Quantification of Sugarcane Crop Water Footprint Using Remote Sensing and Machine Learning Techniques: Case Study of Kolhapur District, Maharashtra, India

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Abstract

Water footprint (WF) analysis assists in measuring the freshwater utilized by the crops, which provides information regarding sustainable water utilization. Growing water scarcity, irrigation requirements, and climatic variability emphasize the need to effectively monitor and regulate water resources. Considering the limited availability of water resources, estimating the water usage of crops such as sugarcane with high water requirements is necessary. This study aims to calculate the blue water footprint (BWF) and green water footprint (GWF) requirements of sugarcane crops using empirical methods and machine learning techniques in the Kolhapur district of India. By employing robust ground truth data and spectral signatures of Sentinel-2 satellite images, the sugarcane crop masks were identified using advanced machine learning techniques: random forest (RF), support vector machines (SVM), and logistic regression (LR). Furthermore, BWF and GWF were quantified for the identified sugarcane crop using empirical methods that utilized precipitation, evapotranspiration (ET), minimum temperature, and maximum temperature data for the years 2018 to 2023. Following these initial estimations, the potential of machine learning techniques was assessed for predicting WF. The efficacy of RF, support vector regression (SVR), gradient boosting regression (GBR), and artificial neural networks (ANN) was assessed by training and validating them based on the identified features. The RF model (R^2:92) outperformed the other models in the precise prediction of sugarcane crop WF. The results show a lower WF in the northern and eastern talukas and a higher WF in the southern talukas of the district. This study can aid in the identification of water-stress areas and sustainable water resource management for sugarcane crops.

1. Introduction

Water scarcity and saving are current global challenges in areas where agriculture is the economic pillar. As water sources continue to decline, it is crucial to quantify agricultural water footprints more precisely. The water footprint (WF) concept by Aldaya et al. (2012) provides a broad framework for computing direct and indirect water usage from an extensive array of activities, such as agricultural output. "WF" is a marker that considers consumers' and producers' direct and indirect water use (Mekonnen, 2011). It represents the consumption behavior of water utilization. The WF of a crop is the volume of water used for its production, and the green and blue WF represent rain and irrigation water use, respectively (Mekonnen, 2014). The water usage is quantified in volumetric terms and expressed as water volume per product unit, which is often expressed in m^3/ton (Aldaya et al., 2012; Zhang et al., 2013; Hoestra, 2017). The WF measures water usage more accurately during crop growth. This can indicate the type and amount of water crops absorb during growth (Feng, 2021). "It also contributes to the discussion of sustainable and equitable water use and allocation, as well as provides a solid foundation for a local assessment of environmental, social, and economic impacts" (Hoekstra, 2019; Hoestra, 2011).

Conventional WF estimation methods utilize field surveys and water balance computations, which may be time-consuming, labor-intensive, and uncertain. The recent technological improvements in remote sensing techniques have introduced new possibilities to monitor WF more efficiently at larger scales(Tampouratzi et al., 2015; Koley & Jeganathan,2020; Deihimfard et al., 2022; Abdel-Hameed et al., 2024). Considering the varying climate conditions and ever-growing food demand with increasing population, there is a pressing need for an automated framework to monitor crop water footprints at a larger scale to guarantee sustainable agricultural practices(Degefu et al., 2018; Elbeltagi et al., 2020; Mokhtar et al., 2021). Considering this need and the limitations of existing WF estimation methods, this study evaluated the potential of machine learning (ML) techniques for sugarcane crop classification and quantification of the identified sugarcane crop's blue and green water usage. The main objectives of this study are as follows:

1. To generate a sugarcane crop type mask using machine learning techniques to enhance crop identification and spatial analysis.
2. To design and develop a machine learning model for sugarcane crop water footprint prediction.
3. To assess the performance of empirical methods and machine learning techniques for sugarcane crop water footprint calculations.

2. Materials and Methods

2.1 Study Area

The study area identified for this research was the Kolhapur district in Maharashtra, India (Figure 1). It covers an area of approximately 7685 square kilometers. The geographical boundaries span between 15° 42' N and 17° 17' N latitude and 73°40' E and 74°42' E longitude (Deshmukh & Ghurake, 2018). It exhibits a warm climatic zone that primarily impacts agricultural production, with an average annual rainfall of 1800 mm. The maximum and minimum temperatures reported were 34.50 °C and 14.20 °C, respectively. A well-developed irrigation system is in place with the support of the Panchganga and Krishna rivers, which reduces water stress even under low

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rainfall conditions.

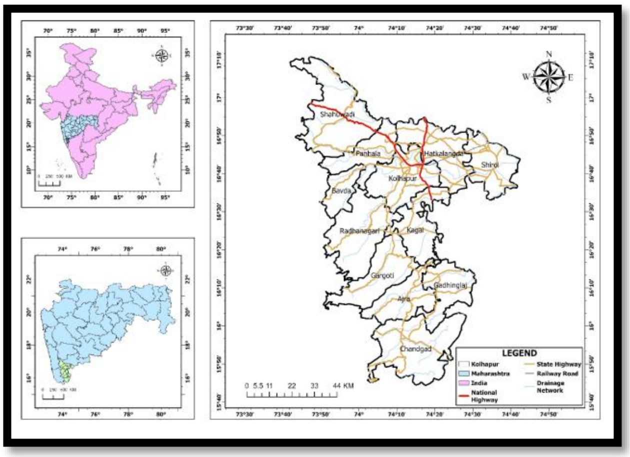

Figure 1 Location Map of Study Area

2.2 Dataset Description

This study was undertaken in two phases: a) sugarcane crop classification and b) Quantification of the WF of the identified sugarcane crop. The first phase used spectral signatures derived from Sentinel-2 satellite imagery for the ground control points. For WF quantification, climatic parameters were used (Table 1). Evapotranspiration (ET) data were obtained from the MOD16A2 version 6 ET/latent heat flux product derived from MODIS data using the Google Earth Engine (GEE) platform. The 8-day ET composites were aggregated into monthly composites for analysis and visualization. To estimate suitable precipitation, the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) gridded rainfall dataset was used in GEE. The GCPs of sugarcane plots were obtained from the district agriculture department and the National Remote Sensing Center (NRSC). The sugarcane crop yield information for the study area was collected from the Department of Economics and Statistics, Kolhapur. The land surface temperature (LST) data were acquired from GEE using the MOD11A1 Version 6.1 product that offers daily LST and emissivity values from MODIS Terra satellite observations. To quantify the crop water footprint in the study area, understanding the predominant crops in each tehsil is crucial. Table 1 presents the details of the datasets used in this study.

3. Methodology

The objective of this study was to assess the performance of ML predictive models in estimating the sugarcane crop water footprint (WF), with special emphasis on the impact of climatic variables (Mudugundu et al., 2018; Hogeboom, 2020; Hiloidhari et al., 2021). Figure 3 shows the methodological flow used for sugarcane crop classification and quantification of the water footprint for the identified sugarcane crop mask. The ground truth information representing sugarcane and non-sugarcane plots was identified (250 plots per class with stratified sampling) to ensure a balanced dataset for classification tasks.

Table 1. Dataset Description

Sr. no	Dataset Details	Type of Data	Year	Source
1	GCPs of Sugarcane Plots	Point Data	2019	Department of Agriculture and National Remote Sensing Centre, India
2	Sentinel 2 Imagery (10-day Temporal Scale)	Raster imagery	2019	Copernicus (through GEE)
3	Crop ET (mm/day)	Raster imagery	2018-2023	MODIS Net ET 8-days (MODIS/061/ MOD16A2GF) (MODIS DATA)
4	Precipitation (mm/day)	Raster imagery	2019	CHIRPS Dataset through GEE
5	Land Cover	Raster imagery	2019	Landsat-8 (Earth Explorer)
6	Crop Yield	Taluka-wise sugarcane crop yield (m^3/ton)	2018-2023	Directorate of Economics and Statistics, Kolhapur
7	Min. & Max. Temperature	Raster imagery	2018-2023	MODIS LST and Emissivity 8-Day Global 1km (MODIS/061/ MOD11A1)

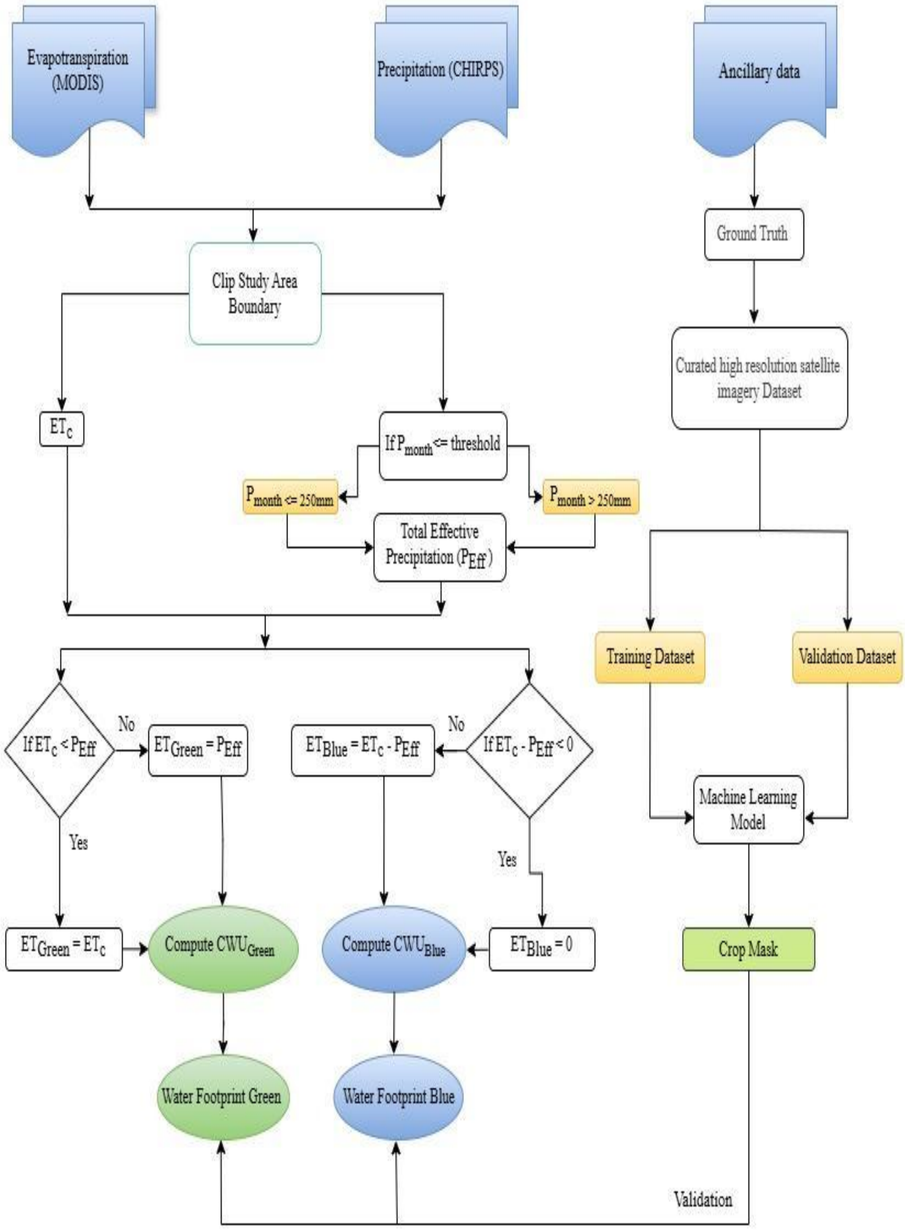

Figure 1. Methodological Flow: Sugarcane Crop Classification and Water Footprint Calculation using Empirical Methods

Non-sugarcane plots included urban, forest, water bodies, and village areas. The identified plots were digitized using Google Earth Pro. The identified plots were later transformed to 49000 points, and spectral signatures related to green, blue, red, and NIR bands were extracted for these points from Sentinel-2 satellite imagery acquired for the study area using the ArcGIS Pro software. The resultant dataset with added spectral values and class labels was exported in CSV format to train the machine learning models. Three ML techniques, namely RF, LR, and SVM(Pisner, 2008; Rigatti, 2017), were trained using this dataset, with the sugarcane/non-sugarcane class as the target. The identified sugarcane crop mask(pixels) by the ML model was used to calculate water footprint (BWF and GWF) in the first phase using mathematical expressions involving precipitation and evapotranspiration values for the identified sugarcane pixels. The second phase of this study involved assessing the potential of ML techniques for predicting crop water footprint values for the same study area. The predicted WF values were compared and assessed against those estimated using empirical formulas (Figure 3). After calculating the GWF and BWF values from 2018 to 2022 using empirical methods, ML regressors were utilized for predictive modeling and cross-validation of WF estimates. A fishnet grid was created over the study region to extract and systematize spatially uniform data points. Climatic variables, including ET, minimum and maximum temperatures, and precipitation, were retrieved from each grid cell along with the corresponding BWF and GWF values to generate a well-curated dataset(CSV) with features such as latitude, longitude, ET, Tmax, Tmin, BWF, and GWF. The dataset was employed to train a group of supervised regression models.

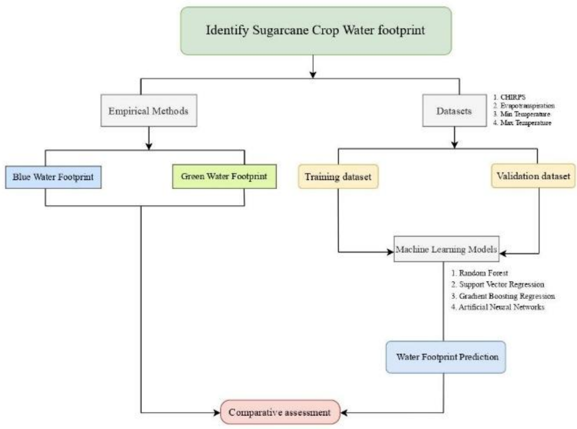

Figure 3. Methodological Flow for Sugarcane Crop Water Footprint Prediction using Machine Learning Techniques

The performance of ML regressors, such as RF, SVR, GBR, and ANN(Jain et al., 2008), was evaluated by training and evaluating these models on the curated dataset. These models were selected based on their different abilities to cope with nonlinear relationships, multicollinearity, and data heterogeneity.
The models were trained on the dataset from 2017 to 2020. The dataset was validated for the years 2021–2023.

4. Results and Discussions

Sugarcane Crop Classification
RF outperformed the other models with an accuracy of 99% through its ensemble approach for managing complex nonlinear relationships. It also highlights the crucial role of the NIR band in distinguishing sugarcane from other land cover types. SVM obtained 93% accuracy and proved very efficient in dealing with high-dimensional data using the RBF kernel; however, it failed in the case of overlapping spectral characteristics. Although LR attained 89% accuracy and provides a simple baseline model, it failed in dealing with complex spectral overlaps, especially in mixed vegetation zones. The sugarcane crop mask identified using the RF is shown in Figure 4.

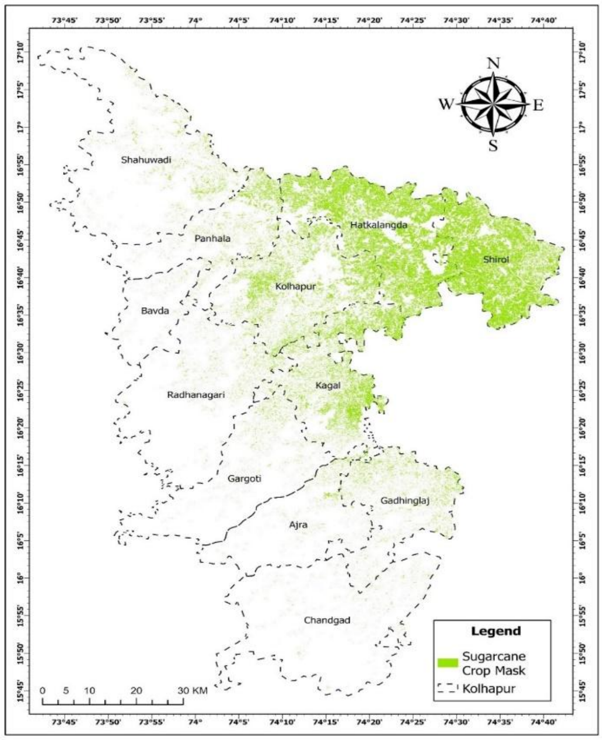

Figure 4. Identified Sugarcane Crop Mask using RF Classifier

4.1 Water Footprint Quantification of the Identified Sugarcane Crop

After identifying the sugarcane mask, the water footprint was calculated using empirical and machine learning techniques.

4.1.1 Quantification using Empirical Methods

Green Water Footprint of Sugarcane Crop
Green water footprint denotes the rainwater retained in the soil and used by crops. Figures 5 and 6 show the spatial and temporal variations in the green water footprint of sugarcane crops for the years 2017 and 2021, calculated using empirical methods.

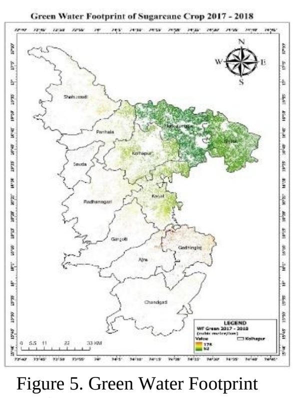

Figure 5. Green Water Footprint of sugarcane 2017-2018

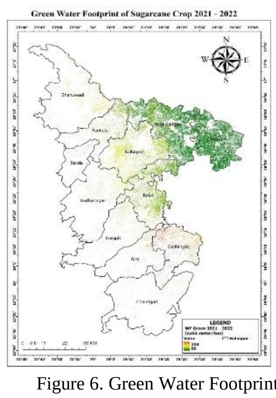

Figure 6. Green Water Footprint of sugarcane 2021-2022

As crop yield and climatic circumstances vary by area, there are notable differences in the green water footprint of sugarcane. The green water footprint of sugarcane for the 12 tehsils in Kolhapur district from 2017 to 2022 ranged from 50 to 350 m3/ton. The spatial distribution pattern depicts the northern and eastern parts, generally Shirol and Hatkanangale, registering the minimum WF values owing to the darkest green shading. These talukas receive intense agricultural activity, rich soil, and favorable rainfall, collectively making heavy use of rainwater for crops. On the other hand, the southern talukas, such as Chandgad, Ajra, and Gaganbawada, show systematically maximum WF values. The Gadhinglaj and Radhanagari areas reported moderate GWF values. A yearly comparative analysis for 2017–2021 showed a minor increment in the green WF. In 2020, the GWF values ranged between 79 and 296 mm, whereas in 2021, they expanded to 64–315 mm. This increase was particularly evident in areas such as Chandgad and Ajra, which already had higher GWF values, indicating improved rainfall distribution, better agricultural practices, or increased crop cultivation. In contrast, very low GWF zones, such as Shirol and Hatkanangale, showed very little change, implying that the areas have a persistent problem: poor rainwater retention or lower agricultural productivity. There was a noticeable expansion of talukas, such as Gadhinglaj, for moderate GWF zones in 2021, showing better rainwater utilization.

Variations in GWF over time reflect the impacts of factors such as crop selection, soil conservation methods, and rainfall variability.

Blue Water Footprint of Sugarcane Crop

The term blue water footprint (BWF) denotes the freshwater sourced from rivers, lakes, or groundwater, further provided through crop irrigation. The blue water footprint for sugarcane crops was calculated for the period from 2017 to 2022. Figures 7 and 8 show the spatial and temporal variations in the blue water footprint of sugarcane crops for the years 2017 and 2021, calculated using empirical methods.

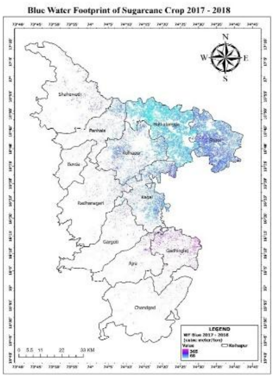

Figure 7. Blue Water Footprint of sugarcane 2017-2018

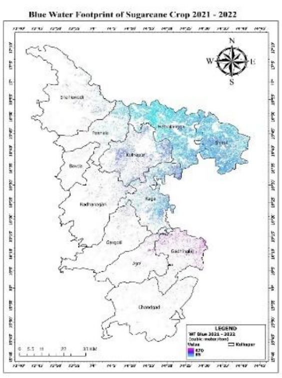

Figure 8. Blue Water Footprint of sugarcane 2021-2022

Sugarcane cultivation in the study area depends primarily on blue water resources, including surface and groundwater, during the Kharif season because of the high water demand of the crop. The BWF analysis of the study area from 2017 to 2022 showed different spatial and temporal patterns that indicated variations in irrigation water use across different talukas. The northern and eastern talukas, particularly Gadhinglaj, Chandgad, and Ajra, show high BWF values throughout all five years. These areas have high agricultural activities, depend on irrigation, and have water-intensive crops, which mainly drive their water demands. The steady increase in BWF over the years indicates intensified irrigation practices, possibly due to expanding crop acreage or variable rainfall patterns. Conversely, the southern talukas, such as Shirol and Hatkanangale, maintain persistently low BWF values, representing their reliance on rain-fed agriculture, with limited irrigation infrastructure and perhaps lower levels of agricultural activity. These areas face factors such as poor soil, hilliness, or higher forest cover, which reduce their potential for intensive farming and irrigation water use.

The middle regions of the district, such as Kagal and Radhanagari, presented moderate BWF values. Steady BWF trends have been observed over the years, symptomatic of balanced agriculture and a proper combination of rain-fed and irrigated farm systems. The analysis revealed an expanded range of BWF values from 68–365 mm in 2017 to 85– 670 mm in 2022. High WF zones, such as Gadhinglaj, Chandgad, and Ajra, indicate a notable increase in BWF and correspond to greater irrigation demand supplements than rainfall, mostly with year-to-year variability. In contrast, low WF regions, such as Shirol and Hatkanangale, showed minimal changes, indicating that the challenges in developing irrigation systems or adopting water-intensive crops remain persistent.

The BWF analysis shows spatial inequality in water resource utilization in the Kolhapur district. Trends from 2017 to 2022 emphasize the need for region-specific strategies to optimize BWF, reduce water stress, and achieve sustainable agricultural development in the district.

4.1.2 Quantification using Machine Learning

ML regression techniques were used to predict the BWF and GWF values for 2021–2023. A comparative analysis of the results obtained using these techniques was performed against those obtained using empirical methods. Figure 9 displays the results for the RF, whereas Figure 10 depicts the performance of the GBR model. For both plots, the data points were closely grouped along the reference line, reflecting a high agreement between the observed and predicted values. The GBR model presents a tight grouping of predictions, especially in the mid-range (100–250 $m^3 t^{-1}$) for blue (50–200 $m^3 t^{-1}$) for green, with relatively low dispersion, reflecting the high precision of the model and low bias. Similarly, the RF model exhibits a concentration of points near the reference line but with a slight spreading on the higher value side, signifying that although it generally performs well, it will slightly under- or overestimate some extreme values of BWF.

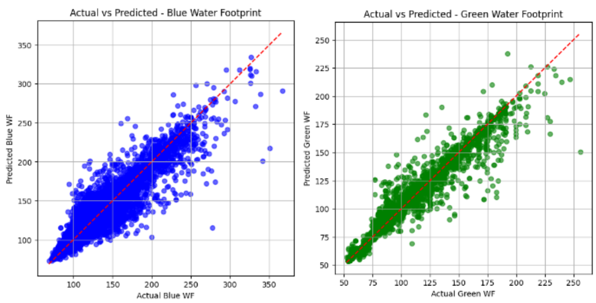

Figure 9. Actual vs Predicted Blue & Green RF

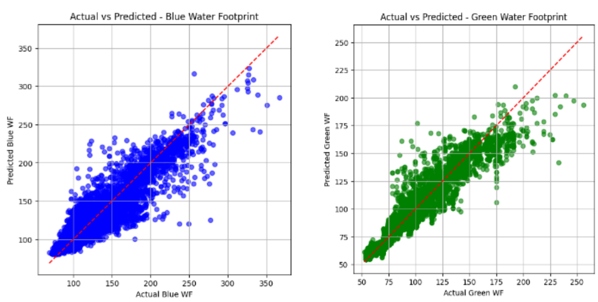

Figure 10. Actual vs Predicted Blue & Green GBR

Quantitatively, RF had the highest R^2 value (0.92), followed closely by GBR (0.88), confirming the visual inspection results. The results confirmed the high predictive power of both ensemble models for forecasting BWF using climatic variables

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such as precipitation, evapotranspiration, and temperature. Statistical and visual concordance confirm that such models are reliable for the spatial and temporal prediction of water use in agricultural planning.

The capability of the ANN model to predict blue water footprint (BWF) is shown in Figure 11. Most of the data points are concentrated around the 1:1 reference line, especially in the 100 to 250 m³ per ton range, showing that the ANN model provided acceptable results. There were a few high-value outliers, but the model handled the interaction between the input parameters and BWF quite well. The second is the ANN model prediction of the GWF. The correlation between the actual and predicted values was very high, particularly within the 75 200 $m^3 t^{-1}$ range. Most of the data points were tightly clustered along the ideal fit line, reiterating that the ANN model successfully represented water availability caused by rainfall. Even with some dispersal at higher ranges, the general accuracy of the model remained high, confirming the model's validity in simulating green water behavior in agriculture.

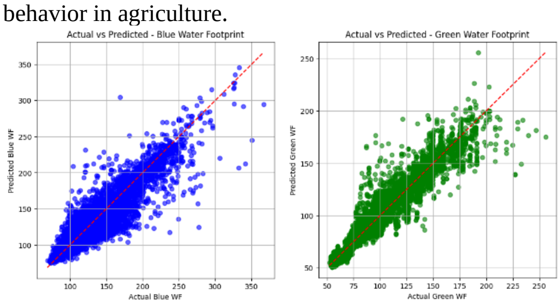

Figure 11. Actual vs Predicted Blue & Green ANN

The prediction of BWF from the SVR model is shown in Figure 12. Compared to ANN, SVR has a broader spread in the predictions and significant underestimation at the higher end (higher than 250 $m^3 t^{-1}$). Although the SVR model is moderately aligned with the 1:1 line for lower ranges, it does not track the variability of BWF consistently, as indicated by its low R^2 value. This indicates that SVR may be unsuitable for complex, high-variance water footprint data without considerable tuning, as seen in the SVR performance in the prediction of GWF. The outcomes represent greater dispersion than ANN, particularly across the mid-to-high ranges of 125–200 $m^3 t^{-1}$. Although SVR performs adequately in estimating low values of GWF (50–120 $m^3 t^{-1}$), the greater scatter and deviation of data from the 1:1 line for higher ranges express the failure of SVR to generalize over the complete dataset. Overall, ANN outperformed SVR in the forecasts of both BWF and GWF, confirming the superiority of neural models in describing nonlinear environmental processes.

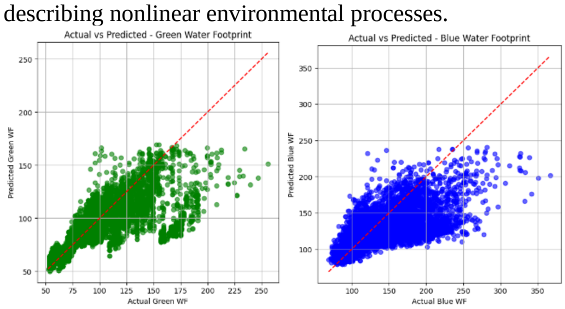

Figure 12. Actual vs Predicted Blue & Green SVR

The comparison between empirical and machine learning techniques for estimating blue and green water footprints showed very high consistency across different locations in Kolhapur district. For example, in Hatkanangale, the empirical green WF is 75.68 mm, the machine learning estimate is 73.91 mm, and the blue WF values are 104.30 mm (empirical) and 105.24 mm (ML), with very slight differences. The same applies to Gadhinglaj, where blue WFs are empirically 156.57 mm and 187.71 mm, and blue WFs are 160.87 mm and 190.81 mm based on empirical machine learning. Even in Shirol and Panhala, the differences were marginal and within acceptable limits for spatial approximations. Such strong congruence between the two approaches over various agro-climatic zones indicates that machine learning models can reproduce the results of empirical computations. This provides increased confidence in ML-based estimates and advocates the operational transition towards automated, scalable, and data-driven water footprinting methods in precision agriculture and regional water resource management.

Table 2. Comparative Analysis of Empirical Methods and Machine Learning Techniques for Sugarcane Crop Water Footprint Quantification

Location	**CHIRPS**	**ET**	**Min. Temp (T_{min})**	**Max. Temp (T_{max})**	**Empirical Methods**		**Machine Learning**	
					BWF	**GWF**	**BWF**	**GWF**
Hatkanangale	1044.52	664.3	292.51	306.97	104.30	75.68	105.24	73.91
Hatkanangale	1184.28	726.3	292.54	307.61	116.58	77.68	123.59	88.18
Gadhinglaj	1439.10	705.2	292.77	309.84	187.71	156.57	190.81	160.87
Kagal	1550.90	808.6	293.35	307.89	121.50	111.63	124.86	91.99
Shirol	907.80	727.6	293.09	306.53	126.74	111.35	113.45	69.79
Kagal	1031.92	716.6	292.71	305.48	128.20	84.91	134.69	80.01
Kolhapur	1315.51	801.2	292.86	307.82	137.47	84.85	137.30	86.90
Kolhapur	1315.51	727.9	292.94	307.94	132.22	100.68	130.02	102.39
Panhala	1472.95	735.5	292.66	306.76	110.17	93.07	113.44	95.87

The results of the experimental studies show that after training and validating the machine learning models, the predicted values of the green and blue water footprints for 2021–2023 closely matched the previously computed values from direct estimation methods.

This comparative study highlights the resilience and flexibility of ensemble and neural models in approximating farm water use under changing climatic conditions (Table 2).

Discussion

The efficacy of ML techniques was assessed for sugarcane and non-sugarcane crop classification using spectral signatures obtained from satellite imagery. RF outperformed the other models in the precise sugarcane crop classification. Subsequently, the BWF and GWF values were computed using climate parameters for the identified sugarcane crop mask using empirical and machine learning techniques. Between 2017 and 2022, GWF was greater in southern talukas, such as Chandgad and Ajra, owing to improved rainwater retention, whereas northern talukas, such as Shirol and Hatkanangale, had reduced GWF owing to dependency on irrigation. BWF was low but rising in the northern parts, indicating increased irrigation dependence, whereas southern talukas had high BWF owing to poor irrigation facilities. The middle areas had a relatively balanced consumption. All machine learning models exhibited differential performance in terms of GWF and BWF predictions. The RF predictive accuracy (R^2 = 92) showed higher performance accuracy for both GWF and BWF predictions, demonstrating the model's capability in identifying the complex nonlinear relations between climatic inputs. It is a good option owing to its stable outcomes and good agreement with the observed values, but it might need to be tuned carefully and trained with a larger number of samples. It coped well with input variability but exhibited some dispersion with higher footprint values. In general, ANN, RF, and GBR were good instruments for water footprint estimation, whereas SVR had limited use. To ensure sustainability, irrigation in high-BWF regions should be optimized, and infrastructural improvements in low-BWF areas should be prioritized to enhance productivity. This study underscores the significance of integrating machine learning and geospatial tools to optimize agricultural practices and water management (Sauvé et al., 2021), promoting balanced growth and sustainability.

5. Conclusion

This study underscores the value of integrating empirical water footprint methodologies with machine-learning–derived crop classification to inform sustainable water resource management. By leveraging Sentinel-2 imagery and rigorous ground truth data, precise sugarcane masks were generated using an RF classifier with 99% accuracy. Furthermore, blue and green water footprints were derived for the identified sugarcane mask using climate parameters such as precipitation, evapotranspiration, and temperature. Spatial analysis revealed that the northern and eastern talukas of Kolhapur district exhibited comparatively low WF values. In contrast, the southern talukas demonstrated substantially higher water demands, reflecting the underlying differences in climatic conditions and irrigation practices. Furthermore, a comparative assessment of the WF values obtained using empirical methods and regression techniques was performed. The RF model (R^2: 0.92) outperformed the SVR, GBR, and ANN models in forecasting the water footprint of sugarcane. This high predictive fidelity suggests that RF-based WF estimation can be a reliable decision-support tool for water-stressed regions. The alignment between empirical and ML-model-derived WF values validates our hybrid framework and offers a scalable approach for other water-intensive crops in semi-arid environments.

This study provides critical insights into the spatial distribution and temporal dynamics of water usage in the Kolhapur district. This highlights the importance of region-specific water management strategies that balance productivity and sustainability. Integrating advanced geospatial analysis and machine learning lays the foundation for precision agriculture, efficient water management, and informed policymaking. Future research should include these methods for other crops and additional environmental variables to address emerging agricultural issues better. This approach offers a promising solution for the sustainable development of agriculture in water-stressed regions by combining water footprint analysis with crop classification.

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