Pak. J. Agri. Sci., Vol. 57(4), 981-991; 2020
ISSN (Print) 0552-9034, ISSN (Online) 2076-0906
DOI: 10.21162/PAKJAS/20.9482
http://www.pakjas.com.pk

A DECISION SUPPORT SYSTEM FOR CROP WATER REQUIREMENT ESTIMATION USING ADVANCED GEOSPATIAL TECHNIQUES

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It is quite challenging to assess the crop water requirement with limited time and resources on a regional scale. The study focuses on developing a spatial decision support system (SDSS) for crop water requirement and to determine the efficacy of existing irrigation systems by utilizing advanced geo-spatial techniques. Selected region was Punjab province of Pakistan that covers a total area of 105227 sq.km. Reflectance based crop coefficient approach was used for crop water requirement estimation. Various metrological, climatic, geographical vector layers and statistical data of irrigation supply along with satellite imageries were used for monitoring the crop health on8-days periodic intervals for the summer (Kharif) season in the year 2018. For accurate quantification and mapping of crop water requirement, Landsat, MODIS and SPOT imageries were processed for crop classification, top of the atmosphere radiation calculation and actual and reference measurements, respectively. Reference evapotranspiration (ETo) was calculated using Penman method leading to provide water demand and consumption by further calculations in each irrigation circle. The results show that the regions lying at the tail of the canal command area (CCA) facing higher water deficit. In addition, irrigation circles facing insufficient irrigation water supplies (upper and lower Jhelum canal, Pothoar region) also demonstrating higher crop water deficits. Comparing southern with northern parts of the province high water deficits observed in images in the year 2018, reflecting these regions are relatively hotter and receive less average precipitation. Similarly, high water deficit observed at northeast of the Punjab due to insufficient irrigation water supply. The results have been validated by comparing the water demand with the irrigation supply in each CCA, which provides the water being utilized other than irrigation sources to satisfy crop water needs. This study is quite effective in water budget estimation and mitigation of water scarcity issues.

Keywords: Spatial decision support system, geospatial, Irrigation system, crop water requirement, crop coefficients, reference evapotranspiration.

INTRODUCTION

Pakistan's economy is largely based on the performance of the agriculture sector. The economic growth rate is highly affected by the performance of its agricultural sector. Experiences show that the periods of high/low economic growth of national economy generally coincide with the trends in the growth of its agriculture sector (Ali, 2000). Due to the rapid increase in population, food security has become a national priority of Pakistan. Worsen situation of water scarcity in the country is causing severe threats to food production and security. Solutions aimed at addressing food security issues such as improved varieties and better management practices cannot be fruitful in the absence of adequate water quantity. The agriculture sector is the prime user of freshwater, which could be managed by ensuring efficient use of water in crop production (Raza *et al.*, 2012; Shakoor *et al*., 2018). Modernization of irrigation practices plays a vital role in improving farmers' income, employment opportunities, cropping intensity, and wage rate (Bhattarai and Narayana, 2003; Lawston *et al.*, 2017).

A rotational 8-day irrigation schemes as a common practice is used in this province to equally satisfy the crop water needs for local farmers (Basharat and Tariq, 2014).This is insufficient water allocation and farmers try to compensate their needs locally through groundwater and water diversion from the neatest rivers. However, it is still a characteristic of the crops to grow under water stress conditions and they do not reach yields than they would otherwise produce under stress-free conditions.

The main challenges in the development of a monitoring system are the size of the Punjab irrigation area, spatial and temporal crop variability, the location specific stress situation of crops that cannot be compared to standard crops, and the developmental status of technically viable monitoring techniques/models. As a solution, such a technique must be chosen that fulfils the monitoring requirements (8-day intervals) and could be easily adjustable to the local conditions (e.g. crop coefficient, locally ideal crop performance) combined with a spatially detailed mapping facility that allows separation/parameterization of individual fields and crop types. The spatial analyses at such a regional scale and at such a short repetitive step are only feasible with remotely sensed satellite images. The operational satellite products and models on actual evapotranspiration and on assessing crop water needs on a regular basis are still in the development phase and are mostly used for scientific purposes (Mu *et al.,* 2011; Gago *et al.,* 2015; Tadesse *et al.,* 2015).

Evapotranspiration measurements through MODIS have not been proved reliable (NASA, 2013). Furthermore, the operationalization of regional evapotranspiration estimates from empirical models or surface energy balance models based on satellite data has not been successful because of the complexity of the procedure and its dependency on a number of hydro-meteorological parameters of limited accuracy at the regional scale (Ambast *et al.*, 2002). The critical remote sensing variables used in surface energy balance models include leaf area index (LAI), thermal IR based surface temperature (Hope *et al.,* 2005), sensible heat flux that is based on thermal IR estimated surface temperature (Gowda *et al.*, 2008), and unaccounted adjective sensible heat flux resulting in higher evapotranspiration than concluded from net incoming radiation (Glenn *et al.,* 2008). An incurring error of more than 50% was observed in calculated ETs. Though algorithms are continuously improved (Mu *et al.,* 2013), they have not yet reached an accuracy that would allow full-scale implementation.

There are two basic approaches that are commonly proposed for monitoring irrigated crops, the first involving the calculation of actual evapotranspiration from remotely sensed data. It is based on the calculation of a range of physical properties derived from the spectral content of satellite images, but also includes empirical relationships and makes various assumptions (weather conditions, agro-climatic conditions). The second is based on reference evapotranspiration and empirical linkages between the remotely sensed parameter NDVI (Normalized Difference Vegetation Index) and crop coefficients (FAO, 1998: Allen, 2000 and 2005; Katerji and Rana, 2014; Chukaliev, 2017).

Preference is given to the reflectance based crop coefficient approach supplemented by a remotely sensed vegetation index due to its simplicity, reproducibility, relatively good accuracy, and transportability among locations and climates. The crop coefficient based estimation of crop evapotranspiration is one of the most commonly used methods for irrigation water management at the field level (FAO, 1998; Er-Raki *et al.,* 2010; Boudhina *et al.,* 2015; Thomas *et al.,* 2018). The possibility to directly derive crop coefficients from remotely sensed data allows the spatial analysis of crop evapotranspiration and crop water needs. This is possible because of strong correlations between the NDVI and plant physiological processes that in turn depend on photosynthesis and evapotranspiration. On the basis of these linkages, reflectance based crop coefficients (KC) have been developed for numerous individual crops (Glenn *et al.,* 2011) as well as general relationships between NDVI and crop coefficients (KC) that are likewise applicable to different crops (Kamble *et al.,* 2013).The simplicity of this approach considering site specific crop characteristics, its applicability at the basin scale and reported accuracies for crop evapotranspiration, summarizes the advantages of the reflectance based crop coefficient approach (Hunsaker *et al.,* 2005; Campos *et al.*, 2017; Thomas *et al.*, 2018).

Currently, conventional techniques are in operation at regional and local scale in Pakistan which becomes a serious challenge for irrigation water resource management (Ihuoma *et al.,* 2017; Ali *et al*., 2018). Recent advances in crop water stress detection are quite helpful in predicting crop yield and thus developing strategies for irrigation management under limited water conditions (Ihuoma *et al*., 2017; Gerhards *et al*., 2019). This research provides an efficient and reliable spatial decision support system to monitor and regulate the irrigation practices in a timely manner. This research incorporates the utilization of freely available remote sensing data to establish a robust SDSS to monitor irrigation water management issues. Objectives of the study are: (i) identification and quantification of different cropping patterns in Punjab province; (ii) designing of prototype SDSS for crop water efficacy at 8-day intervals using hydro-meteorological, geographical and solar parameters; and (iii) scrutinizing the water potential (irrigation scheme, rainfall) deficit by means of water availability for winter (Rabbi) and summer (Kharif) seasons.

MATERIALS AND METHODS

The Punjab irrigation region in Pakistan is an intensely cultivated region covering an area of about 21 million acres (8.4 million hectare) excluding the Greater Thal canal district) of which around 63 km^2 and 75 km^2 (excluding Greater Thal canal district) are under irrigation during winter (Rabi) and summer (Kharif), respectively. The geographic location of canal command areas irrigated by different canals in Punjab is shown in figure 1. However, the spatial distribution of the rivers which are the main water sources for irrigation canals in Punjab are represented in figure 2. This figure illustrates the sources of different irrigation canals (i.e. rivers) in Punjab province. The major source of rivers water originates from snow and glacier melting in the Himalayans and Karakoram regions, discharged by the rivers Indus, Jehlum, Chenab, Ravi and Sutlej and stored in various water reservoirs (i.e. Tarbela Dam, Mangla Dam, Satpara Dam) (Rasul *et al.,* 2011).

Crop water analysis depends on crop area, crop type, climatic conditions and type, soil type, growing seasons and crop production frequencies (World Bank, 2013; Navarro *et al,* 2016). The methodology adopt follows the concept of reference evapotranspiration at various spatio-temporal scales. Wide data set ranges collected from different sources are utilized to demonstrate the crop water requirement in Punjab province and are listed in Table 1.

Table 1. Utilized Datasets and Their Characteristics.

Description	Source	Resolution	Objectives
MODIS: Aqua/Terra - for Actual Kc calculation*	USGS	250 m	NDVI
Landsat 8	USGS GloVis	30 m	Crop Classification
SPOT	USGS GloVis	30 m	Crop Classification
Crop consumption	Actual ET		-
Crop Demand	Reference ET & crop coefficients		-

*(25 May, 2 June, 10 June, 18 June, 26 June, 4 July, 12 July, 20 July, 28 July, 5 Aug, 13 Aug, 21 Aug, 29 Aug, 6 Sep, 14 Sep, 22 Sep, 30 Sep, 8 Oct) For reference NDVI calculation (at every 8 days interval from 2008-2018)

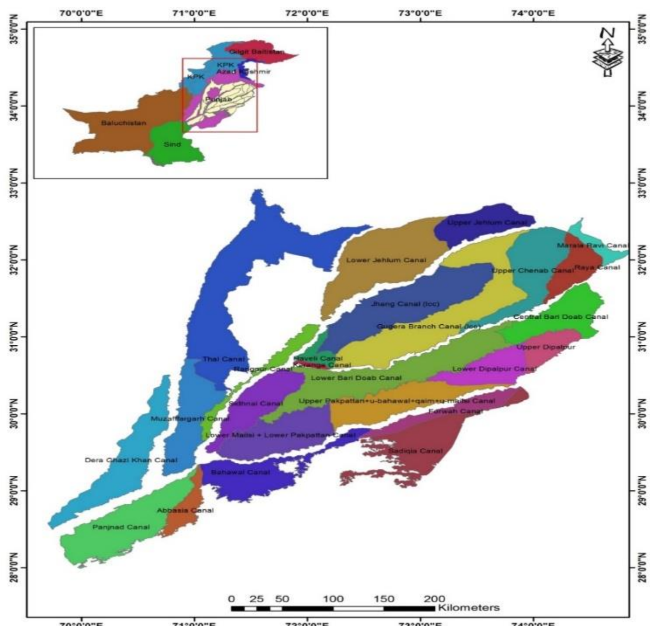


Figure 1. Canal command areas in Punjab Province.

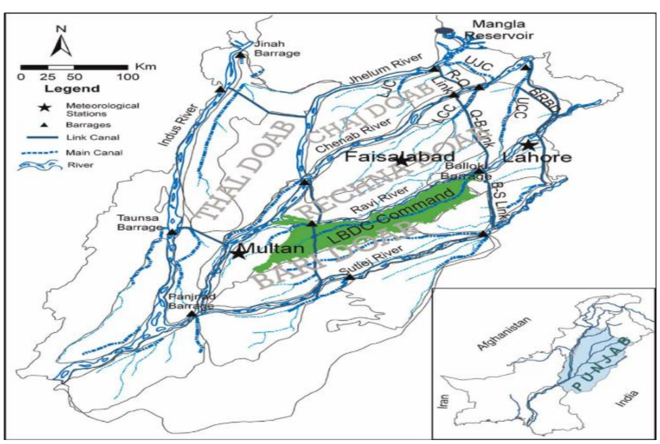


Figure2. Irrigation command areas, Punjab, Pakistan (Basharat, 2014).

Data Processing: Hargreaves method has been used for the estimation of evapotranspiration (ET) for individual identification of crops in the study area. The approach is recommended standard, simple, reliable, and can be used for daily monthly and seasonal calculations of ET (FAO, 98; Boudhina *et al*., 2015; Campos *et al*., 2017). Zhao *et al*. (2013); Beti *et al*. (2014) and Nikam *et al*. (2014) used Hargreaves methods for calculation of ET and proposed this method is more efficient for data poorer areas as it requires less number of variables for ET calculation in comparison to the other techniques which are complex in nature and demands larger number of input parameters. The mathematical equation is given as:

$$ET_o = 0.0023 \times R \times \left(\frac{T_{max} + T_{min}}{2} + 17.8\right) \times \sqrt{T_{max} - T_{min}} \quad (1)$$

Where: T_{max} and T_{min} are average daily maximum and minimum temperatures, respectively.

The variable R in the above equation is extra-terrestrial solar radiation (mm/day). Different techniques are used to calculate the top of atmosphere radiation (TOA), however, in this study satellite imagery has been used for the calculation of R, resulting in a raster formatted output as described in Fig. 3.

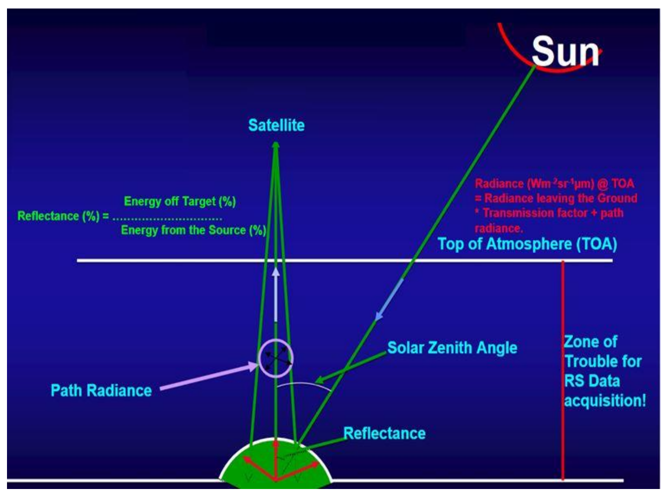


Figure 3. Conceptual framework of TOA calculation.

Landsat 7-8 imagery is incorporated for this process under the platform of PANCHROMA which is a Remote Sensing application suit used for improving satellite imagery and extracting different information from satellite imagery including LANDSAT, SPOT, GeoEye and many others. Landsat and SPOT products have been utilized alternatively to achieve the objectives of TOA at 8-day temporal resolution. Landsat products have a revisit time of 16 days therefore; SPOT imagery is used side by side to calculate TOA for missing days. PANCHROMA requires solar zenith angle and band of the satellite imagery used for calculation of

TOA. The conceptual diagram of TOA and solar zenith angle (Azimuth) is explained in Fig. 3.

Daily temperature data available for weather stations in study reais used to calculate the ETo. To get the ETo monthly measurements, monthly mean temperatures are supposed to resemble that of an average monthly day, so that eq. 1 can be applied and then the result will be multiplied with the total number of days of the corresponding month. Afterward, for spatial interpolation of ETo, Inverse Distance Weight (IDW) has been preferred and chosen over other complex methods (i.e. cokriging) which gave unsatisfactory results. This operation provides the spatial distribution of ET0, at monthly intervals.

These datasets are pre-processed and resampled, if needed, for monthly calculations of crop water requirements for summer (Kharif) season. Hydrometeorology, irrigation and remote sensing satellite information collected from various sources, including organizational and open source platforms, are pre-processed in GIS environment. Figure 4 elaborates the methodological framework of study.

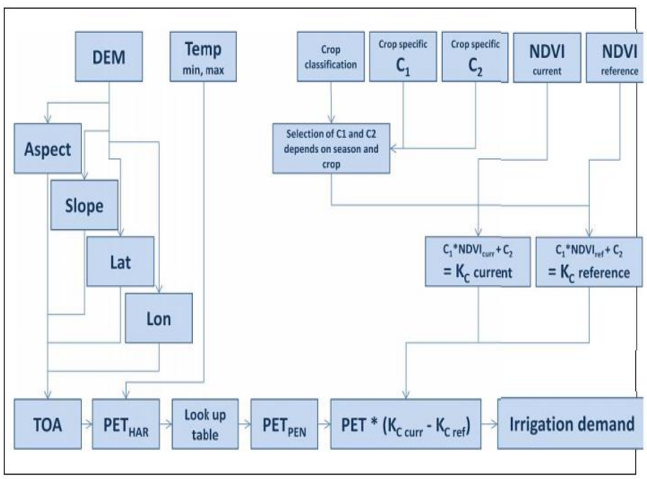


Figure 4. Flow chart showing the processing for irrigation water demand.

***Crop Classification*: ** For accurate quantification of water for crops in the study area, individual crop identification was the basic requirement and needed to be considered in the monitoring system. The intra-class variability check/identification performed using satellite imagery information. Cropping pattern was defined as a spatial arrangement of crops in a given area. It is categorized based on crop season as kharif (summer crop), Rabi (winter crop). The intra-class variability requires differentiation of at least the major crop types grown during winter (Rabi) and summer (Kharif) seasons. Figure 5 demonstrating the samples taken for crop classification in various canal command areas (CCAs). Minimum 2-3 samples were taken in every CCA and for each crop in order to get better results for crop classification.

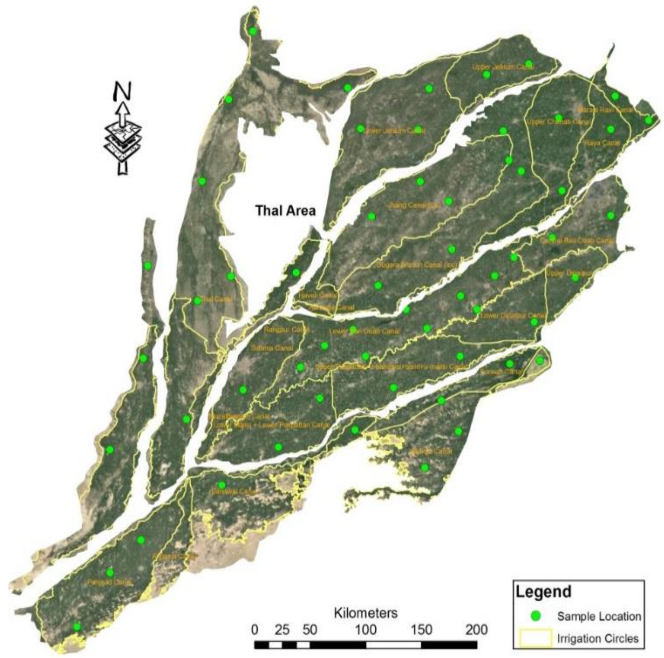


Figure 5. Sample location of crops in various canal command areas.

The cropping pattern map for the year 2018was generated by integration of MODIS' (Aqua and Terra) NDVI (Normalized Difference Vegetation Index) products at 8-day temporal resolution. The two products have a revisit time of 16 days with a shift of 8 days. Therefore, NDVI products from Aqua and Terra are used side by side after every 8-day interval for 10years (2008-2018) to develop a reference NDVI. A layer stack of multi-date NDVI images (450images) resulted in a composite band image. However, information is calculated due to the coarse spatial and high temporal resolution of MODIS' NDVI products. NDVI products of MODIS whose temporal flag is the nearest to the date that Landsat OLI images are being acquired for the year 2018. The correlation analysis was performed between MODIS' NDVI and Landsat OLI. In homogenous crop fields, correlation evaluation samples were selected and subsequently the average NDVI of all Landsat pixels to the corresponding MODIS pixel were calculated. Finally, on the basis of linear correlation, Landsat NDVI is transformed to MODIS' NDVI and then the historical reference NDVI is utilized as training samples in order to classify crop types for the year 2018 at 30m spatial resolution.

***MODIS NDVI and Reference Crop Cycle*: ** NDVI is a remote sensing surrogate for green biomass and is a unitless spectral index calculated from a near infrared band and a red band. The NDVI product of MODIS (AQUA/TERRA) is used for reference crop cycle generation. The reference crop cycle defines the maximum value of crop reflectance observed in the past 10 years. These cycles of individual crops behave near ideally throughout the crop growing to harvesting stage. To meet the ideal condition, it was utmost importance to minimize the data gaps. MODIS provides NDVI from two platforms: AQUA and TERA. The platforms have 16 days temporal resolution, however, harmonizing the two dataset results 8 daily by-products of NDVI. These NDVI images are stacked over a period of 10years for reference cycle identification.

***Crop Coefficients (Kc) and Crop Water Requirement (CWR)*:** Crop coefficients have a strong correlation with satellite derived NDVI values. Reflectance based crop coefficients (Kcrr) are calculated as;

Kcrr = C1 × NDVI + C2 (2)

Where C1 and C2 are coefficients derived from linear regression calculations,

$$\mathrm{Kcr} = 0.0002 \times \mathrm{NDVI} - 0.0302$$

between FAO crop Coefficients and the local NDVI cycles (Allen, 2011; Rossi and Bocchi, 2007; Kamble *et al.*, 2013) are described in figure 6.

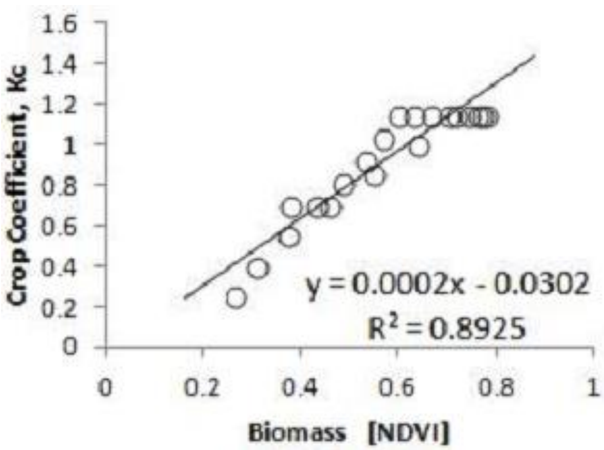


Figure 6. NDVI cycle showing a linear correlation between the two variables C1 and C2

The coefficients are crop specific and need to be determined individually. However, there exist generally applicable C1 and C2 variables (Kamble *et al.,* 2013). The reflectance-based actual crop coefficients (Kcra) calculated against each crop for a calendar year is illustrated in figure 7.

An ideal crop is considered well-performing without water stress. For, 2008-2018 images, where the crop is behaving ideally or having maximum reflectance's and showing least or no water stress is taken as Reference NDVI. Whereas, for actual NDVI (actual crop), images at every 8-days interval were taken (actual crop is one which may lie under water stress conditions), the positive difference between ETc ref minus ETc act defines the crop water need. The reflectance-based reference crop coefficients (Kcrr) and actual crop coefficients (Kcra) are used for crop water requirement using the following equation:

CWR= Kcrr - Kcra × ETo (3)

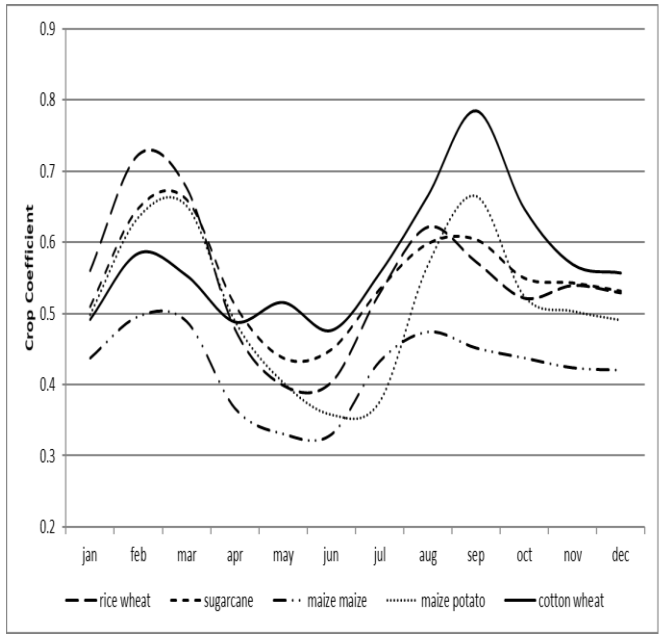
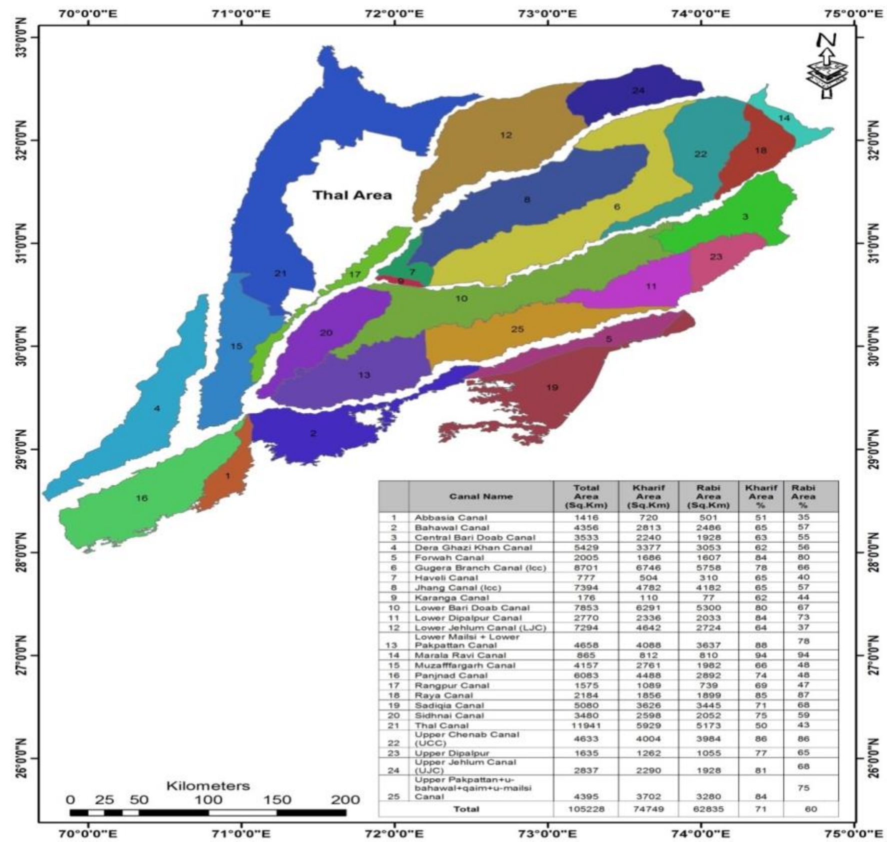


Figure 7. Crop coefficients of various crops for a crop calendar

RESULTS AND DISCUSSION

The vegetation index (NDVI) time-series approach generates a total of 12 land covers in the study area including six major crop types. The classification schemes split area in winter (Rabbi) and summer (Kharif) season crops. The same geographical location results multiple classes throughout the calendar year. The time-series NDVI profiles of each class behave differently due to the intrinsic properties of crops. Statistics were only performed on cultivated areas that fall within the irrigation district limits as shown in figure 8. However, there is considerable cultivation outside district limits, for example in many floodplains; these areas do not appear in any statistics. The total cultivable area for both winter (Rabi) and summer (Kharif) season was calculated for each irrigation circle in Punjab province as presented in figure 8. This table depicts that agricultural practices being increased in summer (Kharif) season in comparison to winter (Rabi) almost in every irrigation circle and as whole.

This is mainly because of the sufficient availability of irrigation supply during summer (Kharif) season. In addition, the study area receives high monsoon rainfall during the summer (kharif) season. So, the areas lying at the tails of irrigation circles or having insufficient irrigation supply are largely depended on rainfall for agricultural practices. Pothowar region falling in upper Jhelum and Lower Jhelum canal circles are highly dependable on rainfall, so the cultivation in these regions in winter (Rabi) season is reduced due to less rainfall and irrigation supply.



	Canal Name	Total Area (Sq.Km)	Kharif Area (Sq.Km)	Rabi Area (Sq.Km)	Kharif Area %	Rabi Area %
1	Abbasia Canal	1416	720	501	51	35
2	Bahawal Canal	4356	2813	2486	65	57
3	Central Bari Doab Canal	3533	2240	1928	63	55
4	Dera Ghazi Khan Canal	5429	3377	3053	62	56
5	Forwah Canal	2005	1686	1607	84	80
6	Gugera Branch Canal (lcc)	8701	6746	5758	78	66
7	Haveli Canal	777	504	310	65	40
8	Jhang Canal (lcc)	7394	4782	4182	65	57
9	Karanga Canal	176	110	77	62	44
10	Lower Bari Doab Canal	7853	6291	5300	80	67
11	Lower Dipalpur Canal	2770	2336	2033	84	73
12	Lower Jehlum Canal (LJC)	7294	4642	2724	64	37
13	Lower Mailsi + Lower Pakpattan Canal	4658	4088	3637	88	78
14	Marala Ravi Canal	865	812	810	94	94
15	Muzafffargarh Canal	4157	2761	1982	66	48
16	Panjnad Canal	6083	4488	2892	74	48
17	Rangpur Canal	1575	1089	739	69	47
18	Raya Canal	2184	1856	1899	85	87
19	Sadiqia Canal	5080	3626	3445	71	68
20	Sidhnai Canal	3480	2598	2052	75	59
21	Thal Canal	11941	5929	5173	50	43
22	Upper Chenab Canal (UCC)	4633	4004	3984	86	86
23	Upper Dipalpur	1635	1262	1055	77	65
24	Upper Jehlum Canal (UJC)	2837	2290	1928	81	68
25	Upper Pakpattan+u-bahawal+qaim+u-mailsi Canal	4395	3702	3280	84	75
	Total	105228	74749	62835	71	60

Figure 8.Season- based cultivable canal command area

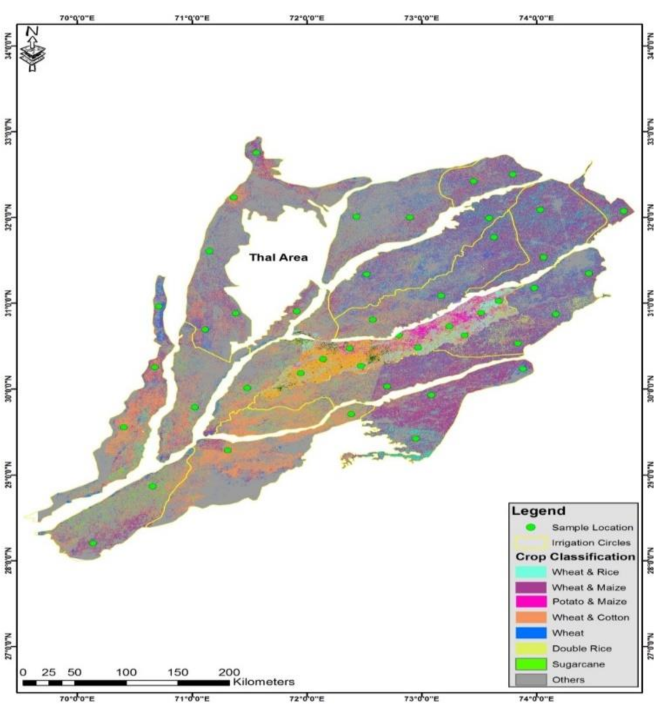


Figure 9. Crop classification & samples distribution in the study area.

Crop classification was performed for both winter (Rabi) and summer (Kharif) season, which resulted in six Major crops across the Punjab province including Wheat, Rice, Cotton, Maize, Sugarcane and Potato presented in figure9. While there are some other classes observed which are cultivated in the limited area. The northeast part of the study area is largely cultivated with wheat and rice crops for winter (Rabi) and summer (Kharif) seasons respectively. Potato cultivation at larger scale is observed in middle part of the province, while moving towards south from middle part of the study area, Crop classification revealed Wheat crop as highest growing crop in winter (Rabi) season across the province. Some scattered sugarcane cultivation observed in middle and southern parts. Similarly, wheat and cotton combinations are observed at central and southwards of the Punjab province. Figure9 also illustrates the ground sample locations for validation of crop classification results. Minimum 4-5 samples were taken against each crop type by keeping in view the spatial distribution of crop types in study area.

Calculated crop coefficients (KC ref and KC act) and reference evapotranspiration (ETo) being used to calculate the crop water requirements at the 8-day periodic interval for summer (Kharif) season for the year 2018 (Figure 10& 11).

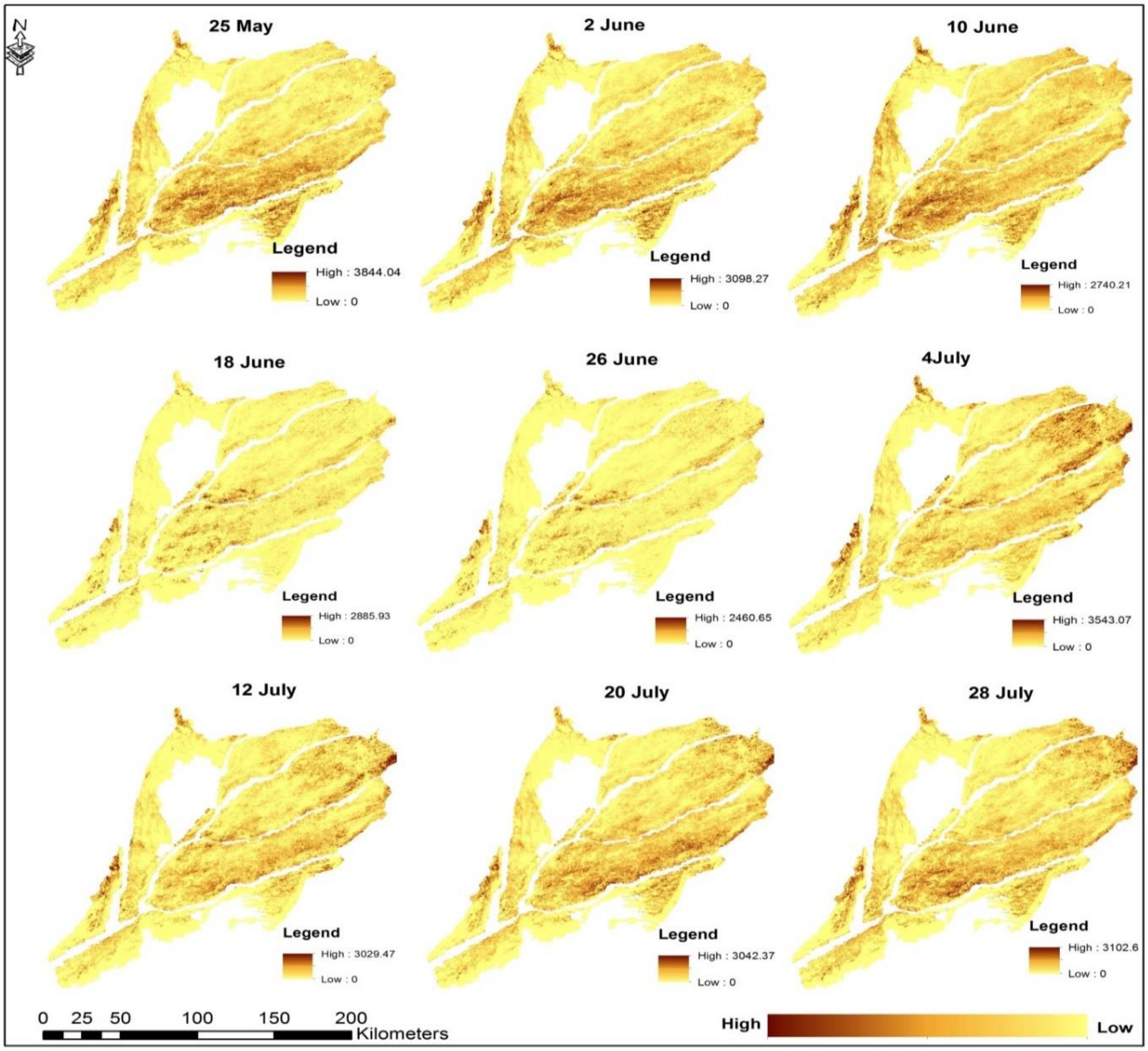


Figure 10. Water deficit at the 8-day interval for summer (Kharif)Season 2018.

Summer (Kharif) actually starts from 15^{th}May and ends on 15^{th}October in Punjab province. A total of 19 water deficits maps for the summer (Kharif) seasons were generated, among them 18 are presented in figures 10 and 11. Very high-water deficit was observed in the month of July and August in comparison to the other months of summer (Kharif) season in the year 2018. This is because summer (Kharif) crops were at middle stage of growth in these months and require high amount of water. Despite high rainfall in these months, both irrigation supply and rainfall do not satisfy the required amount of crop water. These findings are supported by the results of Usman *et al.,* (2009); Naheed *et al.,* (2010); Bhattacharya, (2018); Arshad *et al.,* (2019).

Irrigation circles lying in southern parts of the province faced by high water deficits in comparison to the northern parts across the whole season.. This trend is mainly because; these regions are relatively hotter and received less average precipitation across the season. The increase in temperature during summers (Kharif season) cause high evapotranspiration, which resulted in higher water deficits. Similarly, high water deficit was observed at northeast of the Punjab province in the month of July as shown in figure10. These regions are at such geographical locations where supply of irrigation systems is very low and having high dependency on rainfall. July is the hottest month of the year and received very little rain fall in the year 2018, which is resulted in high water deficits. Same results have been reported by various researchers like Harmsen *et al.*, (2009); Tanasijevic *et al.*, (2014); Perdomo at al., (2017); Bhatt & Hossain, (2019); Arshad *et al.*, (2019). However, months of the august and September received more average precipitation and resulted with less crop water deficit as illustrated in Fig. 11.

Multiplication of reference evapotranspiration (ETo) with the actual crop coefficient (KCact) provided consumption of the water amount while the multiplication of (ETo) with the reference crop coefficients (KC ref) gives demand of water at a specific pixel by considering the crop type and its phenology. Consumption and demand of water in each irrigation circles were calculated at 8-day interval for whole summer (Kharif) season. Figure 12 illustrates the total water demand and consumption in each canal command area (CCA) which was used for clear identification of real-time irrigation water supply. Water deficits and surplus for each canal command area has been shown in this figure.

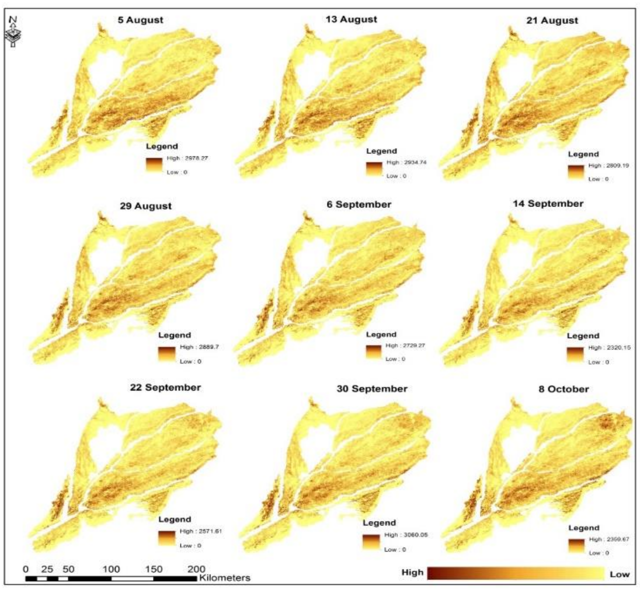
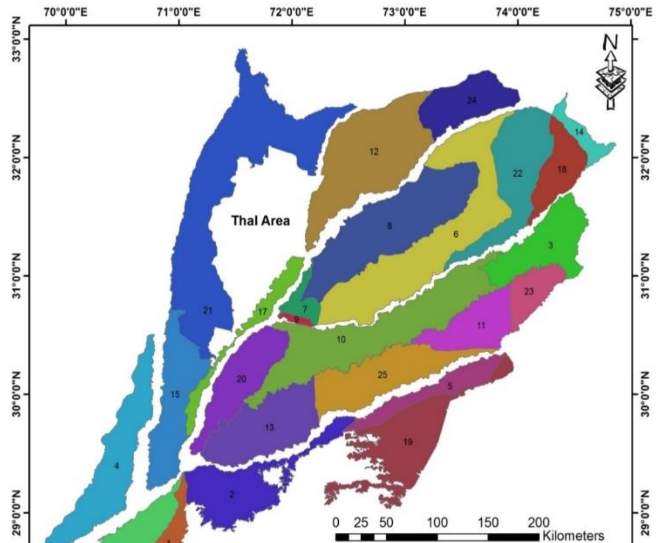


Figure 11. Water deficit at the 8-day interval for summer (Kharif) season 2018.

Moreover, the difference between the supplied amount of irrigation and the amount of water being consumed in each CCA is calculated to estimation the water budget. This difference actually describes that how much amount of water by other sources (Rainfall and groundwater) were utilized for irrigation purposes In all CCAs, irrigation supply has not fulfilled the crop water demand, and amount of water consumed is quite higher than the suppliedirrigation supply. These results are indicating the other water sources contribution (Rainfall and groundwater) in fulfilling the crop water requirement.



No.	Canal Name	Consumption (mm)	Demand (mm)	Deficit(-)/ Surplus (+) (mm)	Irri. Effective Supply (mm)	Difference (IS - Cons.) mm
1	Abbasia Canal	428.76	448.00	-19.24	270.63	-158.13
2	Bahawal Canal	415.83	443.00	-27.17	40.94	-374.88
3	Central Bari Doab Canal	350.62	430.61	-79.99	196.17	-154.45
4	Dera Ghazi Khan Canal	405.90	455.94	-50.04	319.09	-86.80
5	Fordwah Canal	380.47	429.00	-48.53	263.52	-116.96
6	Gugera Branch Canal (LCCE)	346.69	416.80	-70.11	149.90	-196.78
7	Haveli Canal	405.19	464.28	-59.10		
8	Jhang Canal (LCCW)	361.23	407.43	-46.20	113.91	-247.32
9	Karanga Canal	374.87	475.60	-100.72	180.47	-194.40
10	Lower Bari Doab Canal	374.11	448.41	-74.30	202.99	-171.12
11	Lower Dipalpur Canal	410.22	499.19	-88.97	144.04	-266.18
12	Lower Jehlum Canal	412.42	450.37	-37.95	189.34	-223.08
13	Lower Mailsi + Lower Pakpattan Canal	402.55	468.06	-65.51	191.09	-211.47
14	Marala Ravi Canal	297.56	390.40	-92.83		
15	Muzafffargarh Canal	423.90	487.82	-63.91	400.93	-22.98
16	Panjnad Canal	505.80	561.00	-55.20	241.76	-264.04
17	Rangpur Canal	400.59	443.08	-42.49	242.17	-158.41
18	Raya Canal	295.95	357.94	-61.98		
19	Sadiqia Canal	336.36	355.83	-19.47	229.73	-106.63
20	Sidhnai Canal	368.51	445.32	-76.81	245.63	-122.88
21	Thal Canal	356.42	379.99	-23.57	203.22	-153.20
22	Upper Chenab Canal	316.57	385.89	-69.32		
23	Upper Dipalpur	413.70	485.50	-71.80	191.43	-222.27
24	Upper Jehlum Canal	354.04	404.11	-50.07		
25	Upper Pakpattan + Upper Bahawal + Qaim + Upper Mailsi Canal	383.62	474.59	-90.97	253.28	-130.34
	Total	**9521.88**	**11008.17**	**-1486.29**	**4270.24**	**-3582.33**

Figure 12. Effectiveness of irrigation system and other water sources.

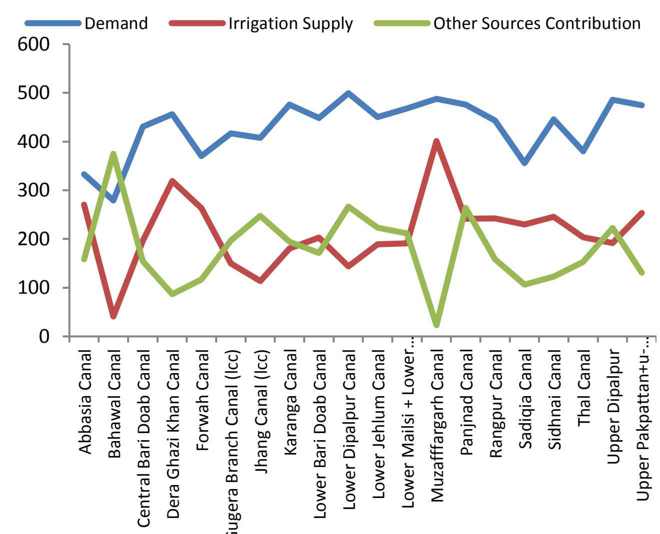


Figure 13. Irrigation supply and other water sources contribution.

Figure 13 presents the water budget estimation in each canal command area of the Punjab province in millimeters. This figure is also demonstrating that insufficient or less irrigation supply may result in water utilization from other sources (i.e. Rainfall, groundwater, etc.) to satisfy the crop water demand. These results are in line with the findings by Latif & Ahmad, (2009); Scanlon *et al*., (2012); Ho *et al*., (2016). Bhalwal canal command area received less irrigation supply (less than 50 mm) resulting in the utilization of other water sources (i.e. 350mm) to meet the crop water needs. Contrary, irrigation supply was high in Dera Ghazi Khan CCA (i.e. 300mm), and demand was around 400 mm, so less amount of water by other sources has been usedin this irrigation circle. A similar pattern was observed in Muzaffargarh CCA, where irrigation supply was higher as compared to all other CCAs, which is almost meeting the crop water demand requirement and resulting in very less contribution of other water sources. Almost same correlation/pattern has been observed across all the CAAs of the study area.

***Conclusion*:** This study provided with the estimation of crop water requirement at 8-days periodic interval and water budget estimation at canal command area scale for summer (Kharf) season of 2018. Higher water deficits have normally been observed in Pothowar region and in those canal command areas lying at southern parts of the study area. These are mainly because of; i) having high evapotranspiration due to high temperature (warmer areas); ii) regions lying at tail of the canal command; iii) where irrigation supply is low, and iv) average rainfall is relatively low. The comparison of irrigation water supply with the actual water demand, water consumption and water deficits elaborated a strong correlation between irrigation water supply and alternative water sources (Rainfall and groundwater). This correlation authenticates the credibility of derived results and efficacy of designed prototype SDSS. This research revealed, current irrigation practices in study area causing exploitation of surface and groundwater sources at large. This prototype would be significant in efficient quantification and utilization of irrigation supply in any particular region by knowing the crop water demand and rainfall patterns. For precise decision making at field level, this system can be improved by incorporating high spatial and temporal resolution imageries and respective derived NDVIs.

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[Received 21 Oct 2019; Accepted 19 Feb 2020; Published (online) 17 July 2020]