differences of average consumptive water use from the 5th and 95th percentile are largely positive. This insight is needed for on-farm water management strategies for water resource optimization. Important steps for future work include further exploration of multi-source high-resolution remote sensing data for various agricultural systems, which could be done by further development of algorithms. Current results are based on the assessment of current data without considering the changes in canal water supplies and crop demands under climate change conditions.

Author Contributions: The manuscript was written with contributions from authors. M.U., conceptualization, methodology, software. T.M., data collection, writing. C.C., conceptualization, methodology, resources, supervision. H.U.B., data, reviewing, local expert opinion. All authors have read and agreed to the published version of the manuscript.

Funding: We are thankful to the funding agency. The research was conducted in the scope of the joint research project, Innovative Impulses Reducing the Water Footprint of the Global Cotton-Textile Industry towards the UN Sustainable Development Goals (InoCottonGROW)" and is supported by the Federal Ministry of Education and Research (BMBF) under the terms of its funding initiative "Global Resource Water (GROW)" [BMBF reference no. 02WGR1422].We acknowledge the financial support within the funding programme Open Access Publishing by the German Research Foundation (DFG).

Conflicts of Interest: The authors declare no conflict of interest.

References

1. *Global Risk Report*, 14th ed.; World Economic Forum: Cologny, Switzerland, 2019; ISBN 978-1-944835-15-6. Available online: https://www.weforum.org/reports/the-global-risks-report-2019 (accessed on 20 September 2020).
2. Momblanch, A.; Papadimitriou, L.; Jain, S.K.; Kulkarni, A.; Ojha, C.S.P.; Adeloye, A.J.; Holman, I.P. Untangling the water-food-energy-environment nexus for global change adaptation in a complex Himalayan water resource system. *Sci. Total Env.* **2019**, *655*, 35–47. [CrossRef]
3. World Population Prospects. United Nations, 2019. Available online: https://population.un.org/wpp/ (accessed on 20 September 2020).
4. Usman, M.; Liedl, R.; Awan, U.K. Spatio-temporal estimation of consumptive water use for assessment of irrigation system performance and management of water resources in irrigated Indus Basin, Pakistan. *J. Hydrol.* **2015**, *525*, 26–41. [CrossRef]
5. Alexandratos, N.; Bruinsma, J. World Agriculture towards 2030/2050: 2012. Available online: http://www.fao.org/fileadmin/templates/esa/Global_persepctives/world_ag_2030_50_2012_rev.pdf (accessed on 20 September 2020).
6. Gowda, P.; Chávez, J.L.; Colaizzi, P.D.; Evett, S.R.; Howell, T.A.; Tolk, J.A. Remote sensing-based energy balance algorithms for mapping ET: Current status and future challenges. *Trans. Asabe.* **2007**, *50*, 1639–1644. [CrossRef]
7. USAID. Securing Water for Food: A Grand Challenge for Development Announces Fourth Call for Innovations. 2016. Available online: https://2012-2017.usaid.gov/news-information/press-releases/aug-15-2016-securing-water-food-grand-challenge-development-announces-fourth (accessed on 20 September 2020).
8. World Bank. *A Water-Secure World for All*; World Bank: Washington, DC, USA, 2016; Available online: http://pubdocs.worldbank.org/en/980511475504050046/Water-GP-Brochure-Final-Oct01-2016-web.pdf (accessed on 20 September 2020).
9. Sanchis-Ibor, C.; García-Mollá, M.; Avellà-Reus, L. Effects of drip irrigation promotion policies on water use and irrigation costs in Valencia. Spain. *Water Policy.* **2017**, *19*, 165–180. [CrossRef]
10. Scott, C.; Vicuña, S.; Blanco-Gutiérrez, I.; Meza, F.; Varela-Ortega, C. Irrigation efficiency and water-policy implications for river basin resilience. *Hydrol. Earth Syst. Sci.* **2014**, *18*, 1339–1348. [CrossRef]
11. Pfeiffer, L.; Lin, C.Y.C. Does efficient irrigation technology lead to reduced groundwater extraction? Empirical evidence. *J. Env. Econ. Manag.* **2014**, *67*, 189–208. [CrossRef]
12. Keller, A.; Keller, J. Effective efficiency: A water use concept for allocating freshwater resources. In *Resources and Irrigation Division Discussion Paper 22*; Winrock Int.: Arlington, VA, USA, 1995; Available online: https://www.pacificwater.org/userfiles/file/IWRM/Toolboxes/WUE/Effective%20Efficiency%20and%20water.pdf (accessed on 20 September 2020).
13. Simons, G.W.H.; Bastiaanssen, W.G.M.; Cheema, M.J.M.; Ahmad, B.; Immerzeel, W.W. A novel method to quantify consumed fractions and non-consumptive use of irrigation water: Application to the Indus Basin Irrigation System of Pakistan. *Agric. Water Manag.* **2020**, 236. [CrossRef]
14. Dagnino, M.; Ward, F.A. Economics of agricultural water conservation: Empirical analysis and policy implications. *Int. J. Water Resour. Dev.* **2012**, *28*, 577–600. [CrossRef]
15. Simons, G.W.H.; Bastiaanssen, W.G.M.; Immerzeel, W.W. Water reuse in river basins with multiple users: A literature review. *J. Hydrol.* **2015**, *522*, 558–571. [CrossRef]
16. Wiener, M.J.; Jafvert, C.T.; Nies, L.F. The assessment of water use and reuse through reported data: A US case study. *Sci. Total Env.* **2016**, *539*, 70–77. [CrossRef]
17. Molden, D. *Accounting for Water Use and Productivity SWIM Paper 1*; International Irrigation Management Institute (IIMI): Colombo, Sri Lanka, 1997; Available online: http://www.iwmi.cgiar.org/Publications/SWIM_Papers/PDFs/SWIM01.PDF (accessed on 20 September 2020).
18. Karatas, B.S.; Akkuzu, E.; Unal, H.B.; Asik, S.; Avci, M. Using satellite remote sensing to assess irrigation performance in Water User Associations in the Lower Gediz Basin, Turkey. *Agric. Water Manag.* **2009**, *96*, 982–990. [CrossRef]
19. Usman, M.; Liedl, R.; Shahid, M.A. Managing irrigation water by yield and water productivity assessment of a rice-wheat system using remote sensing. *J. Irrig. Drain. Eng.* **2014**, *140*. [CrossRef]
20. Awan, U.; Tischbein, B.; Conrad, C. Remote sensing and hydrological measurements for irrigation performance assessments in a water user association in the lower Amu Darya River Basin. *Water Resour. Manag.* **2011**. [CrossRef]

21. Bos, M.G.; Burton, M.A.; Molden, D.J. *Irrigation and Drainage Performance Assessment: Practical Guidelines*; CABI Publishing: Wallingford, UK, 2005; p. 158.
22. Ahmad, M.D.; Turral, H.; Nazeer, A. Diagnosing irrigation performance and water productivity through satellite remote sensing and secondary data in a large irrigation system of Pakistan. *Agric. Water Manag.* **2009**, *96*, 551–564. [CrossRef]
23. Allen, R.G.; Tasumi, M.; Trezza, R. Satellite-based energy balance for mapping evapotranspiration with internalized calibration (METRIC) model. *J. Irrig. Drain Eng.* **2007**, *133*, 380–394. [CrossRef]
24. Bastiaanssen, W.G.M.; Menenti, M.; Feddes, R.A.; Holtslag, A.A.M. A remote sensing surface energy balance algorithm for land (SEBAL) formulation. *J. Hydrol.* **1998**, *212–213*, 198–212. [CrossRef]
25. Menenti, M.; Choudhury, B.J. Parameterization of land surface evapotranspiration using a location dependent potential evapotranspiration and surface temperature range. In *Exchange Processes at the Land Surface for a Range of Space and Time Scale*; Bolle, H.J., Feddes, R.A., Kalma, J.D., Eds.; IAHS Publication: Wallingford, UK, 1993; Volume 212, pp. 561–568.
26. Roerink, G.J.; Su, Z.; Menenti, M. S-SEBI: A simple remote sensing algorithm to estimate the surface energy balance. *Phys. Chem. Earth* **2000**. [CrossRef]
27. Sun, L.; Anderson, M.C.; Gao, F.; Hain, C.R.; Alfieri, J.G.; Sharifi, A.; McCarty, G.; Yang, Y.; Yang, Y. Investigating water use over the Choptank River Watershed using a multisatellite data fusion approach. *Water Resources Res.* **2017**, *53*, 5298–5319. [CrossRef]
28. Yang, Y.; Anderson, M.C.; Gao, F.; Hain, C.; Kustas, W.P.; Meyers, T.; Crow, W.; Finocchiaro, R.G.; Otkin, J.A.; Sun, L.; et al. Impact of tile drainage on evapotranspiration (ET) in South Dakota, USA based on high spatiotemporal resolution ET time series from a multi satellite data fusion system. *J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2017**, *10*, 2550–2564. [CrossRef]
29. Kustas, W.P.; Norman, J.M. A two-source approach for estimating turbulent fluxes using multiple angle thermal infrared observations. *Water Resour Res.* **1997**, *33*, 1495–1508. [CrossRef]
30. Bastiaanssen, W.G.M.; Molden, D.J.; Makin, I.W. Remote sensing for irrigated agriculture: Examples from research and possible applications. *Agr. Wat. Mngmnt.* **2000**, *46*, 137–155. [CrossRef]
31. Allen, R.; Irmak, A.; Trezza, R. Satellite based ET estimation in agriculture using SEBAL and METRIC. *Hydrol. Process* **2011**. [CrossRef]
32. Fang, S.; Jia, R.; Tu, W.; Sun, Z. Assessing Factors Driving the Change of Irrigation Water-Use Efficiency in China Based on Geographical Features. *Water* **2017**, *9*, 759. [CrossRef]
33. Huang, Q.; Xu, Y.; Kovacs, K.; West, G. Analysis of factors that influence the use of irrigation technologies and water management practices in Arkansas. *J. Agric. Appl. Econ.* **2017**, *49*, 159–185. [CrossRef]
34. Samian, M.; Mahdei, K.N.; Saadi, H.; Movahedi, R. Identifying factors affecting optimal management of agricultural water. *J. Saudi Soc. Agr. Sci.* **2015**, *14*, 11–18. [CrossRef]
35. Aslam, M.; Prathapar, S.A. Strategies to mitigate secondary salinization in theIndus Basin of Pakistan: A selective review. In *Research Report 97*; International Water Management Institute (IWMI): Colombo, Sri Lanka, 2006; Available online: https://www.iwmi.cgiar.org/publications/iwmi-research-reports/iwmi-research-report-97/ (accessed on 20 September 2020).
36. Kazmi, S.I.; Ertsen, M.W.; Asi, M.R. The impact of conjunctive use of canal and tubewell water in Lagar irrigated area, Pakistan. *Phys. Chem. Earth.* **2012**, *47–48*, 86–98. [CrossRef]
37. Badruddin, M. *Country Profile. Pakistan Internal Report*; International Water Management Institute (IWMI): Lahore, Pakistan, 1996.
38. Usman, M.; Qamar, M.U.; Becker, R.; Zaman, M.; Conrad, C.; Salim, S. Numerical modelling and remote sensing based approaches for investigating groundwater dynamics under changing land-use and climate in the agricultural region of Pakistan. *J. Hydrol.* **2020**, *581*, 124408. [CrossRef]
39. Latifovic, R.; Olthof, I. Accuracy assessment using sub-pixel fractional error matrices of global land cover products derived from satellite data. *Remote. Sens. Environ.* **2004**, *90*, 153–165. [CrossRef]
40. Kongo, M.; Jewitt, G.; Lorentz, S. Evaporative water use of different land uses in the upper-Thukela river basin assessed from satellite imagery. *Agric. Water Manag.* **2011**, *98*, 1727–1739. [CrossRef]
41. Liaqat, U.W.; Choi, M.; Awan, U.K. Spatio-temporal distribution of actual evapotranspiration in the Indus Basin Irrigation System. *Hydrol. Process.* **2015**, *29*, 2613–2627. [CrossRef]
42. Perry, C.J. *Quantification and Measurement of a Minimum Set of Indicators of the Performance of Irrigation Systems*; International Irrigation Management Institute: Colombo, Sri Lanka, 1996.

43. Bos, M.G.; Nugteren, J. On irrigation efficiencies. In *International Institute for Land Reclamation and Improvement (ILRI)*; ILRI Publication: Wageningen, the Netherlands, 1990; Volume 19, p. 138.
44. Roerink, G.J.; Bastiaanssen, W.G.M.; Chambouleyron, J.; Menenti, M. Relating crop water consumption to irrigation water supply by remote sensing. *Water Resour. Manag.* **1997**, *11*, 445–465. [CrossRef]
45. Bastiaanssen, W.G.M.; Bos, M.G. Irrigation performance indicators based on remotely sensed data: A review of literature. *Irrig. Drain. Syst.* **1999**, *13*, 291–311. [CrossRef]
46. Bastiaanssen, W.G.M.; Brito, R.A.L.; Bos, M.G.; Souza, R.A.; Cavalcanti, E.B.; Bakker, M.M. Low cost satellite data for monthly irrigation performance monitoring: Benchmarks from Nilo Coelho, Brazil. *Irrig. Drain. Syst.* **2001**, *15*, 53–79. [CrossRef]
47. Tischbein, B.; Manschadi, A.M.; Conrad, C.; Hornidge, A.; Bhaduri, A.; Hassan, M.U.; Lamers, J.P.A.; Awan, U.K.; Vlek, P.L.G. Adapting to water scarcity:constraints and opportunities for improving irrigation management inKhorezm, Uzbekistan. *Water Sci. Technol. Water Supply.* **2013**, 337–348. [CrossRef]
48. Reddy, J.M.; Muhammedjanov, S.; Jumaboev, K.; Eshmuratov, D. Analysis of cotton water productivity in Fergana Valley of central Asia. *Agric. Sci.* **2012**, *3*, 822–834. [CrossRef]
49. Sichoongwe, K.; Mapemba, L.; Tembo, G.; Ng'ong'ola, D. The determinants and extent of crop diversification among smallholder farmers: A case study of southern province Zambia. *J. Agric. Sci.* **2014**, *6*, 150–159. [CrossRef]
50. Rahman, S.; Kazal, M.M.H. Determinan.ts of crop diversity in the regions of Bangladesh (1990 e 2008). *Singap. J. Trop. Geogr.* **2015**, *36*, 83–97. [CrossRef]
51. Panahi, F.; Malek-Mohammadi, I.; Chizari, M.; Samani, J. The role of optimizing agricultural water resource management to livelihood poverty abolition in rural Iran. *Aust. J. Basic Appl. Sci.* **2009**, *3*, 3841–3849.
52. Conrad, C.; Löw, F.; Lamers, J.P.A. Mapping and assessing crop diversity in the irrigated Fergana Valley, Uzbekistan. *Appl. Geogr.* **2017**, *86*, 102–117. [CrossRef]
53. Jalilov, S.M.; Keskinen, M.; Varis, O.; Amer, S.; Ward, F.A. Managing the water-energy-food nexus: Gains and losses from new water development in Amu Darya River Basin. *J. Hydrol.* **2016**, *539*, 648–661. [CrossRef]
54. Pereira, L.S.; Oweis, T.; Zairi, A. Irrigation management under water scarcity. *Agric. Water Manag.* **2002**, *57*, 175–206. [CrossRef]
55. Usman, M.; Liedl, R.; & Kavousi, A. Estimation of distributed seasonal net recharge by modern satellite data in irrigated agricultural regions of Pakistan. *Environ. Earth Sci.* **2015**, *74*, 1463–1486. [CrossRef]
56. Panda, R.K.; Behera, S.K.; Kashyap, P.S. Effective management of irrigation water for maize under stressed conditions. *Agric. Water Manag.* **2004**, *66*, 181–203. [CrossRef]
57. Martius, C.; Rudenko, I.; Lamers, J.P.A.; Vlek, P.L.G. *Cotton, Water, Salts and Soums: Economic and Ecological Restructuring in Khorezm, Uzbekistan*; Martius, C., Rudenko, I., Lamers, J., Vlek, P., Eds.; Springer Netherlands: Heidelberg, Germany, 2012. [CrossRef]
58. Usman, M.; Kazmi, I.; Khaliq, T.; Ahmad, A.; Saleem, M.F.; Shabbir, A. Variability in water use, crop water productivity and profitability of rice and wheat in Rechna Doab, Punjab, Pakistan. *J. Anim. Plant Sci.* **2012**, *22*, 998–1003.
59. Löw, F.; Biradar, C.; Fliemann, E.; Lamers, J.P.A.; Conrad, C. Assessing gaps in irrigated agricultural productivity through satellite earth observations—A case study of the Fergana Valley, Central Asia. *Int. J. Appl. Earth Obs. Geoinf.* **2017**, *59*, 118–134. [CrossRef]
60. Simpson, E.H. Measurement of diversity. *Nature* **1949**. [CrossRef]
61. Magurran, A.E. *Measuring Biological Diversity*; Blackwell Publishing: Oxford, UK, 2004.
62. Hastie, T.; Tibshirani, R.; Friedman, J. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*, 2nd ed.; Springer: Berlin/Heidelberg, Germany, 2009; Available online: https://web.stanford.edu/~{}hastie/ElemStatLearn/ (accessed on 20 September 2020).
63. Breiman, L. Random forests. *Mach. Learn.* **2001**, *45*, 5–32. [CrossRef]
64. Gessner, U.; Machwitz, M.; Conrad, C.; Dech, S. Estimating the fractional cover of growth forms and bare surface in savannas. A multi-resolution approach based on regression tree ensembles. *Remote Sens. Environ.* **2013**, *129*, 90–102. [CrossRef]
65. Strobl, C.; Boulesteix, A.L.; Kneib, T.; Augustin, T.; Zeileis, A. Conditional variable importance for random forests. *BMC Bioinf* **2008**, 9. Available online: https://bmcbioinformatics.biomedcentral.com/articles/10.1186/1471-2105-9-307 (accessed on 20 September 2020). [CrossRef] [PubMed]
66. Hothorn, T.; Hornik, K.; Zeileis, A. Party: A Laboratory for Recursive Partitioning. 2006. Available online: https://cran.r-project.org/web/packages/party/vignettes/party.pdf (accessed on 20 September 2020).

67. Hothorn, T.; Hornik, K.; Zeileis, A. Unbiased recursive partitioning: A conditional inference framework. *J. Comput. Graph. Stat.* **2006**, *15*, 651–674. [CrossRef]
68. Mann, H.B. Non-parametric tests against trend. *Econometrica* **1945**, *13*, 163–171. [CrossRef]
69. Kendall, M.G. *Rank Correlation Methods*, 4th ed.; Charles Griffin: London, UK, 1975.
70. Gilbert, R.O. *Statistical Methods for Environmental Pollution Monitoring*; Wiley: New York, NY, USA, 1987.
71. Usman, M.; Reimann, T.; Liedl, R.; Abbas, A.; Conrad, C.; Saleem, S. Inverse Parametrization of a Regional Groundwater Flow Model with the Aid of Modelling and GIS: Test and Application of Different Approaches. *Isprs Int. J. Geo-Inf.* **2018**, *7*, 22. [CrossRef]
72. Hofmann, W.; Gawronski, B.; Gschwendner, T.; Le, H.; Schmitt, M. A meta-analysis on the correlation between the Implicit Association Test and explicit self-report measures. *Personal. Soc. Psychol. Bull.* **2005**, *31*, 1369–1385. [CrossRef] [PubMed]
73. Bos, M.G. Performance indicators for irrigation and drainage. *Irrig. Drain. Syst.* **1997**, *11*, 119–137. [CrossRef]
74. Cheema, M.J.M.; Immerzeel, W.W.; Bastiaanssen, W.G.M. Spatial Quantification of Groundwater Abstraction in the Irrigated Indus Basin. *Groundwater* **2013**. [CrossRef] [PubMed]
75. Arshad, A.; Zhang, Z.; Zhang, W.; Gujree, I. Long-Term Perspective Changes in Crop Irrigation Requirement Caused by Climate and Agriculture Land Use Changes in Rechna Doab, Pakistan. *Water* **2019**, *11*, 1567. [CrossRef]
76. Jabeen, M.; Ahmad, Z.; Ashraf, A. Predicting behaviour of the Indus basin aquifer susceptible to degraded environment in the Punjab province, Pakistan. *Modeling Earth Syst. Environ.* **2020**, *6*, 1633–1644. [CrossRef]
77. Foster, S.; Pulido-Bosch, A.; Vallejos, Á.; Molina, L.; Llop, A.; MacDonald, A.M. Impact of irrigated agriculture on groundwater-recharge salinity: A major sustainability concern in semi-arid regions. *Hydrogeol. J.* **2018**, *26*, 2781–2791. [CrossRef]
78. Qureshi, A.S.; Asghar, M.N.; Ahmad, S.; Masih, I. Sustaining crop production in saline groundwater areas: A case study from Pakistani Punjab. *Aust. J. Agric. Res.* **2004**, *55*, 421–431. [CrossRef]
79. Ali, S.; Liu, Y.; Ishaq, M.; Shah, T.; Abdullah, I.A.; Din, I. Climate Change and Its Impact on the Yield of Major Food Crops: Evidence from Pakistan. *Foods* **2017**, *6*, 39. [CrossRef]
80. Nelson, G.C.; Rosegrant, M.W.; Koo, J.; Robertson, R.; Sulser, T.; Zhu, T.; Ringler, C.; Msangi, S.; Palazoo, A.; Batka, M.; et al. *Climate Change: Impact on Agriculture and Costs of Adaptation*; International Food Policy Research Institute: Washington, DC, USA, 2009; Volume 21, Available online: https://www.ifpri.org/publication/climate-change-impact-agriculture-and-costs-adaptation (accessed on 20 September 2020).
81. Qaseem, M.F.; Qureshi, R.; Shaheen, H. Effects of Pre-Anthesis Drought, Heat and Their Combination on the Growth, Yield and Physiology of diverse Wheat (*Triticum aestivum* L.) Genotypes Varying in Sensitivity to Heat and drought stress. *Sci. Rep.* **2019**, *9*, 1–12. [CrossRef] [PubMed]
82. Duggan, B.L.; Domitruk, D.R.; Fowler, D.B. Yield component variation in winter wheat grown under drought stress. *Can. J. Plant Sci.* **2000**, *80*, 739–745. [CrossRef]
83. Sharif, I.; Aleem, S.; Farooq, J.; Rizwan, M.; Younas, A.; Sarwar, G.; Chohan, S.M. Salinity stress in cotton: Effects, mechanism of tolerance and its management strategies. *Physiol. Mol. Biol. Plants* **2019**, *25*, 807–820. [CrossRef] [PubMed]
84. Rizwan, M.; Bakhsh, A.; Li, X.; Anjum, L.; Jamal, K.; Hamid, S. Evaluation of the impact of water management technologies on water savings in the Lower Chenab Canal command area, Indus river Basin. *Water* **2018**, *10*, 681. [CrossRef]
85. Mahmood, N.; Ah, T.; Ahmad, M.; Maan, A.A. Identification of the adoption level of water saving interventions and reasons for non-adoption in Faisalabad district. *Pak. J. Agric. Sci.* **2015**, *52*, 521–525.