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Estimating Seasonal Water Losses from Supply-Demand Analysis Using Satellite-Derived Cropping Patterns: A Case Study

Mir Moazzam Ali Talpur[1*], Hamza Khalid[2], Tingting Chang[3], Mir Ghazzanfar Ali Talpur[4], Ghulam Hussain Khoso[5]

[1] Hohai University, China; moazzamtalpur@hhu.edu.cn
[2] Hohai University, China; hamzakhosa01@hhu.edu.cn
[3] Hohai University, China; changtt@hhu.edu.cn
[4] Sindh Agriculture University, TandoJam, Pakistan: mirghazzanfaralitalpur@gmail.com
[5] Sindh Agriculture University Tandojam; gh_khoso2000@gmail.com

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Abstract

The irrigation systems that use canal command require effective, but not expensive, strategies to quantify annual water requirements and water losses. Field-based traditional methods are all costly and cumbersome to generalize. The current research paper demonstrates how satellite imagery and a crop water need model were applied to estimate the extent of water lost or utilized during the season in the 354-acre command of watercourse number 5AR in the UC Chukhi district, Hyderabad, Pakistan. The CROPWAT model was used to estimate reference evapotranspiration (ET0) and crop evapotranspiration (ETc) using 5 years of meteorological data. Landsat eight images processed in ArcGIS 10.1 provided a classified map of major crops and their acreage. Wheat (24.5 percent of the hectares under cultivation) was the primary crop, followed by mango (17.5 percent), banana (14.0 percent), sugarcane (7.1 percent), and others. 29.6 percent of the hectares were under cultivation, while the remaining 70.4 percent were not. Berry volumetric demands were 117.7 acre-ft (wheat), 81.56 acre-ft (mango), 169.4 acre-ft (banana), 77.4 acre-ft (sugarcane), and 66.38 acre-ft (other crops). The surface water and ground water were 430.3 and 403.04 acre-ft, respectively, and the seasonal supply was 833.45 acre-ft. The seasonal losses incurred were estimated at 279.6 acre-ft, equal to 33.5 percent of the amount of water supplied, 15.0 percent of the conveyance losses, and 18.5 percent of the application losses; application losses exceeded conveyance losses by about 3.5 percentage points. The results suggest that combining CROPWAT and Landsat-based crop mapping with straightforward discharge measurements can offer a feasible, cost-effective, and transferable method for quantifying seasonal water losses and contribute to planning and policy-making for irrigation decisions in canal-command contexts of a similar nature.

Keywords Supply-Demand; Analysis; Satellite.

Corresponding Author
Mir Moazzam Ali Talpur
Hohai University, China; moazzamtalpur@hhu.edu.cn

1. INTRODUCTON

The world's food and water resources are under unprecedented pressure due to rising population, urbanisation, and changes in dietary habits (Amir & Habib, 2015; Munir et al., 2021). There are growing demands on food crops and competing demands on available freshwater from the agricultural, domestic, and industrial sectors (Abd El-Mageed et al., 2021; McBean, 2016). Given that agricultural activities are the highest users of fresh water, there is a need to ensure that irrigation systems can work

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more effectively to boost food security, sustain rural livelihoods, and protect aquatic life amid the increasing water crisis (Ashraf, 2016). The majority of semi-arid areas, such as Pakistan, continue to use canal systems for surface irrigation during food production (Panella et al., 2020; Talpur et al., 2023; Wang et al., 2024). The country has built one of the largest irrigation systems in the world over the past century, on which Kharif (summer) and Rabi (winter) crops are grown. Some staple and cash crops, such as wheat, rice, sugarcane, cotton, fruits, and vegetables, are highly dependent on canal water levels, which have not been altered (Farooq et al., 2009). Agriculture, therefore, takes a central position in the national economy and the countryside, and it also plays a central role in employment (Commission, 2001). The canal-command system, however, is compromised by low conveyance and application efficiencies; there is no equity between the water passing to the head and tail reaches, and no knowledge of the whereabouts or quantities of water losses along the supply line (Janjua & Mohammad, 2008). The water under a normal canal command is diverted at the headworks and directed into distributaries, which may include minor and watercourses, and thence to specific fields. The losses are made at various stages through seepage, leakage, overtopping, operating wastage, and non-beneficial evaporation (Hulme, 2009). The other losses are incurred at the farm level due to unlevelled fields, improper irrigation patterns, and irrigation at the wrong time. These losses reduce the ratio of water actually used in positive crop evapotranspiration and, consequently, water productivity, which can only increase head-tail inequity (Seckler, 1998). The quantification of seasonal water demand and water losses at the scale of individual watercourses thus enables the identification of technical and socially viable steps to enhance the performance of the irrigation process (Jan et al., 2017).

More traditional steps for assessing the performance of canals and watercourses at a fine scale are based on intensive field trials, such as inflow-outflow tests, seepage tests, ponding tests, and plot-scale water balance, which are time-consuming, labour-intensive, and expensive (Kamal, 2009). They are difficult to duplicate across large areas of command, and in most cases, they can only provide snapshots of what occurred, not an integrated seasonal analysis. Consequently, effective information on high-quality water and high spatial and temporal quality is generally inaccessible to decision-makers because of the assessment of crop water needs, water supply, and losses within a particular command (Khan et al., 2016). The latest developments in satellite remote sensing and geographic information systems (GIS) offer powerful, cost-effective tools to support and expand conventional field-based measurements. Multispectral satellite images are used to delineate land-use and crop patterns, identify areas with various crops, and identify fallow or uncultivated lands (Rosegrant et al., 2002). This may be combined with climatic data and crop-specific models, such as CROPWAT, to predict crop evapotranspiration (ETc) and the seasonal water requirements of each major crop in a command (Gain et al., 2016). These estimates of demand, along with observed canal and groundwater supply, enable the calculation of seasonal water losses at the level of individual watercourses. Nevertheless, even with these benefits, co-location of satellite images, crop water demand models, and field measurements to determine seasonal water losses is not at the watercourse scale in the regions covered by the canal-command systems in Pakistan (Iqbal & Iqbal, 2015). Specifically, planners and managers will employ direct, mobile methods by leveraging convenient access to satellite imagery, hydrometeorological data, and standard software (Brears, 2016). The current study, in this instance, utilizes a hybrid remote sensing and modelling approach to the 354-acre land of watercourse 5AR in Union Council (UC) Chukhi, in the district of Hyderabad, under Kunner-II minor.

The distribution of crop patterns and the area covered by the main crops are mapped in ArcGIS using Landsat imagery, and climatic data are used in the CROPWAT model to estimate crop evapotranspiration and the seasonal water requirement of individual crops. These demand estimates are summed to obtain the seasonal water used in the command area, which is then compared with actual surface water deliveries and groundwater abstraction to obtain the total seasonal water supply (Bangira, 2018; Pereira, 2017). A seasonal supply-and-demand model estimates total water losses and breaks them down into conveyance and application components, providing a viable, cost-effective model for diagnosing irrigation performance and, in the future, similar canals' command models.

2. METHOD

2.1 Study area

The research was conducted in the command area of watercourse 5AR off-take from Kunner-II minor in the district of Hyderabad, Pakistan, in the Union Council (UC) Chukhi. Water is supplied to the watercourse through a closed-type mogha outlet with a 3-inch orifice and a height of 1.2 ft. The area is a mix of orchards and field crops irrigated with a blend of canal water and personal tube wells. An ArcGIS georeferenced boundary of UC Chukhi and the 5AR command watercourse was drawn and served as the spatial mask for all subsequent analyses (Figure 2.1).

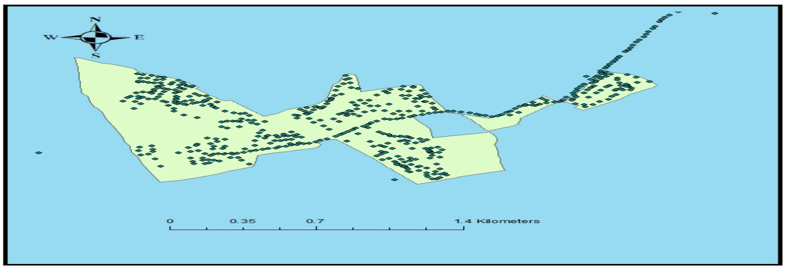

Figure 2.1. Map of the study area of UC Chukhi

2.2 Overall Approach

Seasonal water losses were measured by comparing crop water demand with the total water supplied to the command area during the Rabi season. The procedure had four major elements:

- Estimates on the crop water requirements (demand) based on the CROPWAT model.
- The satellite imagery of Landsat 8 and GIS were employed to map the pattern of the cropping and to compute and calculate the area under each crop.
- Crops water demand transformation and crop land transformation into volumetric water demand of the command area.
- Seasonal surface and ground water supply is estimated, and on the contrary, total, conveyance, and application losses are computed out of the difference between the supply and demand.

2.3 Crop water requirement

2.3.1 Reference evapotranspiration (ETo)

The study computed reference evapotranspiration (ETo) using the CROPWAT model, based on meteorological data from the study area. They were fed monthly climatic inputs (minimum and maximum air temperature, relative humidity, wind speed, and sunshine or radiation) into CROPWAT, and ETo was computed for each month of the year using the software's standard procedure. Monthly ETo values (mm day^{-1}) were then calculated to estimate crop evapotranspiration.

2.3.2 Crop evapotranspiration (ETc)

The CROPGWAT calculated crop evapotranspiration (ETc) of each crop as the product of reference evapotranspiration and crop coefficient:

$$ETc = ETo \times Kc$$

We have the expression ETc = ETo, where ETc is the depth (mm), ETo is the reference evapotranspiration (mm day^{-1}), and Kc is the crop coefficient for the crop and growth stage. Crop calendars (planting and harvesting dates) and stage-specific Kc values were provided for each of the major crops grown in UC Chukhi (wheat, mango, banana, sugarcane, berries, lentil, and other minor crops). Monthly and seasonal ETc of every crop in the Rabi season were then calculated using CROPWAT (Reddy et al., 2020).

2.3.3 Leaching requirement

To account for the additional water needed to control soil salinity, the leaching requirement (LR) was estimated using the Rhoades equation:

- LR: minimum fraction of leaching needed to maintain root zone salinity at the salt tolerance of the crop (ECe).
- ECw: salinity of the used irrigation water (dS $^{-1}$).
- ECe: mean salinity of soils to which the crop can be subjected on saturation extract (dS m $^{-1}$).

ECw was divided by ECe to obtain the leaching requirement per crop, and the leaching depth was calculated and subtracted from ETc to achieve the total depth of water that was needed at the field per crop.

2.4 Satellite imagery and cropping pattern

2.4.1 Image acquisition

The area of each crop in the study area was determined using the Landsat 8 imagery. Data from the Multispectral Landsat 8 Operational Land Imager (OLI) captured in December 2017 (Rabi season) were downloaded from the USGS GloVis portal (https://glovis.usgs.gov) (Figure 2). The spectral signatures of the key Rabi crops were to be taken at the developed growth stages of the crops, which was the reason why this period was chosen. Radiometric data (gain, bias, sun elevation, etc.) needed for pre-processing were extracted from the image metadata (Pereira, 2017).

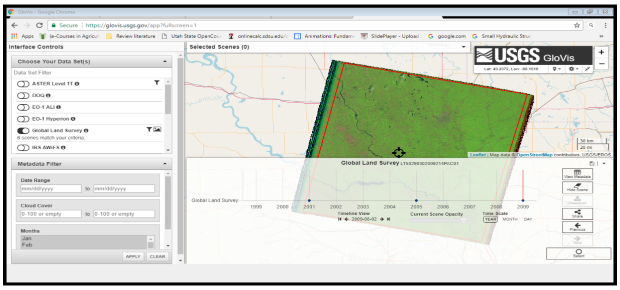

Figure 3.3. *The Landsat image was acquired for the study from USGS GloVis*

2.4.2 Image preprocessing and clipping

The Landsat 8 image of the Hyderabad district was imported into ArcGIS 10.1. The original image was clipped into two steps with the help of the district boundary shapefile and the UC Chukhi boundary:

- The Hyderabadi district was extracted from the entire Landsat picture.

S#	Image Acquisition date	Path	Row	DOY	*D*	θ_s
1	13-Dec-2021	151	42& 43	347	0.98446	38.033677

- The UC Chukhi and watercourse 5AR command area was extracted from the district image by the Spatial Analyst toolbox using the Extract by Mask function.

The obtained subset image was classified, and the area within the command location was estimated.

2.4.3 Supervised classification

Supervised classification of the Landsat 8 image subset in ArcGIS 10.1 was performed to classify it into land-cover/crop classes. The principal crops and other land uses in the command (e.g., wheat, mango orchards, banana, sugarcane, berries, lentils, various crops, fallow land, and non-agricultural areas) were digitised into training samples (Kingra, 2018). The multispectral bands were used to create a thematic map of land-cover classes using a maximum likelihood classifier. The obtained classified map was visually verified and filtered using local information on the cropping pattern and the spatial distribution of orchards and field crops (Babu et al., 2015).

2.5 Estimation of crop-wise area

Polygons that represented each class of land-cover in the classified raster were selected as polygons for each class, transformed to the required format of the attribute table, and their areas were calculated in ArcGIS (Fritz et al., 2015). All polygons of a single crop category were added together to have the total area of the given crop in the command. Hectares or acres were used to report area, in line with local practice.

2.6 Computation of total water volume required in the study area

The seasonal water demand of each crop was calculated as the seasonal water requirement (ETc and leaching depth in mm) of a crop multiplied by the area (in hectares or acres) of the crop. Depths were converted to volumes using standard unit conversions (acre-mm and acre-ft). The volumetric requirements of each crop were then added to get the cumulative water seasonal requirement of the watercourse 5AR command area (Hegde et al., 2024).

2.7 Water quantum available

Irrigation supplies in the study area are derived from both surface water and groundwater:

2.7.1 Surface water

The supplies at Canal 5AR were measured at the Mogha outlet. Discharge measurements were conducted in the channel, and the hours of operation of the watercourse during the Rabi season were determined. Seasonal surface-water volume was calculated by summing discharge over the total operating time and dividing by that time.

2.7.2 Groundwater

The discharge and operating hours of tube wells in the command area provided an estimate of the groundwater supply available in this area. The rate of each tube well was determined, and the number of hours of pumping per day or season was recorded to determine the quantity of groundwater pumped during the season. The groundwater volume was obtained by summing the contributions from all operating tube wells. The seasonal water quantum that could be applied to the command area was determined as the sum of surface water and groundwater quantities (MacLean & Congalton, 2013).

2.8 Estimation of seasonal water losses

Total seasonal water losses in the command area were derived as the difference between total water supplied (surface plus groundwater) and total crop water demand (including leaching requirement) for all crops:

$$Total\ losses = Total\ supply - Total\ demand$$

The total losses were apportioned into conveyance and on-farm application components by measuring conveyance losses along the watercourse (Hunt et al., 2024). The conveyance losses consisted of the percentage of supply lost between the watercourse head and the fields due to seepage, leakage, and operational wastage. The balance of total losses and conveyance losses was termed application losses and was non-beneficial when used in field application and distribution.

This hybrid application of CROPWAT, Landsat-based crop imaging, and measured irrigation supply provided a consistent, seasonal measure of water demand, water supply, and routine conveyance and application losses for the 5AR control of the watercourse in UC Chukhi.

3. FINDINGS AND DSICUSSIOUN

3.1 Climatic conditions and reference evapotranspiration

Weather statistics confirm the semi-arid conditions of the UC Chukhi during the Rabi season, which were entered into CROPWAT. The lowest temperatures ranged from 10.9 C in January to 25.9 C in September, and the highest temperatures were 25.2 C and 37.6 C, respectively. Relative humidity was about 46.5 and a little more in September-December. Solar radiation of 14.4-20.5 MJ m -2 day $^{-1}$, wind speeds of 156-467 km day $^{-1}$, and bright sunshine of 8.2 h day $^{-1}$ were experienced during the Rabi months. These circumstances led to an apparent seasonal trend of reference evapotranspiration (ETo) computed by CROPWAT. September had the highest of 8.06 mm day $^{-1}$, and December had the lowest of 3.58 mm day $^{-1}$, and slightly higher in February, 4.44 mm day $^{-1}$. The average ETo during the period was 5.12 mm day^{-1}, indicating that even in the winter season, evaporative demand cannot be neglected and must be considered in irrigation planning.

Table 3.1. The CROPWAT model was used to calculate the reference evapotranspiration (ETo) during the study period at UC Chukhi.

Month	Min Temp	Max Temp	Humidity	Wind	Sun	Rad	ETo
	°C	°C	%	km/day	hours	MJ/m²/day	mm/day
September	25.9	37.4	58	467	8.4	20.5	8.06
October	22.4	37.6	43	233	9	18.9	6.57
November	17	32.5	42	156	8.1	15.5	4.43
December	12.2	26.8	48	173	8.1	14.4	3.58
January	10.9	25.2	45	190	7.5	14.5	3.62
February	13.7	29	43	190	8.1	17.3	4.44
Average	**17.02**	**31.42**	**46.5**	**234.8**	**8.2**	**16.85**	**5.12**

3.2 Crop water requirements

The CROPWAT simulations provided monthly and seasonal crop water demand (ETc) for the primary crops in the 5AR command area of the watercourse.

3.2.1 Wheat

The seasonal water requirement of wheat, which is planted between October and February, reached the highest water demand in October, when the weather is quite warm, and the crop grows at a very high rate. Still, it goes down as the temperature and the crop's coefficient decrease in January and February.

Table 3.2. Water demand of wheat monthly and seasonally (ETc).

Month	Eto mm/day	Kc Value	Days	Etc mm/month
October	6.57	0.7	31	142.56
November	4.43	0.775	30	102.99
December	3.58	1.15	31	127.62
January	3.62	0.192	31	21.54
February	4.44	0.15	28	18.64
Total			**151**	**413.38**

3.2.2 Mango

Mango orchards, being perennial crops, exhibited seasonal ETc of 605.73 mm in September and February. The most significant monthly ETc (278.07 mm) was observed in September, when ETo was high, and the canopy was well developed, but this gradually decreased in the cooler months.

Table 3.3. Mango monthly and seasonal water requirement (ETc).

Month	Eto mm/day	Kc Value	Days	ETc mm/month
September	8.06	1.15	30	278.07
October	6.57	0.6	31	122.20
November	4.43	0.6	30	79.74
December	3.58	0.6	31	66.58
January	3.62	0.25	31	28.05
February	4.44	0.25	28	31.08
Total(mm)			**181**	**605.73**

3.2.3 Banana

Banana had the highest seasonal water requirement, with an ETc of 1041.56 mm and a monthly ETc of 290.16 mm, indicating that it is a highly water-demanding crop.

Table 3.4. Banana monthly and seasonal water requirement (ETc).

Month	ETo mm/day	Kc Value	Days	ETc mm/month
September	8.06	1.2	30	290.16
October	6.57	1.2	31	244.40
November	4.43	1.2	30	159.48
December	3.58	1	31	110.98
January	3.62	1	31	112.22
February	4.44	1	28	124.32
Total(mm)			**181**	**1041.56**

3.2.4 Sugarcane

The volume of water required by sugarcane during the study period was 951.83 mm, and the maximum ETc occurred in October, when both atmospheric demand and crop coefficients were high. The duration of its growth and constant water requirement highlight its effect on the seasonal water budget, despite the lower areal coverage compared to wheat and mango.

Table 3.5. Water Requirement of Sugarcane Crop

Month	ETo mm/day	Kc Value	Days	ETc mm/month
September	8.06	0.4	30	96.72
October	6.57	1.25	31	254.58
November	4.43	1.25	30	166.12
December	3.58	1.25	31	138.72
January	3.62	1.25	31	140.27
February	4.44	1.25	28	155.4
Total(mm)			**181**	**951.83**

3.2.5 Berries and lentils

The seasonal ETc for berries was 373.85 mm, and greater demand was observed in November and December. Lentil had a demand of 472.87 mm, with the highest demand in October. Even though their individual ETc values are lower than those of banana and sugarcane, they still contribute to total demand, primarily when concentrated in particular sub-areas.

Table 3.6. Berry's monthly and seasonal water requirement (ETc).

Month	ETo mm/day	Kc Value	Days	ETc mm/month
September	8.06	0.3	30	72.54
October	6.57	0.3	31	61.10
November	4.43	0.5	30	66.45
December	3.58	0.5	31	55.49
January	3.62	0.5	31	56.11
February	4.44	0.5	28	62.16
Total(mm)			**181**	**373.85**

Table 3.7. Monthly and seasonal water demand (ETc) of lentil.

Month	ETo mm/day	Kc Value	Days	ETc mm/month
September	8.06	0.4	30	96.72
October	6.57	0.63	31	128.31
November	4.43	0.86	30	114.29
December	3.58	0.9	31	99.88
January	3.62	0.3	31	33.66
Total(mm)			**153**	**472.87**

On the whole, the findings indicate the dominance of perennial orchard crops (banana, mango) and sugarcane in the seasonal distribution of water demand per unit area. In contrast, the water demand of wheat and lentil is less significant.

3.3 Cropping pattern and area under each crop

The Landsat 8 image of the 354 acres of the command of watercourse 5AR was classified to depict a broad range of cropping, primarily wheat and orchards. The wheat, mango, banana, and sugarcane were 86.8 acres (24.5% of the command), 62 acres (17.5%), 49.6 acres (14.0%), and 25 acres (7.1%), respectively. The total of the berries and lentils was 24.6 acres (6.9%). The uncultivated or fallow was also interestingly 105 acres (29.6) in the Rabi season. The availability of high-value and high-water-need perennials (banana and mango) and staple wheat, along with lesser quantities of sugarcane, berries, and lentils, indicates that the system is combined and that productivity and risk are diversified. However, the relatively large share of uncultivated land suggests that there is some restriction on the water supply, land, or care options, which may limit the productive use of the soil in the command. This spatial arrangement results in a steep water-use gradient over a relatively small area, making water management difficult.

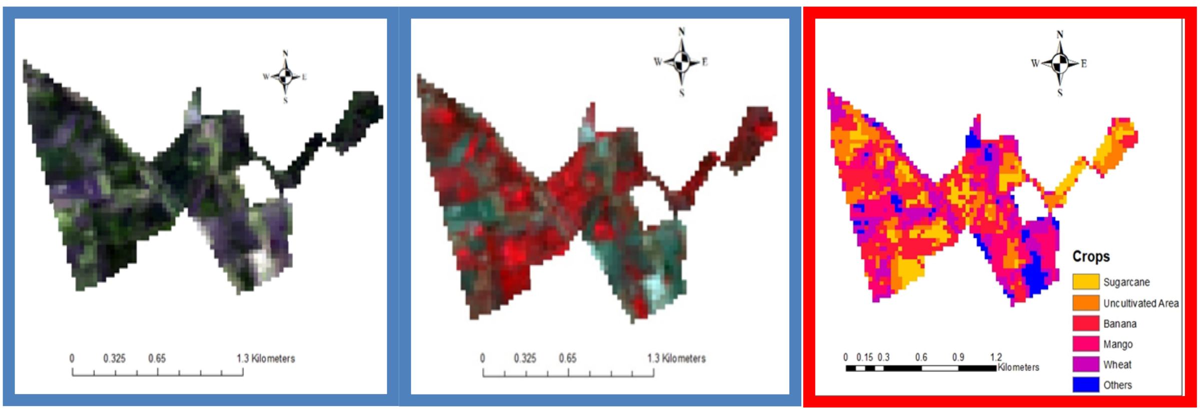

Figure 3.1. UC Chukhi (watercourse 5AR command) has been derived from Landsat 8 imagery to produce a natural colour image, a false-colour composite, and a supervised classified land-cover map.

Table 3.8. Watercourse 5AR command areas are based on the location of each crop and uncultivated

Crops	Wheat	Mango	Banana	Sugarcane	Others	Uncultivated Area	Total
Area (acres)	86.8	62	49.6	25	24.6	105	354
Area (%)	24.5	17.5	14	7.1	6.9	29.6	100

land, derived from classified Landsat 8 imagery.

The visual representation of raw satellite imagery converted to a classified crop map is shown in Figure 3.1. The natural and false-colour composites highlight vegetation patterns and irrigated areas. In contrast, the classified image provides a clear outline of wheat, mango, banana, sugarcane, berries, lentils, and other crops, as well as uncultivated areas. This spatially explicit map is used to calculate crop-specific regions of the command. Table 3.8 provides a quantitative summary of the areas for each class in Figure 3.1, enabling a direct connection between land-use and water-demand calculations.

3.4 Volumetric crop water demand

The volumetric water requirements of crops per season were estimated using crop areas derived from satellite imagery (Table 3.8) and crop water requirements (Tables 3.2-3.7). It was discovered that wheat required 35,882.08 acre-mm, Mango required 24,861.72 acre-mm, Banana required 51,661.57 acre-mm, Sugarcane required 23,605.45 acre-mm, Berries required 7,656.98 acre-mm, and Lentil required 5,940.25 acre-mm (Figure 3.2). Banas, wheat, mango, and sugarcane accounted for about a third of the total ETc volume, relative to the others. The berries and lentils brought smaller shares, though by no means negligible. The results highlight that the general seasonal demand is primarily affected by high-ETc perennial crops (banana and mango) and sugarcane, rather than wheat, even though wheat has the highest area. Such findings have tremendous implications for water-saving strategies. Examples could include the efficiency of irrigation in banana and sugarcane field, transition to partial root-zone drying or deficit irrigation regime where the agronomically viable scale of these crops would suffer a significant drop in seasonal demand, or a reassessment of the scale of these crops under extreme water stress which could lead to substantial reductions in seasonal demand where interventions in low-demand crops would only have relatively small effects.

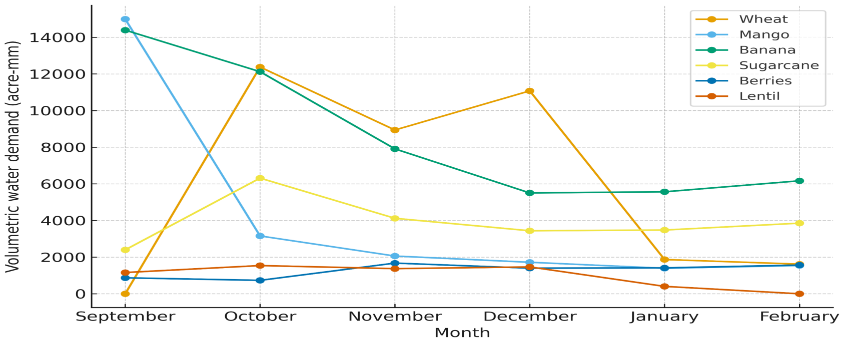

Figure 3.2 The volumetric crop water demand in the watercourse 5AR command (UC Chukhi) of wheat, mango, banana, sugarcane, berries, and lentil during the study season using CROPWAT-derived ETc and satellite-derived crop area of the same.

3.5 Water supply to the command area

The water supplies to the watercourse 5AR command include groundwater pumped from tube wells and surface water diverted into the mogha outlet of the Kunner-II minor. Groundwater abstraction was estimated based on discharge from tube wells and hours of operation during the Rabi season. The total groundwater contribution was 403.04 acre-ft. Likewise, discharge measurements at the 5AR outlet, coupled with records of running hours, yielded a seasonal surface-water supply of 430.3 acre-ft. In this way, the total water supply was 833.45 acre-ft, consisting of nearly equal portions of surface water and underground water. Such almost equal reliance on canal water and tube wells indicates an unmistakable tendency toward conjunctive use. Conjunctive use may be used to stabilise irrigation supply in the face of unpredictable canal delivery, but it may strain groundwater resources unless pumping is controlled and regulated. The findings thus highlight the importance of integrated planning that considers canal operations and groundwater sustainability.

Table 3.9. Tube-well discharge measurements in the watercourse 5AR command

S. No.	Diameter (cm)	X-Coordinate (cm)	Y-Coordinate (cm)	Flow type	Discharge (L s^{-1})
1	12.7	46	43	Full flow	19.70
2	12.7	42	47	Full flow	17.20
3	12.7	44	45	Full flow	18.40
4	12.7	40	42	Full flow	17.32
5	12.7	41	45	Full flow	17.15
Average	**12.7**	–	–	**Full flow**	**17.95 ≈ 18.0 L s^{-1} (0.635 cusecs)**

Table 3.10. Mogha outlet discharge and seasonal water availability

(a) Discharge at 5AR Mogha outlet

S. No.	Diameter (cm)	X-Coordinate (cm)	Y-Coordinate (cm)	Flow type	Discharge (L s^{-1})	Discharge (cusecs)
1	25.4	68	76	Full flow	87.56	3.10
2	25.4	64	73	Full flow	84.08	2.97
3	25.4	63	69	Full flow	85.13	3.00
Mean	**25.4**	–	–	**Full flow**	–	**3.02 cusecs**

(a) Discharge at 5AR Mogha outlet

Source	Volume (acre-ft)	Share of total supply (%)
Surface water	430.30	51.6
Groundwater	403.04	48.4
Total	**833.45**	**100.0**

3.6 Seasonal water losses and irrigation performance

Seasonal water loss was estimated by comparing total water supplied (Tables 3.15-3.17) with total seasonal water demand (Tables 3.9-3.14). The analysis found that about 33.55 percent of the water flowing into the command during the Rabi season went to waste before being put to good use for crop evapotranspiration and leaching. This loss of around 280 acre-ft was a loss of the total supply of 833.45 acre-ft, and the losses were as follows: on-farm application losses were 18.49 percent, and conveyance losses were 15.0 percent of the total supply in the watercourse network. Application losses were determined to be approximately 154 acre-ft, and conveyance processes (seepage, leakage, overtopping, and operational wastage) in the watercourse were approximately 125 acre-ft. These magnitudes are in line with expectations for unlined earthen watercourses and traditional surface irrigation techniques in non-levelled fields. The application losses are relatively significant, which indicates that the scope of improvement in on-farm management of water is high: precision land levelling, the use of enhanced channeling on the field, the use of more efficient systems of irrigation where possible, and the timing of irrigations based on the needs of crops rather than on recreational rotation or the visual display. The significant losses of conveyance also indicate that selective lining or rehabilitation of the worst reaches of the watercourse might produce real water savings.

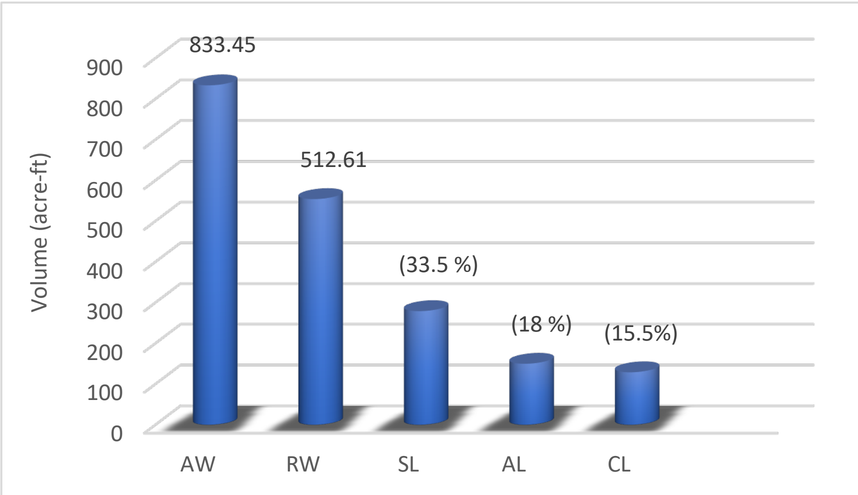

Figure 4.2. Seasonal water losses in the watercourse 5AR command, showing the percentage of total supply lost as conveyance and application losses, and the percentage that is effectively utilised to meet crop water demand.

The overall supply, as shown in Figure 4.2, yields beneficial consumption and losses. It shows that one-third of the diverted and pumped water is put to productive use in crops, two-thirds are wasted, and a third is used for on-farm purposes, slightly higher than the conveyance losses. This chart-based analysis can be used alongside numerical data to help practitioners and policymakers more easily understand which areas are poised to deliver the highest returns from more efficient irrigation. Overall, the joint analysis of satellite-based cropping patterns, CROPWAT-calculated crop water models, and measured canal and groundwater data has produced a consistent, season-based diagnosis of irrigation performance in the 5AR watercourse command. The results indicate that (i) the seasonal water demands are dominated by regions of perennial orchard and sugarcane, (ii) groundwater and canal water are slightly different contributors to total water supply as well as the losses associated with the delivery are slightly more than the losses associated with the application, and (iii) about one-third of the water delivered is wasted, and slightly less than half of the water losses refer to the application. This fact provides a solid basis for developing interventions at the farm and watercourse levels to increase water-use efficiency and promote sustainable irrigation control within such a canal-command regime.

CONCLUSIONS

This study revealed that the combination of satellite-based crop maps, the CROPWAT model, and an approximation of discharge measures is an effective and inexpensive design that can be used to diagnose seasonal irrigation effectiveness at the watercourse level. We have estimated the communication of water demand space and the seasonal volume of water lost in the 354-acre command of watercourse 5AR in UC Chukhi, district Hyderabad, using cropping patterns derived from Landsat 8 imagery and quantitative supply from canals and tube wells. The results show that high consumption of perennial crops is the most significant factor affecting seasonal crop water demand. Although wheat was the main crop on cultivated land, banana, mango, and sugarcane required high water because they had very high seasonal ETc per unit area. Banana had a cover of about a third of the total calculated crop water, followed by wheat, mango, and sugarcane, with berries and lentil contributing minor but not negligible percentages. This will bring into perspective that a change in the management or size of orchard and cane lands will have a greater impact on the total water budget than a change in the production of lower-demand products. Water was provided to the command by surface and ground water in almost equal volumes during the Rabi season, with the canal being pumped by 5AR mogha and tube-well pumping, which supplied about half of the total 833.45 acre-ft of water supply. It is almost even, and this emphasis shows the de facto conjunctive use policy, roughage with which farmers buffer the variability of canal flows. Though this conjunctive application enhances short-term irrigation reliability, it also indicates that any attempt to optimise the system's functioning would need to integrate canal operations, the condition of water-reach conveyance, and the sustainability of groundwater abstraction. The cumulative supply and crop water demand were forced to be set against each other; therefore, about a third of the cumulative seasonal water into the command was wasted before it could be utilized beneficially as either evapotranspiration or leaching demand. These break-even losses indicate that application losses on farms were slightly greater than conveyance losses in the watercourse. The tendency is identical with the non-lined earthen canals as well as the traditional surface irrigation of non-levelled lands. It also clearly defines two complementary fields of intervention that must be met to attain the desired outcome: (i) selective lining or structural improvement of the critical watercourse reaches to reduce seepage and water wastage during operation, and (ii) improve on-farm water management through levelling of the land, upgrading field channels, and timely irrigation to adjust to the crop water requirements. Along with these site-specific findings, the research also raises other methodological implications. The process used in this case is grounded in free satellite imagery, basic climatic data, commercially obtained software (ArcGIS and CROPWAT), and simple discharge data. It can therefore be transferred to other watercourses and canal-command areas where there is no elaborate hydrometric network and continuous observation. The method can help make more informed water allocations, identify specific efficiency enhancements, support evidence-based policy choices within the framework of irrigation systems with limited data, provide spatially explicit crop-specific water-demand estimates, and offer explicit accounting of supply and loss at a seasonal scale. In conclusion, as the case of watercourse 5AR shows, (i) crop choice and area allocation, in particular, to high-demand perennials, is the core of the seasonal water demand; (ii) conjunctive utilization of both canal water and groundwater is already one of the primary features of the local irrigation practice; and (iii) there is a potential which can be reduced significantly by some simple technical and management interventions. Scaling such assessment efforts to canal-command systems would provide a powerful platform for maximizing water productivity, reducing strain on groundwater supplies, and increasing the resiliency of irrigation-intensive agriculture to water shortages.

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