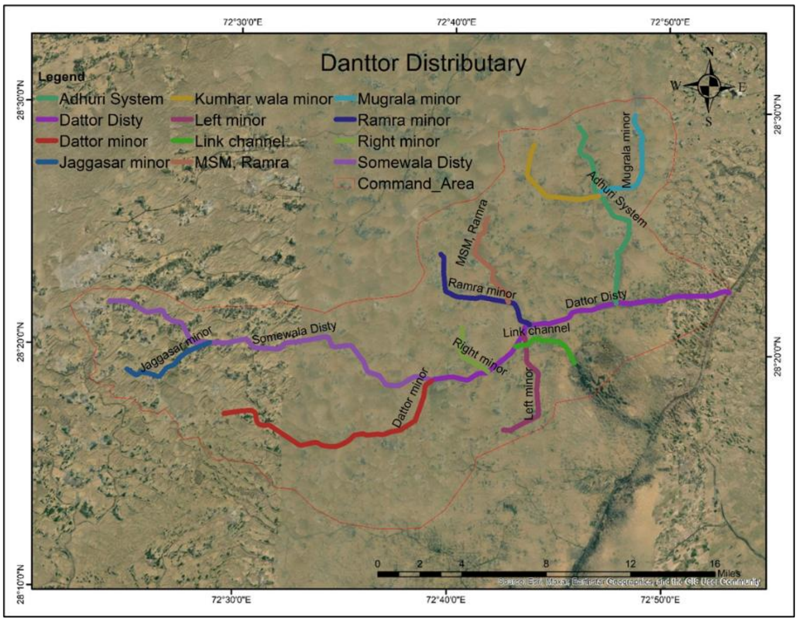
Identification of Different Crops at Farm Scale Using Remote Sensing Data in Danttor Distributary of IGNP Command Area
(Internal Study)
(Dec. 2023 – March 2025)

FINAL REPORT



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Summary

With the global population projected to reach 9.7 billion by 2050, the challenge of ensuring food security through sustainable agricultural practices has become increasingly critical. In this context, accurate mapping and monitoring of agricultural land are essential for optimizing crop production and water resource management, particularly in densely populated and water-scarce countries like India. As agriculture consumes approximately 81% of India's total freshwater, efficient irrigation planning and crop classification are necessary to sustain both food production and water availability.

This study presents an integrated remote sensing and GIS-based approach for crop identification and water requirement estimation in the Danttor distributary region of the Indira Gandhi Nahar Project (IGNP) canal command area in Rajasthan. The Danttor distributary, extending 145 km with a cultivable command area (CCA) of 28,305 ha and 11 sub-branches, was selected due to its gravity-fed irrigation system and agricultural significance.

Two primary objectives guided the research: (1) developing a reliable model for identifying heterogeneous crop types using satellite imagery and machine learning, and (2) planning crop-specific water requirements to support irrigation management.

High-resolution Sentinel-2 optical imagery and field survey data from the Rabi seasons of 2023–24 and 2024–25 were used. Initial preprocessing involved excluding non-vegetated areas based on an NDVI threshold (>0.2). A Random Forest classifier was then implemented in Google Earth Engine, using all Sentinel-2 spectral bands and NDVI as inputs. Ground-truth crop data were divided into training and validation subsets (80:20 split), and classification accuracies of 71.96% and 75% were achieved for Rabi seasons of 2023–24 and 2024–25, respectively. The major crops identified were Wheat, Mustard, Gram, Raida, and Isabgol, covering an area of 12,580 ha in 2023–24 and 11,259 ha in 2024–25. Variations in crop area were attributed primarily to seasonal canal water availability.

To assess crop-wise irrigation demands, the FAO CROPWAT model was employed using climatic data from CLIMWAT and the India Meteorological Department (IMD), alongside crop-specific parameters such as crop coefficients and growth stages. The model simulated reference evapotranspiration (ET_0) and crop evapotranspiration (ETc), allowing precise estimation of crop water requirements (CWR). Based on the spatial crop distribution from the classification maps, total water demands were calculated as 42.50 million cubic meters (MCM)

for Rabi 2023–24 and 37.44 MCM for Rabi 2024–25. These values were then evaluated against available canal supply to identify potential irrigation deficits.

Field surveys conducted in February 2024 and 2025 provided additional insights into irrigation practices and water sourcing within the command area. The integrated methodology demonstrated in this study serves as a decision-support framework for agricultural planners, offering actionable insights for crop selection, irrigation scheduling, and long-term water resource sustainability. This approach highlights the value of remote sensing and machine learning in addressing the dual challenges of food security and efficient water use in arid agricultural systems.

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CHAPTER 1 INTRODUCTION

1.1 Introduction

The population of the world is rapidly increasing and is expected to reach 9.7 billion by the year 2050 (UN, 2019). This huge increase in population will create enormous pressure on the biosphere. As the population of the whole world is growing continuously, major challenges of the 21st century that policy makers, government agencies, and researchers will face are increasing food demands and global food security. Food and Agriculture Organization (FAO) estimates that by the year 2030, some of the developing countries (approximately 12%) will face the problem of insufficient food supply (FAO, 2006). Such challenges are especially prominent in developing countries, where food supply is already an issue. However, climate variability (very less rainfall condition leading to drought condition or heavy rainfall causing flood) is also a key factor for increasing the vulnerability to food insecurity (FAO, 2013). Boosting agricultural practice may be one alternative to fulfil this increasing demand for food security globally (Foley et al., 2011).

Mapping and monitoring of agricultural land have become essential for sustainable agricultural practice, and to manage natural resources efficiently (Singh, 2000). Presently, agriculture land which includes crops, as well as pasture, occupies nearly 40% of the earth's ice-free surface. However, the expansion of cropland is limited and the situation is more difficult with highly populated countries. Although, it was a great achievement that the production of major crops has doubled between 1985 and 2005, on the other hand, nearly 10% expansion in agricultural land has been reported (FAO, 2013; Foley et al., 2011). Against this background of the continuing rise in population and limited scope to increase the land for agriculture, sustainable agricultural practices (technologically enhanced) have become a significant and cost-effective means to improve the food supply globally (Wichelns and Oster, 2006).

Climate change is another major driver to impact agriculture as the availability of water changes and the frequency of extreme weather events, like floods or droughts may be increased. These extreme events disrupt whole agricultural production. Such conditions may completely disturb the average growth of yield production and change the pattern of crops in an area that is highly sensitive to such extreme events (Godfray et al., 2010). To meet out the demand for food, intensification of crop land may lead to issues, such as global warming. Therefore, under such a scenario, it is required to increase the production of crops with the limited landscape (Foley et al., 2011).

India is an agrarian economy and nearly two-third of its population are directly or indirectly involved in agricultural activities (National Portal Content Management Team, 2011). India has reported a remarkable growth in the agricultural sector in the past few decades and holds a share in the world's export market. The agricultural sector has a significant contribution (nearly 17%) to Gross Domestic Product (GDP) growth. In this context, several revolution programs, such as white revolution i.e. in the dairy sector, and the green revolution, which signifies the production of food grains, achieved great success. These revolution programs greatly helped to fulfil the domestic food requirements, as well as to export agricultural commodities throughout the World. Similar to the factors affecting agricultural production globally, in India, agricultural risks are triggered by factors, such as floods, droughts, variability in climate, unavailability of water, lack of efficient crop management practices, etc. These factors may lead to uncertainties in crop production and the prices of grain. Therefore, statistical information regarding crops (yield estimation, crop diversity, forecasting, etc.) may play a key role to identify the problem domain and the nature of required intervention to address the identified problems.

1.2 Global Operational Agricultural Monitoring Systems

In sustainable agricultural practices, accurately identifying crops is very important for decision-making purposes, to design various schemes for agricultural sectors (Jiang et al. 2020). Wrong agricultural practices may affect natural resources like ground water (Singh, 2000). Natural resources must be utilized efficiently. Therefore, the cropping pattern of a specific region is an essential input to make policies for sustainable agriculture. Classification of land cover has been always an active area of research for decades in the remote sensing domain. In the past few decades, some operational agricultural monitoring systems have been developed that utilize Earth Observation (EO) data and provide Cropland Mapping and Monitoring (CMM) applications. However, the generation of accurate and timely crop maps is still a scientific challenge, due to the spectral similarity of crops.

The 3rd Earth Observation Summit (February 2005), established a Group on Earth Observations (GEO) to build Global Earth Observing System of Systems (GEOSS). The agricultural component of GEOSS includes the following three primary components:

i) Global monitoring and mapping of changes in the distribution of irrigated land (which includes crop type distribution and area covered by crops)

ii) Global monitoring of agricultural production and forecasting shortfall in crop production

iii) Early warning of shortfalls and famine.

National Aeronautics and Space Administration (NASA) initiated a project in the year 2002, named Global Agriculture Monitoring (GLAM) in collaboration with other U.S. organizations. This project provides information regarding agriculture on a global scale (Becker-Reshef et al., 2010). Furthermore, other major components of the projects are yield forecasting, and crop growth monitoring. Another program is Global Monitoring for Environment and Security (GMES) that aims to promote more sustainable management of natural resources by using EO data. Presently, in the U.S., the information regarding the crop area estimation is provided by a program namely National Agricultural Statistical Service (NASS). Whereas, in Europe, a programme established to collect statistical data regarding agricultural production is named as the Monitoring Agricultural Resources (MARS) (van Diepen and Boogaard, 2009). China Crop Watch System (CCWS) is another monitoring programme of the Chinese Academy of Sciences run in China, which is the country’s leading crop monitoring system. Other crop monitoring systems may be found in countries like India, Brazil, and Russia. All these projects mainly emphasis on the relevance of remote sensing data in agricultural monitoring systems (Justice and Becker-Reshef, 2007).

1.3 Use of Space Technology in the Agriculture Sector of India

The space technology is one of the most suitable approaches to obtain information about crop distribution, yield estimation, crop classification, etc. (Mondal et al., 2014). It becomes practically relevant when the primary objective is to cover a large area. Advance satellites can provide data of the whole country in a very short duration. The retrieved information is useful for various analyses, which requires reliable information about crop type, crop condition, yield estimation, crop pattern, crop damages, crop growth, etc.

In India, the Ministry of Agriculture and Farmers Welfare (MoAFW), has been continuously emphasizing to employ space technology in the domain of agricultural mapping. Here, in the early 1980s, the government started funding various projects for agricultural monitoring, for which methodologies have been developed by the Indian Space Research Organization (ISRO). Recently, the Department of Agriculture, Cooperation, and Farmers Welfare (DAC&FW) had launched KISAN crop Insurance during October 2015. The DAC&FW also established a Centre in 2012, named as Mahalanobis National Crop Forecast Centre (MNCFC), which is dedicated to the forecasting of eight major crops production.

MoAFW also launched a programme known as FASAL (Forecasting Agricultural output using Space, Agro-meteorology, and Land based observations) in 2006 (FASAL Technical Report, 2017). ISRO developed the technology for the project by collaborating with various organizations working at the state or national level (Parihar and Oza, 2006). The FASAL scheme has several functions, however, they may be grouped into the following core activities:

i) Image Analysis and Pattern Recognition Group (IAPRG): This group is mainly responsible to handle the large volume of RS data as well as the screening of data. Other objectives are the geo-referencing and perform different types of analysis to drive the outcome. This group utilizes different methods or models to analyse the data coming from different sources.

ii) Crop Growth and Yield Modeling Group (CYMG): The task of this group to develop agro-meteorological models for monitoring crop status as well as yield information. This group is also responsible to enhance spatial representativeness and robustness by integrating remotely sensed information into the models.

The horticulture sector is very important for the overall growth of the agricultural sector in India. DAC&FW has launched a project in 2014, known as CHAMAN (Coordinated Horticulture Assessment and Management using geoINformatics) (Ray et al., 2016). This project's objective is to develop the scientific methodology for the assessment of horticulture i.e. area estimation and production forecasting of seven major horticulture crops in the selected areas within the country during the project's Phase-I. This project has mainly two following component (FASAL Technical Report, 2017):

i) Remote sensing Technology,

ii) Sample Survey methodology

The first component of the project was developed by MNCFC in collaboration with other centres like ISRO. Whereas, the second component of the project has been developed by the Indian Agricultural Statistics Research Institute (IASRI). In this project, either LISS III or LISS IV satellite data have been used, the selection of satellite data depends on the spatial extent of the crop. At a specific time or during crop growing season, if Indian satellite data are not available then foreign satellite data may be explored. Presently, the CHAMAN project is in phase-II and expanding to more states (15) of the country.

1.4 Underlying Data and Techniques for Crop Mapping

Mapping of crops at regional and national levels gives input to various agencies like insurance agencies, geoportal, regional agricultural boards, etc. Crop classification is important to understand crop diversity that affects environmental conditions within the region (Singh, 2000). Advanced remote sensing techniques are used to access cost-effective tools for acquiring a large amount of information. Efficient classification algorithms and good quality satellite images are essential for producing accurate maps. A variety of classification approaches such as Machine Learning (ML), soft classification have been adopted to obtain more accurate results.

Earth observation (EO) data are very useful in the domain of agricultural monitoring applications (Justice and Becker-Reshef, 2007). In the past few decades, with the advancement in technology, a variety of approaches have been developed to provide statistics about agricultural production or mapping and monitoring purposes (Carfagna and Gallego, 2005). However, spatially explicit monitoring of agricultural production needs data such as total land area used for agricultural purpose, precipitation data, availability of water resources, and requires to update such information on a regular basis (Ozdogan et al. 2010). Several models require additional information regarding the spatial distribution of crops as an input to delivermore concrete outcomes (Jiang et al. 2020). Agricultural monitoring and mapping applications use a variety of remotely sensed data having different spectral and spatial properties. When the selected study area is very large then low spatial resolution data seems to be a good choice (Doraiswamy et al. 2007). On the other hand, Very High Resolution (VHR) data are effectively used for precision agriculture (Upadhyay et al. 2012). Recently, advance satellite mission like Sentinel-2 provides data globally at the medium spatial resolution, have been explored by many researchers for agricultural monitoring (Belgiu and Csillik, 2018; Forkuor et al., 2018).

1.5 Agricultural Mapping and Monitoring – Opportunities and Challenges

As the remote sensing technology has grown, a variety of data have been available to the research community, like optical, hyperspectral, Synthetic Aperture Radar (SAR), etc. These data may have different radiometric resolutions (12–16 bit), spatial resolutions, revisit times, and spectral properties (few bands to few hundreds of bands). To meet the demand for mapping crops at a regional or global scale, satellite data of appropriate spatial resolution have to be used. Satellite imagery consists of large data, specifically in case hyperspectral, handling this high volume of data is also a tedious job (Lawrence et al. 2004).

Image classification is the principal technique to identify and map crops in the field of remote sensing. One major challenge is the selection of suitable classification algorithms, as the same technique may not perform well with a high dimensional dataset and in complex classification scenarios. Data provided by future satellite missions may be even more complex. Therefore, the development of appropriate methodologies to handle this type of data efficiently is a key step that may affect the results up to a great extent. (Stehman and Milliken, 2007). Another issue is the requirements of revisit time and geographical coverage as for some specific applications such as crop growth analysis, for such applications frequent data assess is required (McNairn et al. 2002).

Crop mapping applications usually require remotely sensed data that cover a large geographic area, especially when the objective is to gather information locally or globally (Wardlow and Egbert, 2008). However, this may result to have a spatial resolution that is coarser than desired, as the satellite missions that provide data for such purposes usually have a coarser spatial resolution (MODIS with 250m spatial resolution). Therefore, when the chosen study region is heterogeneous, the selection of such kind of coarser resolution may lose the information, and results may be highly impacted due to the presence of mixed pixels. The coarser spatial resolution provides more fundamental information such as vegetation or non-vegetation, cropland area, rather than crop-specific information in a heterogeneous agricultural environment. There is a lack of such a framework or guidelines to select the appropriate EO data for the mapping of crops in complex agricultural landscapes.

1.6 Crop Water Requirement

Water, a precious and scarce natural resource, is essential to life, livelihood, food security, and long term sustainable development. “Potential changes in climate can impact agriculture and water resources” (Ludwig et al.., 2014). With the prolonged drought, declining water level in dams, sedimentation of rivers, and water restrictions due to constant competition from other sectors, the need for judicious use of available water for sustainable development of agriculture. Agriculture consumes the most water in India (81 per cent); thus, making the most effective use of water in agriculture should be a top focus (Surendran et al.., 2013; Dhawan, 2017). Soil moisture comprises a little portion (0.15%) of the world's available freshwater (Dobriyal et al., 2012). The water available in the form of soil moisture is used to help produce crops and support plant growth. Management of soil water is critical to numerous hydrological, ecological, and biogeochemical activities. For effective resource planning, accurate information on evapotranspiration, crop water requirements, and net irrigation requirements is essential (Levidow et al., 2014). As a result, profitability and long-term viability might improve. Effective water resources management impact agricultural productivity, water usage efficiency, and reduces the negative impact on the environment through nutrient leaching, eutrophication, waterlogging, and pollution of surface and groundwater (Scanlon et al.., 2007).“Crop water requirement (CWR) is defined as the depth of water (millimetres) required to meet the water consumed by evapotranspiration (ETc) by a disease-free crop growing in fields under non-restrictive soil conditions, including soil water and fertility, and achieving full production potential under the given growing environment”. Accurate CWR estimation is a vital part of proper water management in agriculture. Such assessment requires specific instrumentation and methodologies (Rafeet, 2002). The most common criteria for assessing CWR are currently based on the climatic water balance (i.e., evapotranspiration, lysimeter), plant physiological properties, soil water status measurements, remote sensing, surface energy balance algorithm, or a combination of these factors (Gaddikeri et al., 2022). Where meteorological data are available, assessing the CWR is based on the atmospheric water demand called reference evapotranspiration (ET0) is used. Under limited weather data condition, CROPWAT may used for assessing the ETo, crop water requirement and irrigation scheduling. It is a decision support tool developed by the Land and Water development division of the Food and Agriculture Organization (FAO). CROPWAT is a computer-based software that calculate agricultural water and irrigation needs based on soil, climate, and crop data. CLIMWAT is a climatic database to be used in combination with the computer program CROPWAT. Besides, both the software combinedly used to develop irrigation practice guidelines, the creation of irrigation schedule under diverse water allocation needs, and estimates under rainfed or shortfall irrigation situations. Khan et al., 2021 applied CROPWAT software in the Al-Qassim Province, Saudi Arabia, to estimate the topographical sustainability of the crop water requirement. Furthermore, they explored the utility of CROPWAT and CLIMWAT software for irrigation scheduling of the main crops. Several studies were conducted using CROPWAT software for estimation of crop water requirements for various purposes like evaluating the performance of canal command system, estimating the potential command area of pulp and paper mill effluent (Rajput et al., 2021), Irrigation scheduling (Prattoyee et al., 2021), deficit irrigation scheduling (Diro and Tilahun, 2009), climate change impact on crop water (Naik et al., 2015), and water footprint studies (Ewaid et al., 2019) and Reference evapotranspiration modelling (Pawar et al., 2021). CROPWAT uses meteorological data from over 5000 climate stations worldwide to crop water requirements, and helps in crop planning. The CLIMWAT provides data for estimating ET_0, including daily maximum (Tmax) and minimum temperatures (Tmin), relative humidity (RH), daylight hours/solar radiations (SR), wind speed (WS), and precipitation (P). In the CROPWAT model, the FAO-Penman Monteith equation was used to estimate ET0 using data from the CLIMWAT.

On the basis of this the following objective are formulated for the study area

1.7 Objective of study

There are two objectives are formulated

- Development of model for **heterogeneous crop identification** using RS & GIS along with **Machine learning techniques.**
- Planning of **water demand** according to different type of crops in the study area.

Chapter 2 STUDY AREA AND DATA COLLECTION

2.1 Study Area

In this study danttor distributary of IGNP canal is selected which is started at RD 710 of the IGNP Canal as shown in Figure 1. In this distributary water supply is free flow according to the gravity flow. The total length of danttor distributary 145 km and CCA is 28305 ha and it have 11 subbranches.

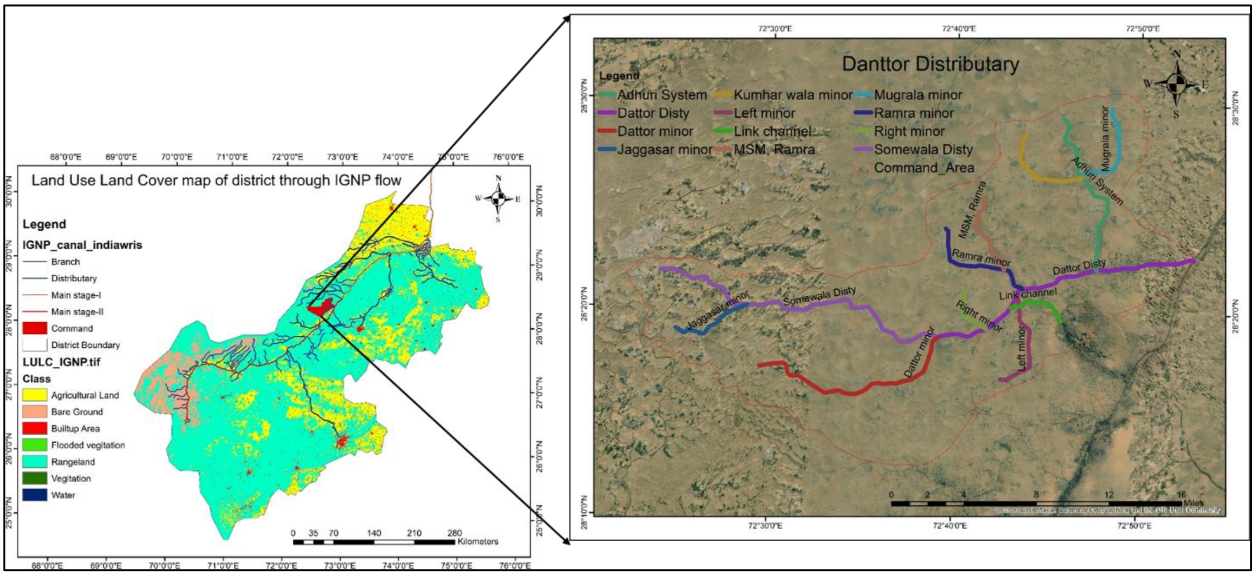


Figure 1 – Study area map

The details of branches of danttor distributary are listed in table 1. Total farmer practices agriculture in danttor distributary are approx 6550 and total cropped area during rabi 11945 ha and during kharif 9193 ha.

2.2 Climate Data-

Danttor distributoray, located in the northwestern part of Rajasthan, India, experiences a hot desert climate (Köppen BWh), characteristic of the Thar Desert region. The area is marked by extreme temperatures and minimal rainfall. Summers are intensely hot, with average maximum temperatures peaking around 42°C in May and June, and historical highs reaching up to 49.5°C. Winters are cooler, with average minimum temperatures dropping to approximately 7.7°C in January, and record lows dipping to -4.0°C. Annual rainfall is scarce and highly variable, averaging between 229 mm and 325 mm, predominantly occurring during the monsoon months from July to September. July typically stands out as the wettest month, receiving about 95 mm of rainfall. The district enjoys abundant sunshine throughout the year, averaging over 3,800 hours annually, and experiences low humidity levels, especially during the pre-monsoon summer months. These climatic conditions significantly influence the region's agriculture, water resources, and daily life, necessitating adaptations to the arid environment.

Table 1 – Details of sub distributaries of Danttor canal

S. No.	Canal	Length (km)	CCA (Ha)
1	Danttor Disty	25.39	5398.75
2	Aduri Disty	15.85	2706.02
3	Kumhar wala minor	8.75	1985.71
4	Mugrala Minor	9.14	1704.77
5	Ramra Minor	10.23	1127.97
6	Makeri sub Minor	7.83	2243.33
7	Danttor left Minor	7	1772.61
8	Danttor Right Minor - II	4.51	753.58
9	Danttor Minor	19.81	4380.66
10	Jaggasar Minor	7.47	850.03
11	Somewala Disy.	28.95	5381.73
	Total	144.93	28305.16

2.3 Field Data Collection

In this study, two field surveys were conducted, one is during month of Feb 2024 for collection of Rabi season 2023-24 and another is in month of Feb 2025 for collection of Rabi season 2024-25. During this field visit it is observed that main crop grown in study area are Wheat, Mustard, Raida, Gram and Isabgole.

2.3.1 Wheat crop

A total 388 and 350 wheat crop location for Rabi 2023-24 and 2024-25 respectively. It is observed that wheat crop is grow in large area near the head and in small area toward the tail end. The location of wheat crop collected during field visit are shown figure 2 and figure 3.

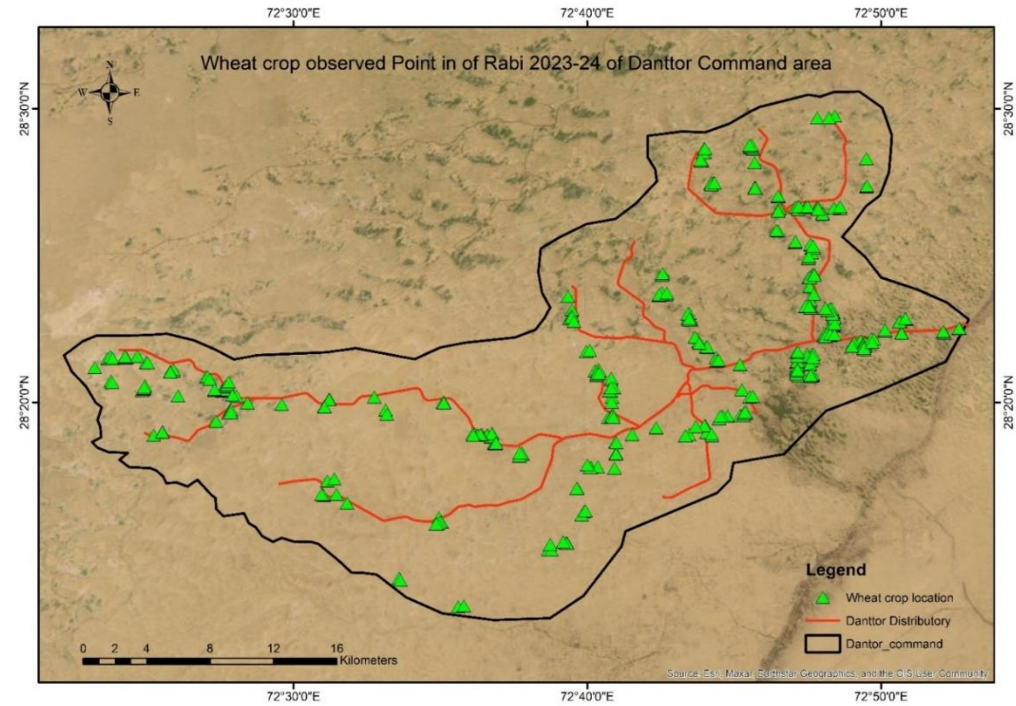


Figure 2 – Location of wheat crop during Rabi 2023-24

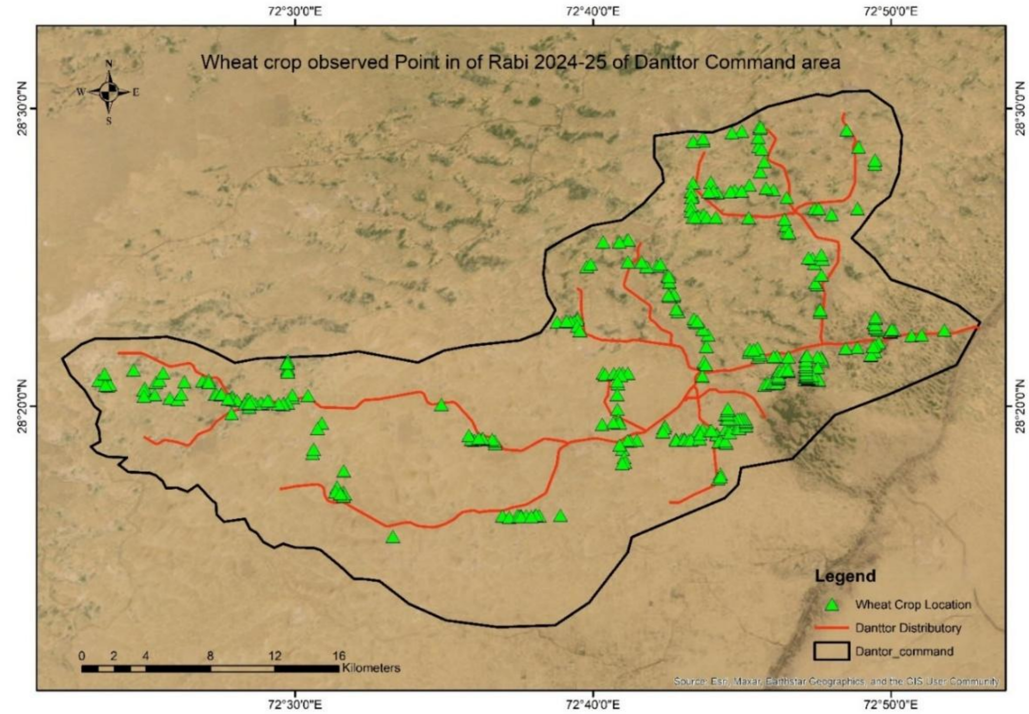


Figure 3 - Location of wheat crop during Rabi 2024-25

2.3.2 Mustard Crop

A total of 289 mustard crop location were collected during the rabi season of 2023-24 and 270 mustard crop location were collected during the rabi season 2024-25. It is observed that mustard crop grown in more area near the tail end as it required less water compare to wheat crop. The location of mustard crop location collected during field visit are shown figure 4 and figure 5.

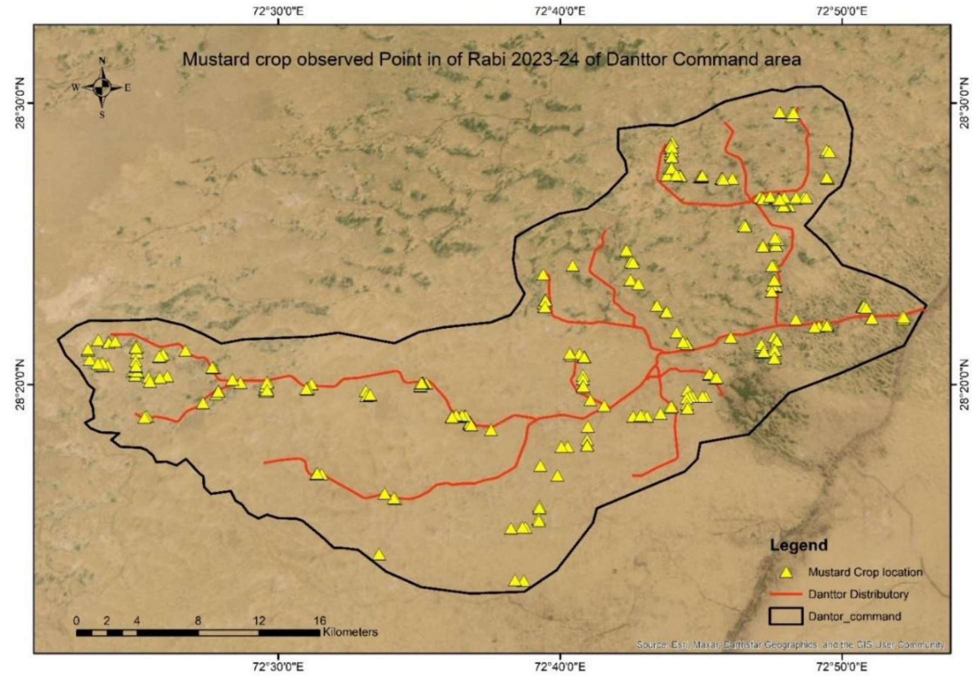


Figure 4 – Location of Mustard crop during Rabi 2023-24

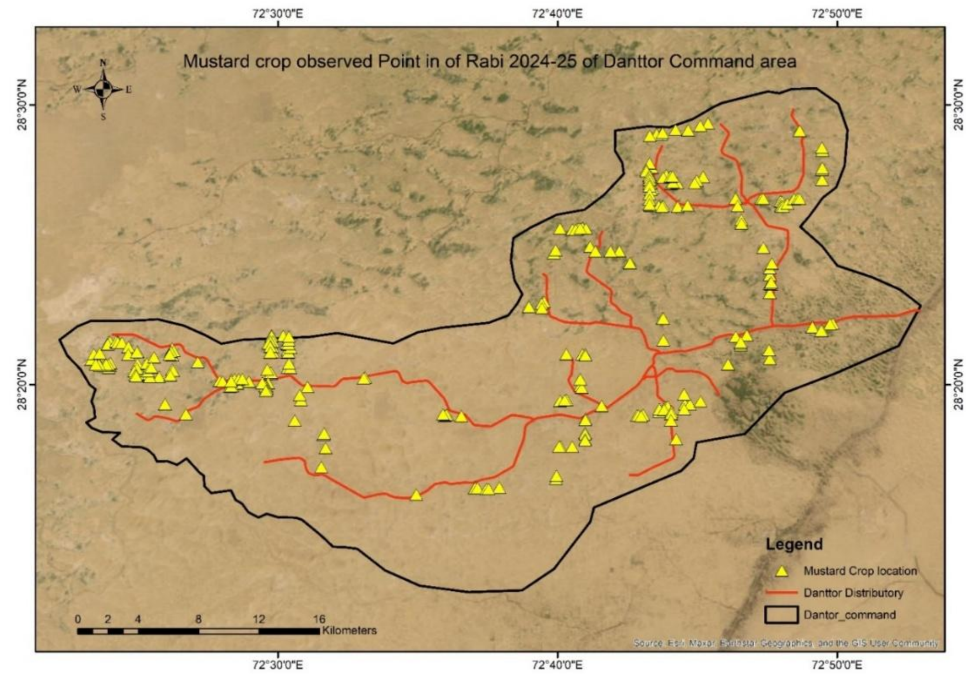


Figure 5 – Location of Mustard crop during Rabi 2024-25

2.3.3 Raida Crop

The Raida crop also known as “Desi Mustard” or “Pili Sarso” in local. A total of 69 Raida crop location were collected during the rabi season of 2023-24 and 50 Raida crop location were collected during the rabi season 2024-25. It is observed that raid crop is mainly grow near the head of canal. The location of Raida crop location collected during field visit are shown figure 6 and figure 7.

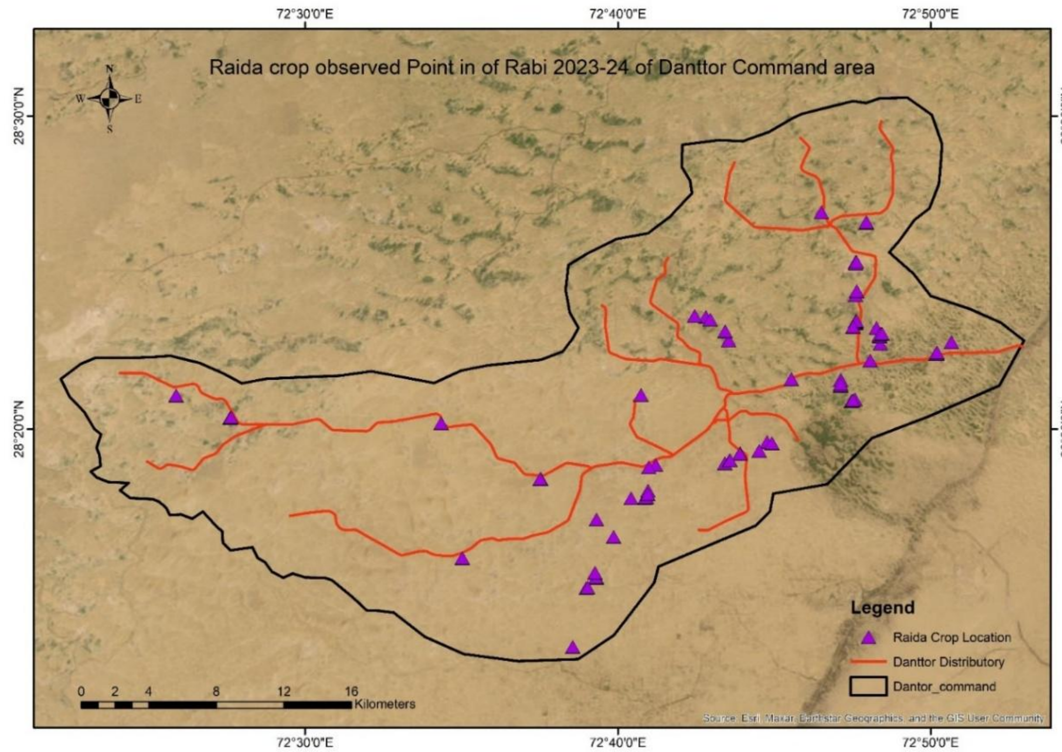


Figure 6 – Location of Raida crop during Rabi 2023-24

2.3.4 Gram Crop

A total of 196 gram crop location are collected during the rabi season of 2023-24 and 142 gram crop location are collected during the rabi season 2024-25. It is observed that gram crop is grown in whole command area. The location of gram crop location collected during field visit are shown figure 8 and figure 9.

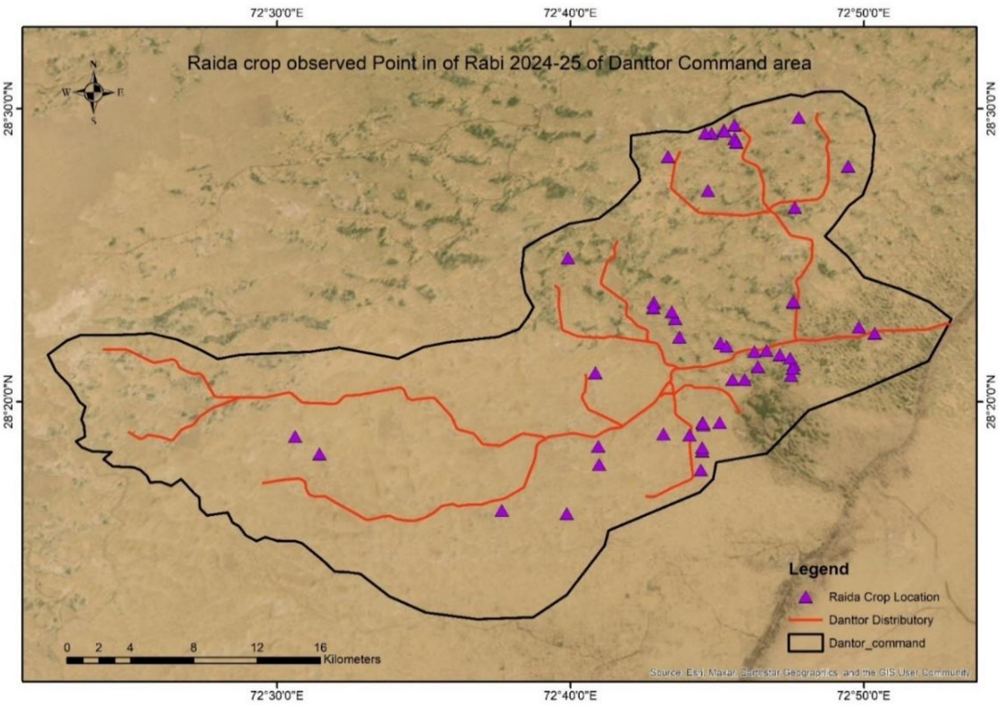


Figure 7 – Location of Raida crop during Rabi 2024-25

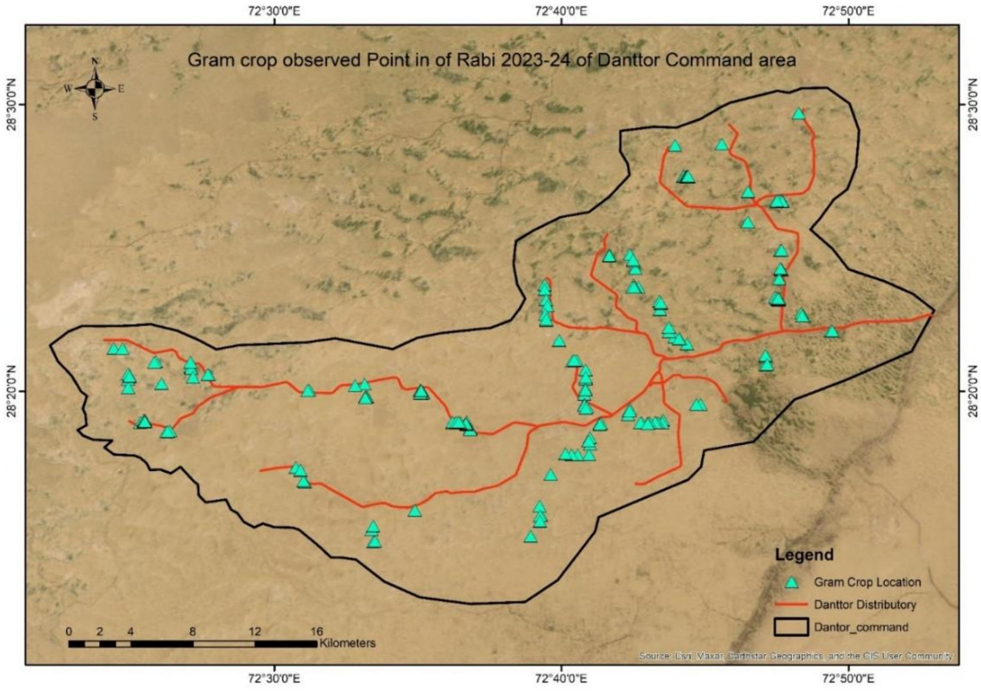


Figure 8 - Location of Gram crop during Rabi 2023-24

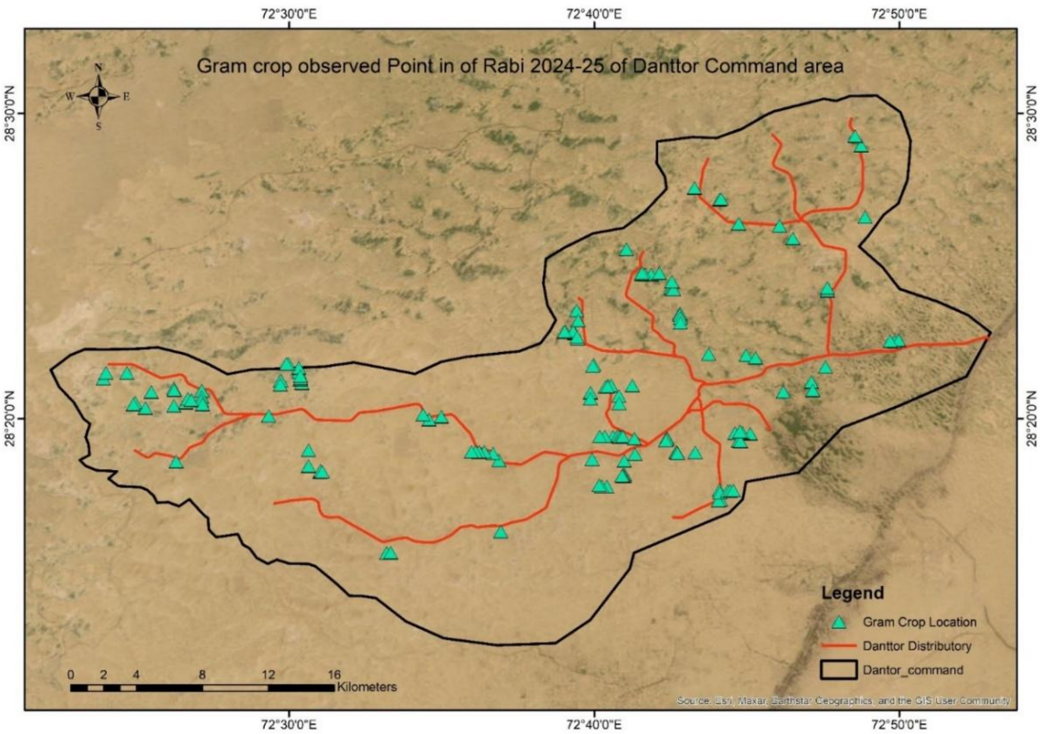


Figure 9 - Location of Gram crop during Rabi 2024-25

2.3.5 Isabgole crop

A total of 115 isabgole crop location are collected during the rabi season of 2023-24 and 150 isabgole crop location are collected during the rabi season 2024-25. It is observed during rabi 2024-25 isabgole crop is sown in large area compare to rabi 2023-24. Also it observed that at tail end and farther from canal the isabgole crop is grown more. . The location of gram crop location collected during field visit are shown figure 10 and figure 11.

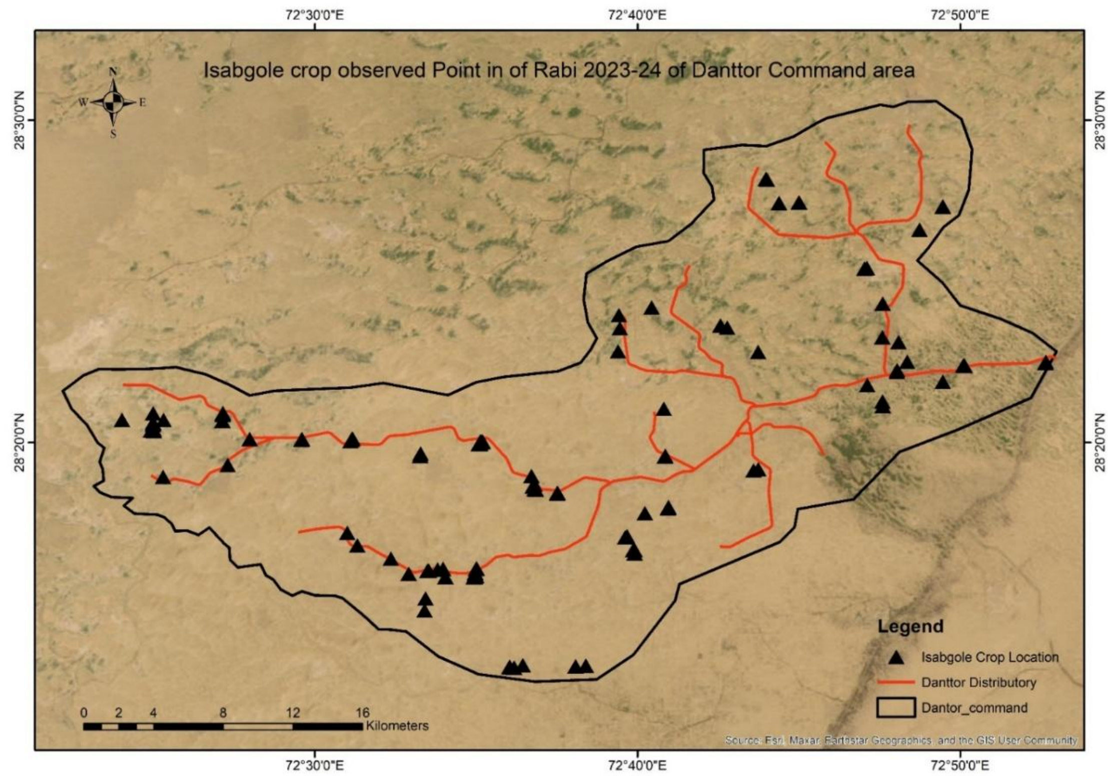


Figure 10 - Location of Isabgole crop during Rabi 2023-24

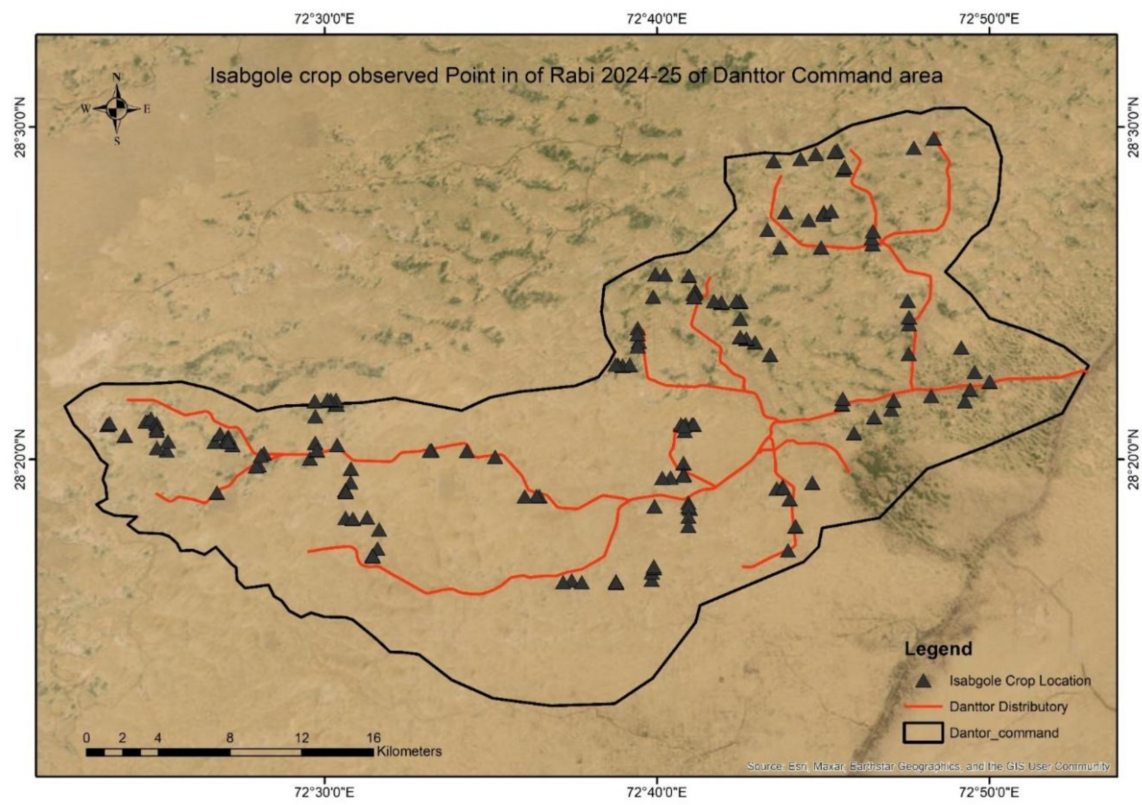


Figure 11 - Location of Isabgole crop during Rabi 2024-25

2.4 Satellite data collection

Sentinel-2 satellite data is used in this study. Sentinel-2 is an optical satellite with two complementary satellite systems (Sentinel-2A and Sentinel-2B). The opposite orbit of Setintel-2A and Sentinel-2B improved the revisit frequency from 10 days to 5 days. Both the Sentinel-2A and Sentinel-2B carry a Multi-Spectral Instrument (MSI), which can acquire images in 13 spectral bands of variable resolution (10 m: B2 (Blue), B3 (Green), B4 (Red), and B8 (Near Infrared (NIR)); 20 m: B5 (Vegetation red edge (Vredge)), B6 (Vredge), B7 (Vredge), B8A (Vredge), B11 (Short wave infrared (SWIR)), and B12 (SWIR); 60 m: B1(Coastal aerosol), B9 (Water vapour), and B10 (SWIR-Cirrus)) shown in table 2 . Sentinel image collection is used in Google earth engine for image processing.

Table 2 – Central wavelength and resolution of different bands of sentinel 2.

Sentinel-2 Bands	**Central Wavelength (μm)**	**Resolution (m)**
Band 1 – Coastal aerosol	0.443	60
Band 2 – Blue	0.490	10
Band 3 – Green	0.560	10
Band 4 – Red	0.665	10
Band 5 – Vegetation Red Edge	0.705	20
Band 6 – Vegetation Red Edge	0.740	20
Band 7 – Vegetation Red Edge	0.783	20
Band 8 – NIR	0.842	10
Band 8A – Vegetation Red Edge	0.865	20
Band 9 – Water vapour	0.945	60
Band 10 – SWIR – Cirrus	1.375	60
Band 11 – SWIR	1.610	20
Band 12 – SWIR	2.190	20

Chapter 3 DEVELOPMENT OF CROP CLASSIFICATION MODEL

3.1 Model Development

The flowchart (Figure 12) illustrates a systematic methodology for generating crop maps through the integration of remote sensing data and field observations. Initially, Sentinel-2 optical imagery and field-observed data regarding the types of crops sown are collected. As a preprocessing step, barren land is excluded from the analysis by applying an NDVI threshold; only pixels with NDVI > 0.2 are retained for further processing, ensuring the focus remains on actively vegetated areas.

Following preprocessing, machine learning techniques are employed for crop classification. Specifically, a Random Forest Classifier is used, utilizing both the NDVI and all available Sentinel-2 spectral bands as input features. The observed crop data is divided into a 80:20 ratio, where 80% is used for training (model calibration) and 20% for validation of the model's performance.

After model training, a crop map is generated, classifying the different crop types across the study area. The classification output undergoes an accuracy assessment by comparing the predicted classes with the ground-truth observed data. If the accuracy is not satisfactory, model refinement is undertaken by adjusting parameters or reselecting features. If the accuracy is satisfactory, the process concludes with the production of the final crop map.

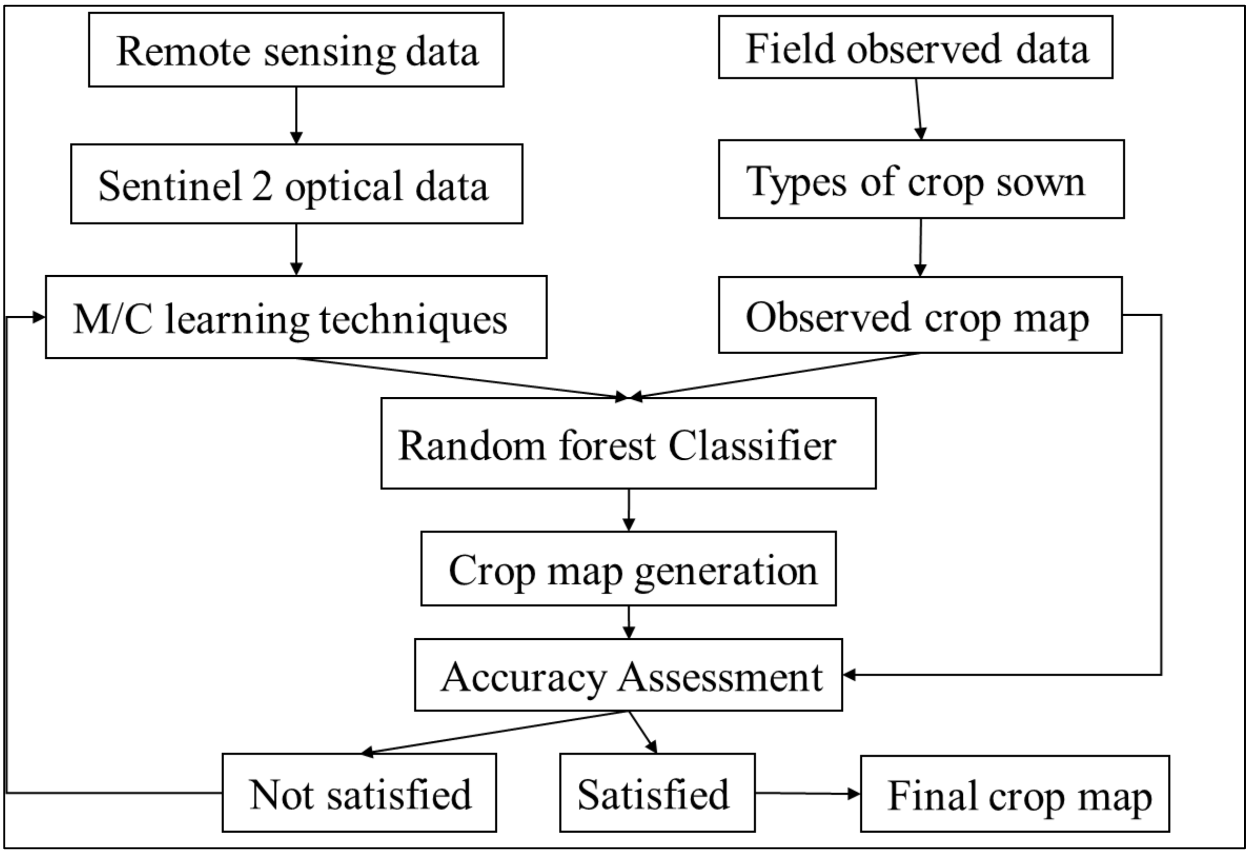


Figure 12 – Flow chart of methodology for crop classification

3.2 Crop map of Rabi 2023-24

For generating the crop map of rabi 2023-24, median value of sentinel data from 12 Feb 2024 to 20 March 2024 is used. The Final crop map is generated with overall classification accuracy of 71.96 % as shown in Figure 13.

From the map it observed that total area under the crop is 12580 ha that is near to reported crop area 11954 ha in dantor distributary report. Also it observed that max area is under the wheat crop that is 5660 ha. Wheat and Gram have the 2560 ha and 2760 ha respectively. The details of different crop with their area are illustrated in table 3.

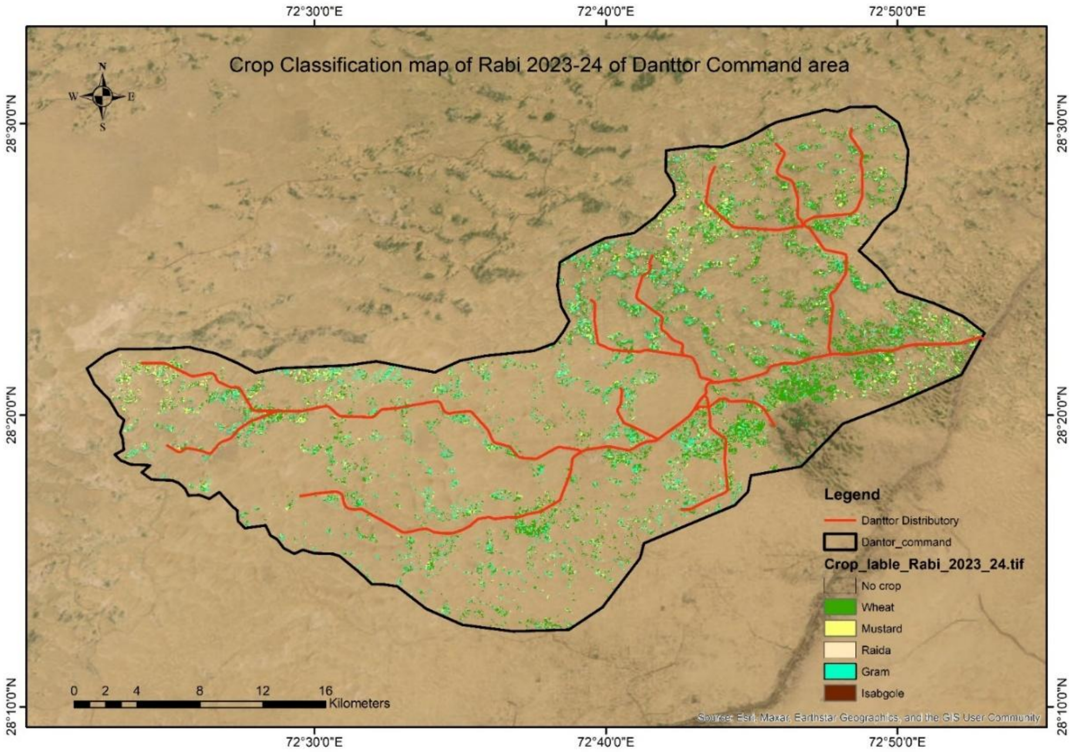


Figure 13 – Classified crop map of Rabi 2023-24

Table 3 – Crop area under different crop in Rabi 2023-24

Crop	Area (ha)
Wheat	5660
Mustard	2560
Raida	690
Gram	2760
Isabgole	910
Total	**12580**

From the confusion matrix it also observed that wheat crop is classified with accuracy of 82.58 % . and from area table it also seen that max area is comes under the wheat crop. The mustard and Gram crop were classified with accuracy of 73.44 % and 70.27 % respectively as shown in table 4. From table it also observed that Raida crop is classified with accuracy of 23.08 only and it find that it mix with mustard crop it is because the raida crop have scientific family of mustard and have the same plat structure except it have less plant height that is why it mix with mustard crop.

Table 4 - Confusion matrix of crop with accuracy for classification of Rabi 2023-24

Crop	Wheat	Mustard	Raida	Gram	Isabgole	User	Accuracy (%)
Wheat	**65**	6	2	2	4	79	82.28
Mustard	8	**47**	2	7	0	64	73.44
Raida	3	5	**3**	1	1	13	23.08
Gram	2	8	0	**26**	1	37	70.27
Isabgole	2	1	0	5	**13**	21	61.90
Producer	81	66	7	41	19	**214**	

3.3 Crop map of Rabi 2024-25

For generating the crop map of rabi 2024-25, median value of sentinel data from 20 Feb 2025 to 20 March 2025 is used. The Final crop map is generated with overall classification accuracy of 75 % as shown in Figure 14.

From the map it observed that total area under the crop is 11259 ha that is near to reported crop area 11954 ha in danttor distributary report. In rabi 2024-25 observed area is less because in this season water supply through the less compare to other year so farmer sowed less area in rabi 2024-25. From the result it also observed that wheat crop have total area 4783 ha that is less than the area under the wheat crop in rabi season 2023-24 and Isabgole have total area is 2030 ha that is more than the area under isabgole crop in rabi 2023-24. This happen because of due to less water supply in rabi 2024-25 farmer grow isabgole in larger that as water requirement of isabgole is less. The details of different crop with their area are illustrated in table 5.

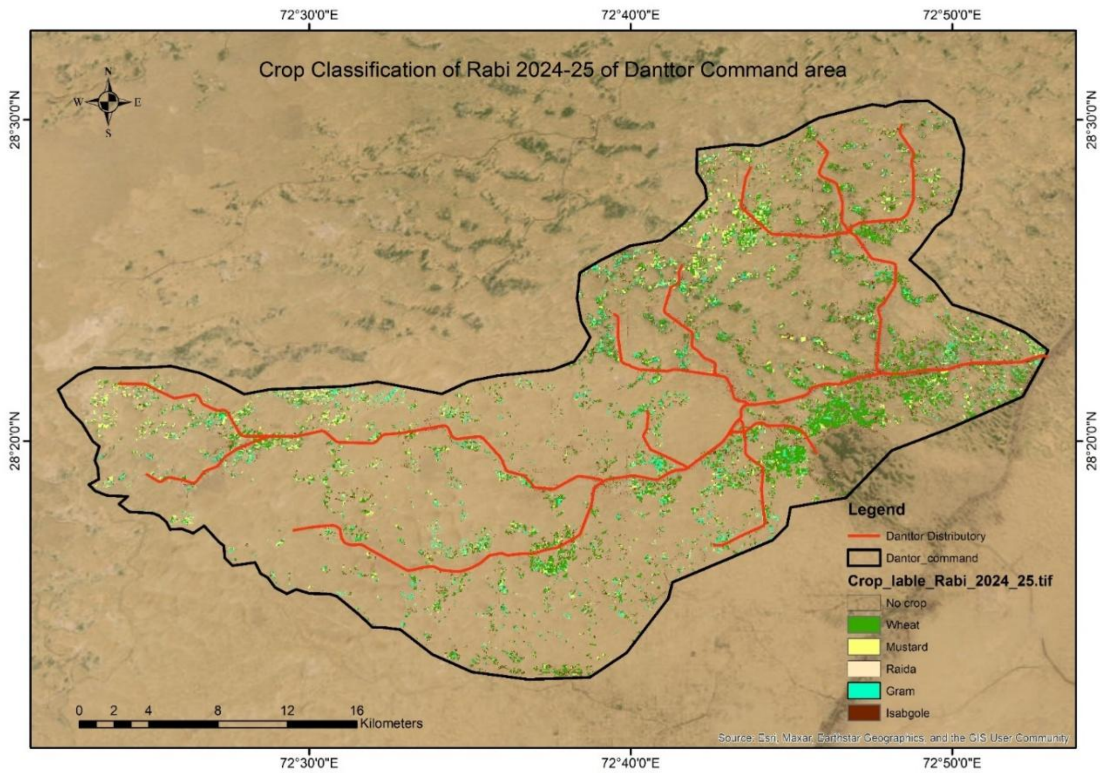


Figure 14 – Classified crop map of Rabi 2024-25

Table 5 – Crop area under different crop in Rabi 2024-25

Crop	Area (ha)
Wheat	4783
Mustard	2423
Raida	490
Gram	1533
Isabgole	2030
Total	**11259**

From the confusion matrix it also observed that wheat crop is classified with accuracy of 81.3 % . and from area table it also seen that max area is comes under the wheat crop. The mustard and Gram crop were classified with accuracy of 80.7 % and 70.4 % respectively as shown in table 6. From table it also observed that Raida crop is classified with accuracy of 42.9 only and it find that it mix with mustard crop it is because the raida crop have scientific family of mustard and have the same plat structure except it have less plant height that why it mix with mustard crop.

Table 6 - Confusion matrix of crop with accuracy for classification of Rabi 2024-25

Crop	Wheat	Mustard	Raida	Gram	Isabgole	User	Accuracy (%)
Wheat	**52**	7	0	5	0	64	81.3
Mustard	6	**46**	0	4	1	57	80.7
Raida	2	1	**6**	1	4	14	42.9
Gram	2	3	0	**19**	3	27	70.4
Isabgole	2	3	2	2	**21**	30	70.0
Producer	64	60	8	31	29	**192**	

Chapter 4 ESTIMATION OF CROP WATER REQUIREMENT

4.1 Methodology of crop water requirement

The presented flowchart (Figure 15) outlines a systematic approach for estimating crop water requirements and assessing the demand-supply balance of canal irrigation. The process begins with the collection of climate data, sourced primarily from CLIMWAT and the India Meteorological Department (IMD). Key climatic parameters such as maximum and minimum temperature, relative humidity, wind speed, sunshine hours, and rainfall are extracted for the study area. Concurrently, a literature review is conducted to obtain essential crop-specific parameters like the crop coefficient (Kc), growth stages, and root zone depth for the major crops cultivated in the region.

Using these inputs, the CROPWAT software is employed to simulate and calculate the crop water requirements (CWR) for individual crops. The CROPWAT model integrates both climate variables and crop characteristics to determine the reference evapotranspiration (ET_0) and crop evapotranspiration (ETc) over the different growth stages. Additionally, spatial crop distribution information, obtained from the crop map generated through remote sensing classification, is used to estimate the area under each crop.

Subsequently, the total water requirement is determined by aggregating the individual crop water needs across the entire command area. This total demand is then compared with the available canal water supply to evaluate the demand-supply balance. The results highlight any existing gaps between water requirements and canal availability, which are crucial for effective water management planning and scheduling irrigation releases.

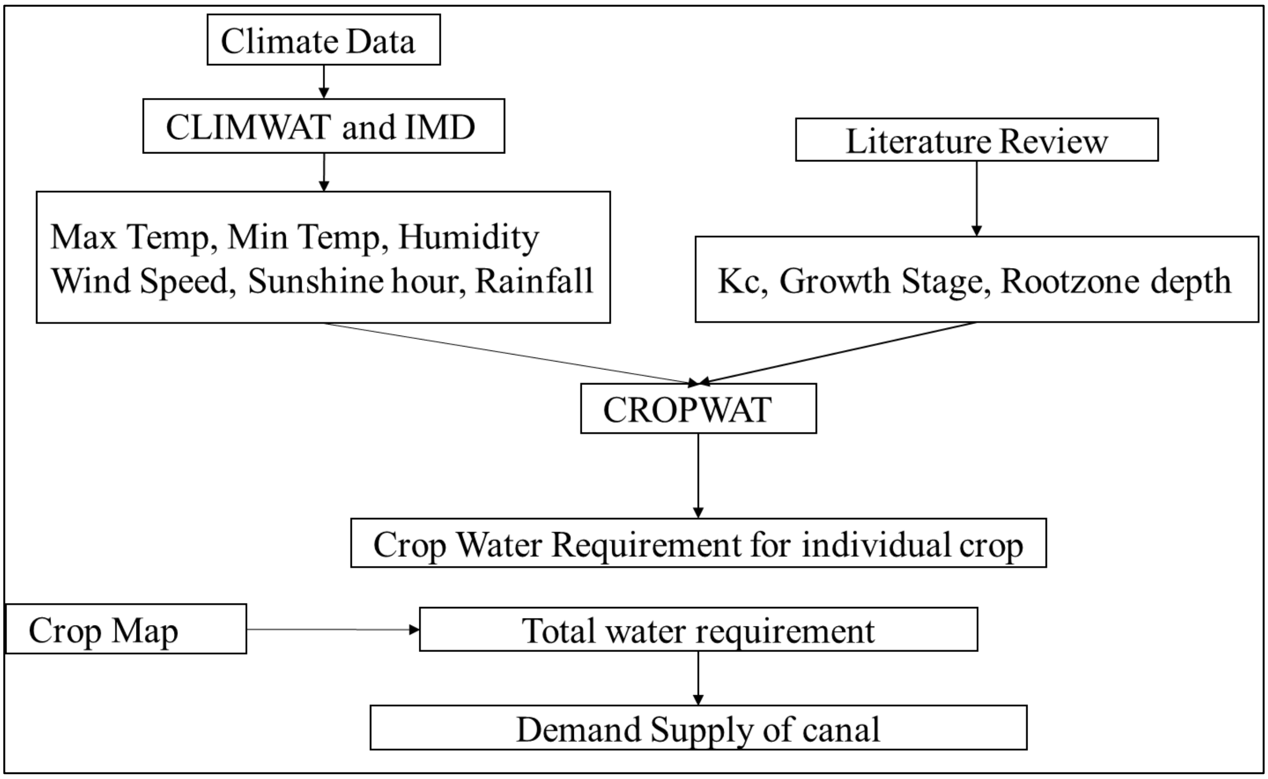


Figure 15 - Flow chart of estimation of crop water requirement

4.2 CROPWAT

CROPWAT is a decision-support tool developed by the Food and Agriculture Organization (FAO) of the United Nations, designed to facilitate the calculation of crop water requirements and irrigation requirements based on climate, crop, and soil data. It is widely used in the fields of agricultural water management, irrigation scheduling, and planning of water resources. CROPWAT assists researchers, planners, and engineers in determining the optimal use of water in agricultural production, thus promoting sustainable water resource management.

At its core, CROPWAT utilizes climate parameters such as temperature, humidity, wind speed, sunshine hours, and radiation to estimate reference evapotranspiration (ET_0) using the Penman-Monteith equation, which is the FAO-recommended method. Using crop-specific data such as crop coefficient (Kc), growth stages, and root depth, the software calculates crop evapotranspiration (ETc), which reflects the actual water requirement of a crop during its development stages.

4.2.1 Climate data

For climate data CLIMWAT software is used. CLIMWAT is a climatic database software developed by the Food and Agriculture Organization (FAO) to support irrigation planning and crop water requirement calculations. It provides long-term average climate data — such as rainfall, temperature, humidity, wind speed, and sunshine hours — for over 5,000 locations worldwide. As study area lies near to Bikaner so climate data of Bikaner location (shown in figure 16) is used in this study. Data is save from CLIMWAT and Read in CROPWAT software. The min temperature is very from 5.6 ºC to 28.8 ºC and the max temperature is very from 23 ºC to 41.6 ºC in study area. The sun shine hours are min in month of January as 7.4 hr and max in month of May as 10 hr. The details of different climate data used in this study are shown in figure 17. Refraining the climate data using Penman-Monteith equation ETo (mm/day) were calculated. The ETo 2.1 to 8.74 mm/day in study area.

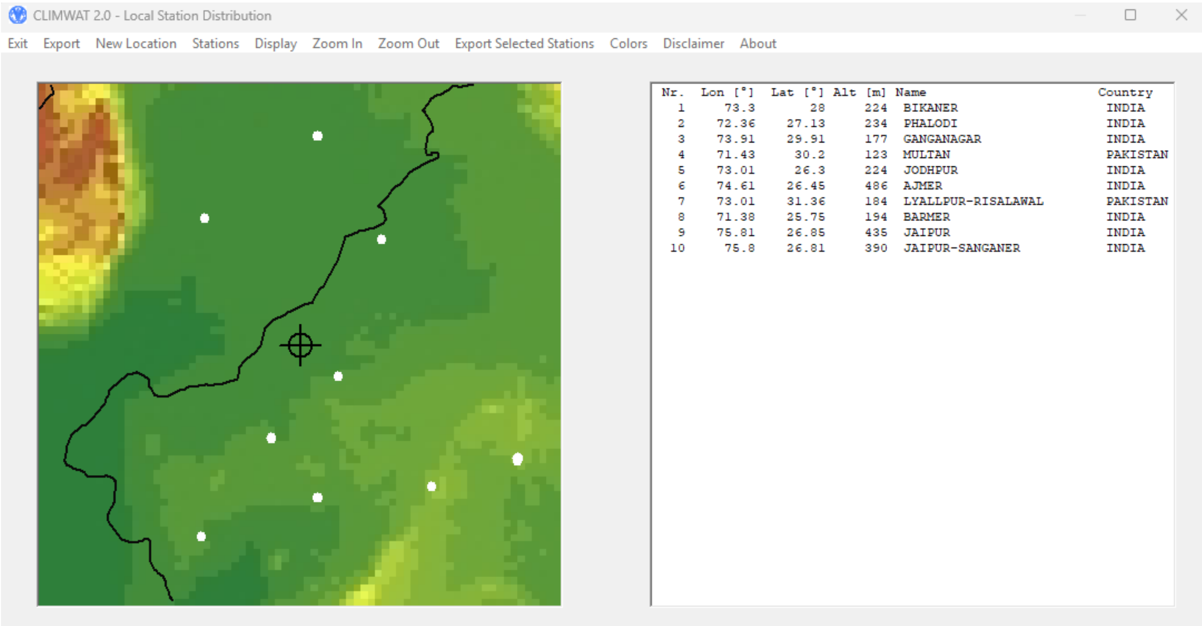


Figure 16 – Local station distribution for climate data in CLIMWAT

Monthly ETo Penman-Monteith - C:\danttor\BIKANER.pem

Country: Location 1 Station: BIKANER

Altitude: 224 m. Latitude: 28.00 °N Longitude: 73.30 °E

Month	Min Temp	Max Temp	Humidity	Wind	Sun	Rad	ETo
	°C	°C	%	km/day	hours	MJ/m²/day	mm/day
January	5.6	23.0	43	69	7.4	13.6	2.12
February	8.8	25.5	39	95	8.1	16.5	2.98
March	15.0	31.8	25	121	8.8	20.1	4.62
April	22.1	38.2	17	147	9.7	23.5	6.55
May	26.8	41.7	23	216	10.0	24.9	8.74
June	28.8	41.6	38	242	9.2	23.9	8.72
July	27.7	37.8	57	190	9.1	23.6	6.90
August	26.8	36.6	61	190	9.8	23.8	6.52
September	24.7	36.7	51	147	9.7	21.9	5.90
October	19.1	36.2	28	95	9.0	18.3	4.49
November	12.1	30.7	34	69	8.3	15.0	2.97
December	6.9	25.3	49	52	7.6	13.1	2.01
Average	**18.7**	**33.8**	**39**	**136**	**8.9**	**19.8**	**5.21**

Figure 17 – Climate data input in CROPWAT software

The daily grided rainfall data is collected from IMD for year 2024. After converting it into monthly data and provided in CROPWAT. For calculating the effective rainfall USDA soil conservation method is used, where effective rainfall can be calculated according to:

Monthly step:

Peff = Pmonth * (125 - 0.2 * Pmonth) / 125 for Pmonth <= 250 mm

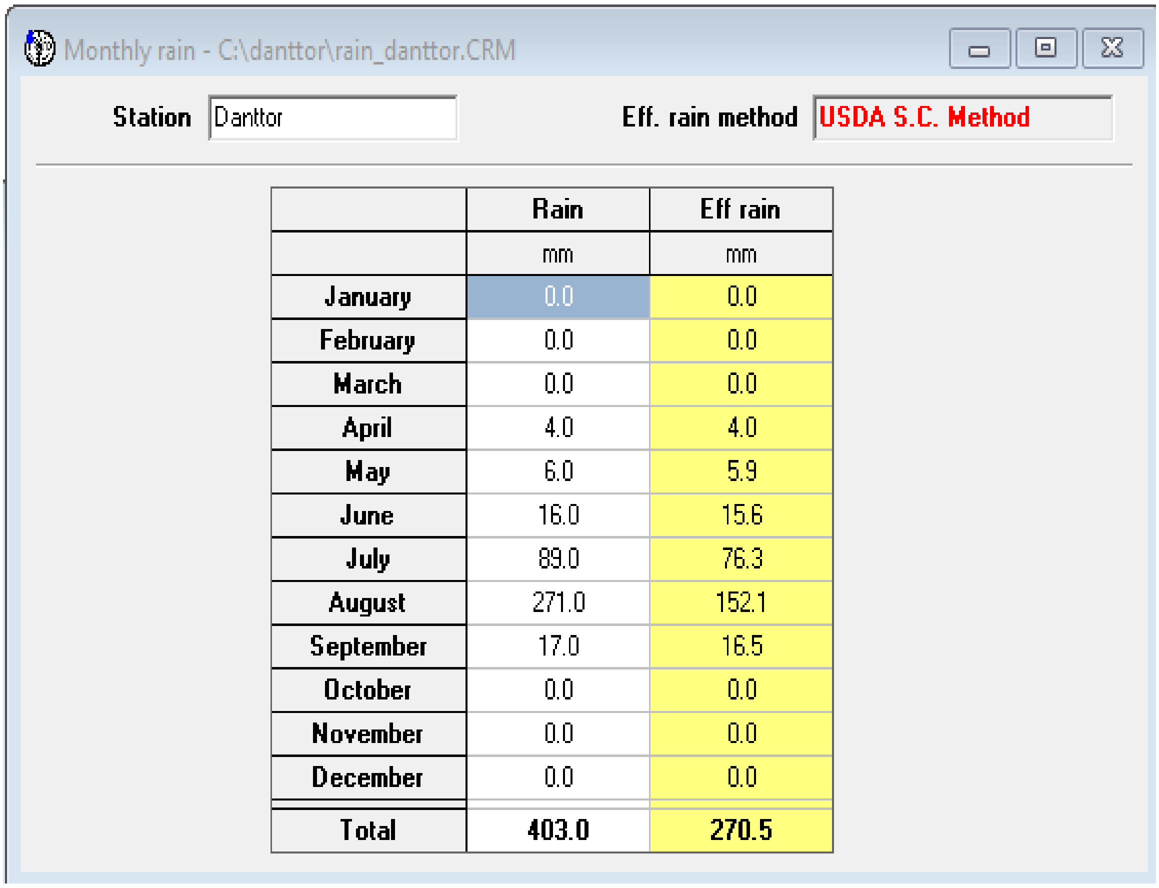
Peff = 125 + 0.1 * Pmonth for Pmonth > 250 mm

Decade step:

Peff(dec) = Pdec * (125 - 0.6 * Pdec)) / 125 for Pdec <= (250 / 3) mm

Peff(dec) = (125 / 3) + 0.1 * Pdec for Pdec > (250 / 3) mm

The total effective rainfall of study area is 270.5 mm and for monthly basis effective rainfall is shown in figure 18.



Monthly rain - C:\danttor\rain_danttor.CRM

Station: Danttor | Eff. rain method: USDA S.C. Method

	Rain	Eff rain
	mm	mm
January	0.0	0.0
February	0.0	0.0
March	0.0	0.0
April	4.0	4.0
May	6.0	5.9
June	16.0	15.6
July	89.0	76.3
August	271.0	152.1
September	17.0	16.5
October	0.0	0.0
November	0.0	0.0
December	0.0	0.0
Total	**403.0**	**270.5**

Figure 18 – Effective rainfall in CROPWAT software

4.2.2. Crop Parameter

The crop parameter like crop coefficient Kc at different growth stage, root zone depth, growth stage days from sowing time and other parameter are collected from literature review (*Gaddikeri et al. (2024), Mehta, R., & Pandey, V. (2016), Tiwari et al. (2017)and Megha et al.(2013)*) and provided in CROPWAT software. Table 7 show the Kc value at diifrent stages of different dominating crop grown in study area.

Table 7 – Kc value of different crops at different crop growth stages and Root zone depth

	Kc			
Crop	**Initial**	**Mid season**	**Late season**	**Root zone (m)**
Wheat	0.3	1.15	0.5	1
Mustard	0.3	1.10	0.35	1
Raida	0.28	1.10	0.30	0.96
Gram	0.27	0.96	0.51	0.6
Isabgole	0.3	0.80	0.40	0.45

4.2.3. Soil data

The soil map is taken from ICAR-National Bureau of Soil Survey & Land Use Planning as sown in figure 19. In study area main dominating soil type is sandy soil. For CROPWAT general soil data is taken from FAO and provided to software as shown in figure 20.

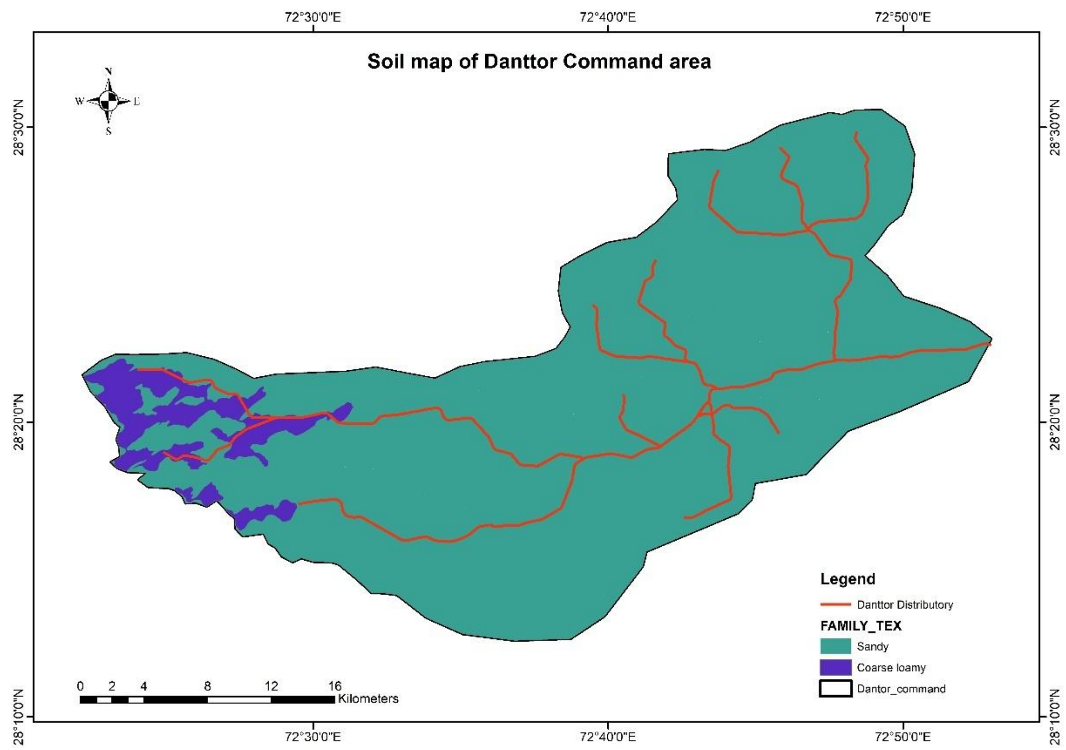


Figure 19 - Soil map of study area

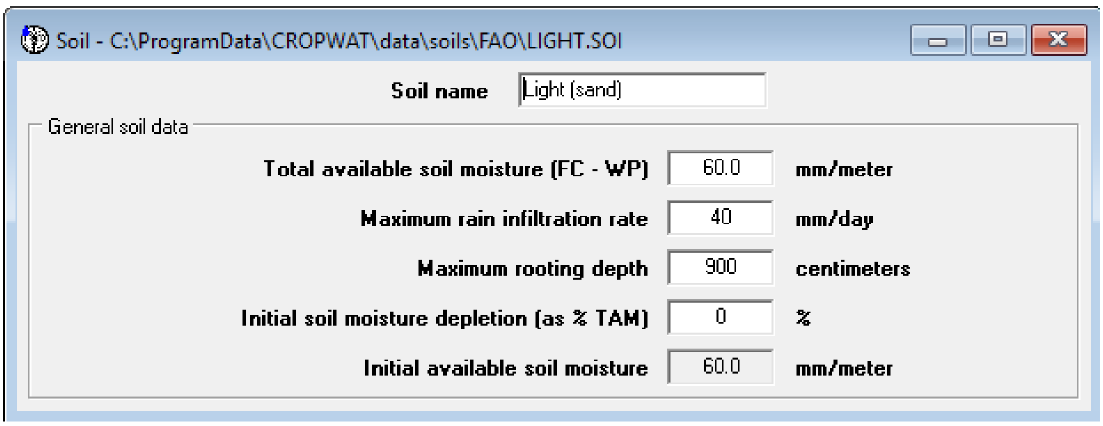


Figure 20 – Soil parameter used in CROPWAT software

4.3 Estimation of Crop Water Requirement

To assess the irrigation water demand for various crops grown during the Rabi season, the CROPWAT software was employed to estimate the crop water requirement (CWR) for each crop. CROPWAT computes water needs based on climatic data, crop characteristics, and soil conditions. The crop water requirement is expressed in millimetres (mm), representing the total depth of water needed over the growing period for optimal growth.

4.3.1 Crop Water Requirement from CROPWAT

The estimated water requirement for each crop, as derived from CROPWAT, is summarized in Table 8.

Table 8 - Crop-wise Water Requirement

Crop	**WR (CROPWAT) (mm)**
Wheat	396
Mustard	296
Raida	288
Gram	297
Isabgole	264
Total Water Requirement	**1541**

These values serve as a basis for calculating the total irrigation demand across the study area when integrated with the respective crop areas.

4.3.2 Total Crop Water Requirement for Rabi 2023–24

Using the crop-wise water requirement values and the respective crop areas derived from remote sensing-based crop identification, the total crop water requirement for the Rabi 2023–24 season was calculated. The detailed computation is presented in Table 9.

Table 9 - Total Crop Water Requirement for Rabi 2023–24

Crop	**WR (CROPWAT) (mm)**	**Crop Area (2023-24) (ha)**	**Total Water Requirement (MCM)**
Wheat	396	5660	22.14
Mustard	296	2560	7.58
Raida	288	690	1.99
Gram	297	2760	8.20
Isabgole	264	910	2.42
	Total Water Requirement		**42.50**

Wheat constitutes the highest water requirement due to both its large area and relatively high CWR. Other crops such as Mustard, Gram, and Isabgole also contribute significantly to the seasonal irrigation demand.

4.3.3 Total Crop Water Requirement for Rabi 2024–25

Similarly, the total crop water requirement for the Rabi 2024–25 season was computed using crop area of rabi 2024-25. The results are presented in Table 10.

Table 10 - Total Crop Water Requirement for Rabi 2024–25

Crop	**WR (CROPWAT) (mm)**	**Crop Area (2024-25) (ha)**	**Total Water Requirement (MCM)**
Wheat	396	4783	18.94
Mustard	296	2423	7.17
Raida	288	490	1.41
Gram	297	1533	4.55
Isabgole	264	2030	5.36
	Total Water Requirement		**37.44**

In 2024–25, there was a noticeable reduction in wheat and gram cultivation area, resulting in a decline in the overall water demand compared to the previous year. Despite an increase in the

Isabgole area, the net water requirement decreased to 37.44 MCM, indicating more efficient water use or a shift in cropping pattern.

The analysis reveals year-on-year variability in irrigation demand, largely influenced by crop area dynamics. This assessment helps in better planning and allocation of irrigation resources and supports decision-making in water-scarce regions. The CROPWAT-based approach offers a reliable methodology for quantifying seasonal water needs and contributes to sustainable agricultural water management.

Chapter 5 Summary and Conclusions

This study presents a comprehensive assessment of crop identification and irrigation water requirement estimation in the Danttor distributary region of the Indira Gandhi Nahar Project (IGNP) command area. Located in the arid landscape of the Thar Desert, the IGNP is one of India's largest canal irrigation systems, designed to support agriculture in a water-scarce environment. The sustainable management of this limited water resource is vital for agricultural productivity and the livelihood of dependent communities.

The research focused on two primary objectives: (1) the identification and spatial mapping of crops sown in the Danttor distributary command area during the Rabi seasons of 2023–24 and 2024–25, and (2) the estimation of crop-wise and seasonal water requirements to support efficient irrigation scheduling.

To achieve the first objective, a combination of high-resolution Sentinel-2 satellite data and field-collected observations was utilized. Field surveys conducted in February 2024 and February 2025 recorded essential information, including the geographic location of crop plots, the types of crops cultivated, irrigation methods used, and water sources accessed by farmers. The major crops identified in the study area were Mustard, Wheat, Gram, Isabgol, and Raida, which are characteristic of Rabi season cultivation in the region.

For crop classification, the study implemented a machine learning approach using the Random Forest algorithm within the Google Earth Engine platform. This method employed NDVI and the full suite of Sentinel-2 spectral bands to generate crop classification maps. Barren land was filtered out using an NDVI threshold of >0.2 to focus on actively cultivated areas. The model training and validation followed an 80:20 split of the ground-truth data. The crop classification achieved an overall accuracy of 71.96% for the Rabi 2023–24 season and 75% for the Rabi 2024–25 season. The total estimated crop area was 12,580 hectares in 2023–24, which decreased to 11,259 hectares in 2024–25, reflecting inter-annual variability in crop coverage that is likely influenced by fluctuations in canal water availability.

To address the second objective, the FAO CROPWAT model was used to estimate the crop water requirement (CWR) for each identified crop. The analysis integrated climate data from CLIMWAT and the India Meteorological Department (IMD), including temperature, relative humidity, wind speed, sunshine hours, and rainfall. Crop-specific parameters such as crop coefficients, growth stages, and rooting depths were also considered. The model simulated reference evapotranspiration (ET_0) and crop evapotranspiration (ETc) to calculate crop-wise water demands. Based on spatial crop distribution data derived from the classification maps, the total seasonal water requirements were estimated at 42.50 million cubic meters (MCM) for the Rabi 2023–24 season and 37.44 MCM for the Rabi 2024–25 season. These values were compared with canal water supply data to identify potential mismatches and inform irrigation planning.

Conclusions

This study demonstrates the effectiveness of integrating remote sensing, field-based observations, and agro-hydrological modelling for agricultural monitoring and water management in arid canal command areas. The successful application of the Random Forest classification algorithm, coupled with Sentinel-2 imagery, provides a cost-effective and scalable method for identifying spatial crop distribution with good accuracy. Furthermore, the use of the CROPWAT model offers a reliable estimation of crop water demands based on scientifically derived inputs and real-time climatic data.

The findings underscore several key conclusions:

- **Timely and accurate crop classification** is feasible using freely available satellite data and open-source machine learning tools, even in heterogeneous agricultural landscapes.
- **Crop water requirements vary seasonally** and are sensitive to climatic factors and canal water delivery patterns, highlighting the need for dynamic water planning approaches.
- **Integration of crop maps with water requirement models** allows for a better understanding of demand-supply gaps in irrigation, supporting more equitable and efficient water allocation.
- **Field-level validation is essential** for improving the reliability of remote sensing-based assessments and refining classification models for future applications.

Overall, the methodology developed in this study offers a practical decision-support framework for agricultural planners, irrigation managers, and policymakers. By enabling informed decisions on crop selection, irrigation scheduling, and water resource allocation, this approach contributes to enhanced agricultural sustainability and resilience in water-stressed environments such as the IGNP command area.

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