AQUA
Water Infrastructure, Ecosystems and Society

 AQUA — Water Infrastructure, Ecosystems and Society Vol 72 No 12, 2396 doi: 10.2166/aqua.2023.413

Multi-spectral remote sensing for current irrigated area mapping of the Rift Valley Lakes Basin in Ethiopia

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MM, 0009-0004-6251-7352

ABSTRACT

The study was conducted in the Rift Valley Basin in 2020–2022, with the objective of evaluating the newly developed techniques for irrigated area mapping of spatially large areas and assessing the current irrigated area in the basin. Methods used for irrigated area mapping are imagery analysis using the NDVI and EVI methods and land use classification. All results were verified with ground-truthing data using the sample locations selected. A 10 m $\times$ 10 m spatial resolution image derived from the European Space Agency Sentinel-2 satellite was used to create a time series spanning 2020, 2021, and 2022. Irrigated area maps from all three techniques were obtained and evaluated. Metric indicators were used to evaluate the performance of the irrigated area mapping techniques, the mean overall accuracy was 0.82, with a kappa coefficient of 0.76 and an F1-score of 0.86 with the highest and lowest overall accuracy observed in 2020 (0.86) and 2022 (0.76), respectively. Coefficient of determination was used to quantify the correlation of geospatial information and the multispectral remote sensing data analysis results maps agreed with irrigated area mapping with respect to ground truthing with R^2 mean value of 0.87 which suggests a strong agreement.

Key words: analysis, evaluation, image, irrigated, mapping

HIGHLIGHTS

- No previous study has been done for the basin.
- The study will have an impact on managing water resources, strategic water allocation planning and climate change mitigation options.
- Appropriate references are used.

1. INTRODUCTION

Irrigation plays a key role in increasing crop production, especially in areas where water is scarce (Yin *et al.* 2016). Irrigated agriculture is the main user of the available water resources. About 70% of the total water withdrawals and 60–80% of total consumptive water use are consumed in irrigation (Huffaker 2008). Imposing sustainable water conservation policies at the core requires quantifying the spatial extent of the irrigated areas. Currently, the extent of irrigated areas on a global scale is principally derived from country-level statistics and remains uncertain. Although national statistical data gives the list of irrigated areas and water use, these data may lack precision especially when irrigation is not reported by the farmers. Irrigated areas are mostly being estimated at the project level to calculate the cropping intensity (Kaini *et al.* 2020a, 2020b). To address the need for a precise large-scale mapping of irrigated areas, remote sensing provides a powerful tool for mapping irrigated areas (Hajj *et al.* 2013). With the availability of several operational cost-free and open-access satellites (e.g., Landsat and Sentinels), remote sensing has been widely used for monitoring and managing agricultural crops from the field level to large domains (Ndikumana *et al.* 2018).

Irrigation extent mapping using optical satellite data has been explored in several studies using various methodologies to distinguish between irrigated and rainfed crops (Xiang *et al.* 2019). Nevertheless, these methods are developed based on a similar principle that the phenological differences between irrigated and non-irrigated crops (e.g., growth rate, greenness) are detectable by the vegetation spectral information derived from satellite optical sensors. Most of the prior studies using optical data tend to classify irrigated/non-irrigated areas only for one specific crop type. The transferability of the methods based on optical data is further limited in humid regions due to the cloud cover, and the marginal difference in crop phenology between irrigated and rainfed crops (Maselli *et al.* 2020).

Climate change and variability are also having a high impact on the irrigated area with spatial and temporal variability of available water resources, resulting in the inconsistency of the estimation of the irrigated area with time (Kaini *et al.* 2020a, 2020b). Climate change impacts on precipitation and temperature could increase irrigation water requirements (Kaini *et al.* 2022). The current challenge to mapping irrigated areas is that existing data sets differ in their results and accurately mapping irrigated areas still represents a challenge for land use classification. This is because approaches that are restricted to statistics alone are hard to verify and may include errors. Additionally, there are discrepancies between official statistics and remote sensing-based data, indicating that the irrigated area might be underestimated or overestimated by the official statistics. The politicized nature of data reports and different definitions of irrigated areas contribute to these discrepancies. Furthermore, better inventorying and investigation of irrigated areas are needed to improve water resource management and sustainable land use (Zhu *et al.* 2014). Hence, the outcomes of this study are useful in addressing the challenges explained above on estimating the current irrigated area using newly established multispectral imagery data analysis with ground truth verification procedures.

The Rift Valley Lake Basin (RVLB) is one of the 12 major river basins in Ethiopia. The RVLB is considered a high priority because it is an area of significant ecological and environmental interest, with a system of lakes and wildlife parks and reserves, having substantial areas of productive rainfed agricultural land and good rangelands. The RVLB is primarily an agricultural basin and agriculture will continue to be an important part of the economy. According to the master plan study report, the potential of irrigation in the basin was estimated to be 153,000 ha, of which 22,000 ha was under irrigation (Halcrow & GIRD 2009). The traditional measuring unit irrigated land of area in most of the parts in Ethiopia uses 'qurt' which is approximately 0.25 ha, and the database organized at district and regional levels based on the traditionally estimated way, however, it lacks precision and the reported data are inflated. The first national database for the irrigated area estimated using GPS measurement in Ethiopia was reported by MoWR (2002) as 1.97 Mha, Awulachew *et al.* (2007, 2010) also reported the irrigated area in Ethiopia as 0.107 and 0.64 Mha, and based on the CSA (2016) report irrigated area is 1.82 Mha while MoA reported on the same year the irrigated area is 2.7 Mha (MoA *et al.* 2016). According to the assessment conducted by IWMI using the IDVI-MODIS method, the irrigated area in Ethiopia is estimated to be 1.35 Mha (Chandrasekharan *et al.* 2021) and in a very recently published review paper the irrigated area in Ethiopia is 2.47 Mha (Belachew *et al.* 2022). As a result, there is no uniform and credible inventory of the current irrigated area in Ethiopia especially in the study area.

All discrepancies and inconsistent reports generated regarding the actual current irrigated areas in Ethiopia are mainly due to the lack of use of standard and precise techniques of measurement. This will have an impact on the sustainable and efficient utilization and planning of water resources. Hence, determining the precise quantification of the irrigated area helps with water resource planning, sustainable and efficient utilization of water and land resources, mitigate climate change and variability and optimize water allocation. Therefore, this study will assess the current irrigated area of the Ethiopian RVLB, so that irrigation water use will be estimated based on the results and other additional data (major crops growing, agroecology, LGP, cropping pattern and cropping calendar) for optimized water resource planning. The study also uses multispectral satellite imagery data and new techniques for the assessment of irrigated areas, and results of the remote sensing techniques are compared and evaluated based on ground truthing.

2. MATERIALS AND METHODS

2.1. Study area

The RVLB is one of the 12 major river basins in Ethiopia with a total area of about 52,000 km^2. The basin is characterized by a chain of lakes varying in size as well as in hydrological and hydrogeological settings. It constitutes seven lakes, Lake Ziway, Lake Langano, Lake Abiyata, Lake Shalla, Lake Hawassa, Lake Abaya, and Lake Chamo (Figure 1), and all are located south and southwest of the Ethiopian capital, Addis Ababa. The RVLB is shared administratively between four regional states, Oromia, Sidama, Central and South Ethiopia regions.

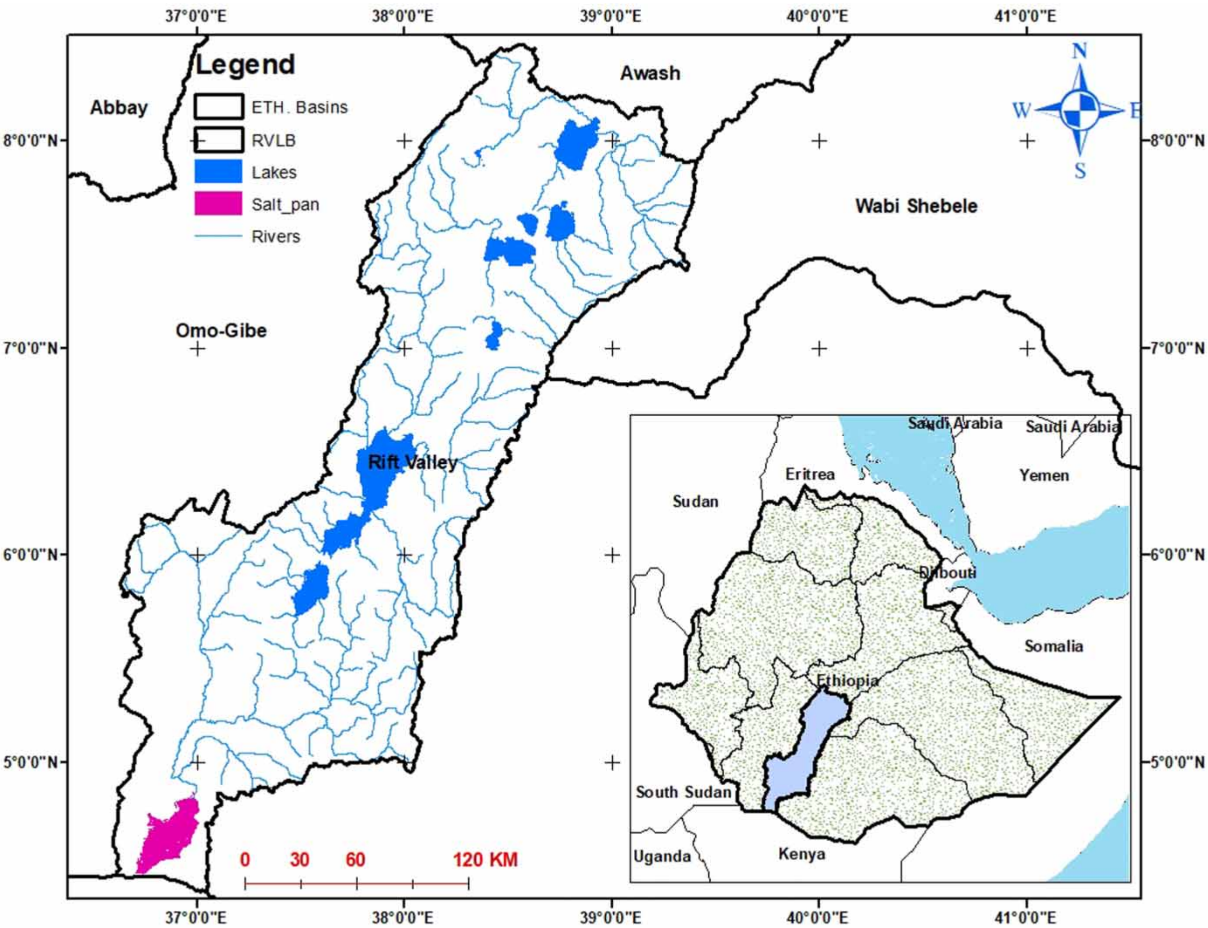

Figure 1 | Map of the Rift Valley Lake Basin.

2.2. Normalized difference of vegetation index

Relationships between the Normalized Difference of Vegetation Index (NDVI) time series and vegetation activities have been well-established theoretically and empirically. The NDVI curve properties and characteristics can generate a set of metrics (such as on-set of greening, senescence, the timing of maximum NDVI, growing season length) that measure the timing and magnitude of NDVI response and summarize the spatial and temporal distribution of crop growth and phenology, therefore being used widely as an input for classification.

Recently developed methodologies are used for irrigated area mapping. Ready-made images of raw data were downloaded cost-free at high resolutions (10×10 m spatial and 5 days of temporal resolution): Sentinel. Available raw data consists of different reflection bands that can be composed into a 'normal' photo (RGB image), but the infrared (and thermal band) gives more information about vegetation growth (Zanter 2015). More specifically, the ratio of the infrared and red bands results in the NDVI. This ratio is widely used to identify green areas in a landscape. Inspired by the published studies (Thenkabail & Wu 2012), NDVI is used as a measure to validate and identify irrigated land in RVLB.

For this reason, Sentinel-2 images with fine resolution (10×10 m) have been used with the ability to identify individual plots in several grid cells. To calculate the NDVI of satellite images taken by Sentinel-2A, Band 4 (Red Band) and Band 8 (Near-Infrared (NIR) Band) were used for the analysis.

NDVI is a standardized index considering the ratio of the infrared and red band results (Liu & Huete 1995):

$$\mathrm{NDVI} = \frac{(\mathrm{B8} - \mathrm{B4})}{(\mathrm{B8} + \mathrm{B4})} \quad (1)$$

where NDVI refers to Normalized Difference Vegetation Index; B8 refers to NIR band; B4 refers to red band.

Three years (2020–2022) of Sentinel-2 images of a 15-day time series are downloaded from the Copernicus open access hub at levels S2A and S2B. Levels S2A and S2B for Sentinel data refer to the at-top of the atmosphere reflectance with geometric corrections including ortho-rectification and spatial registration. The sentinel imagery is based on tile/grid and the .kmz gridding/tilling file was downloaded from the sentinel hub and overlaid with the basin boundary, rainfall regime and land use/land cover (LULC) in ArcGIS that the exact dry season or irrigation time of the basin was identified. Figure 2 shows the steps followed in irrigated are mapping in this study.

2.3. Enhanced Vegetation Index

The Enhanced Vegetation Index (EVI) method is a spectral index that is used to map irrigated areas. The EVI is a modified version of the NDVI that is more sensitive to changes in vegetation caused by irrigation. Similar procedures as the NDVI were followed regarding the data management except for the additional band which is B2 (blue).

The EVI is calculated from satellite imagery using the following formula: (Matsushita *et al.* 2007):

$$\mathrm{EVI} = 2.5 \times \left(\frac{(\mathrm{B8} - \mathrm{B4})}{(\mathrm{B8} + 6 * \mathrm{B4}) - (7.5 * \mathrm{B2} + 1)}\right) \quad (2)$$

where B2: Blue; B4: Red; B8: visible and near-infrared (VNIR).

The EVI is a more sensitive measure of vegetation greenness and it takes into account the absorption of light by water vapor in the atmosphere. This makes the EVI more reliable for mapping irrigated areas, especially in areas with high levels of atmospheric water vapor.

2.4. Land use classification (LULC)

Image classification procedures such as geometric correction, visual interpretation, identifying training sites, supervised classification, maximum likelihood ground truthing, and accuracy assessment were followed for LULC irrigated area mapping. To support classification algorithms in interpreting input data patterns and producing reliable outcomes, specific training data is necessary. The training dataset was created in this study by delineating polygon features representing areas irrigated by commercial farms, state farms, riparian cash crop-producing farmers, irrigated areas around the lakes, and center pivots visible in high spatial resolution imagery data from the sentinel-2 imagery with (10×10 m) spatial resolution.

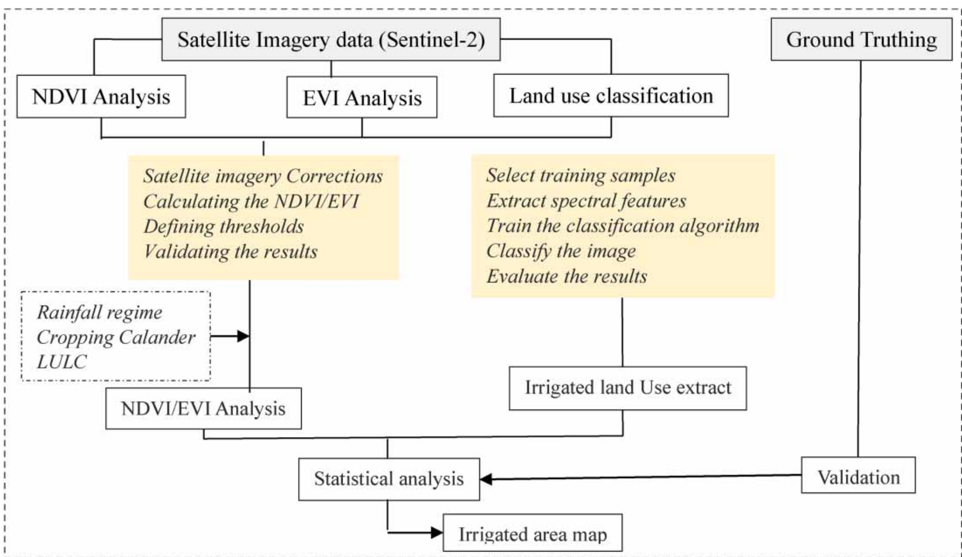

Figure 2 | Flowchart of the irrigated area.

2.5. Accuracy assessement

The accuracy assessment consists of validation through ground truth data, comparison with existing irrigation products, and statistical data analysis. for overall accuracy (OA), kappa coefficient, F1-score, and coefficient of determination (R^2):

$$\mathrm{OA} = \frac{\text{Number of sampling classes classified correctly}}{\text{Number of reference sampling classes}} \quad (3)$$

$$K = \frac{\text{Percent of overall correct value} - \text{percent correct aggreement to observed values}}{\text{Total number of class} - \text{percent correct aggreement to observed values}} \quad (4)$$

A field survey was conducted for validation of the irrigated area during the image accusation time in line with the cropping calendar of the study area. Sample sites were clustered based on the type of irrigation (modern and traditional), irrigation technology (pressurized, gravitational), irrigation scale (large, medium, small, and micro), source of water (river, lake, and groundwater), irrigated and non-irrigated farms. Based on the above parameters set, 996 sample sites were selected and data were collected, including time of sowing/planting, growth stage (initial, vegetative maturity, and senescence), canopy cover, type of crop, variety, date of harvesting, area, greenness (qualitative), and source of water. The irrigated area was measured using GPS.

3. RESULTS

Irrigated area mapping is a crucial aspect of agricultural management and planning. The use of remote sensing techniques such as NDVI, EVI, and land use classification methods have proven to be effective tools in accurately mapping and monitoring irrigated areas. As shown in Figure 3, the rainfall regime of the study area is bimodal with the main season being during July–September, and the second rainfall (Belg) is in March–May (Berhanu *et al.* 2014) and the cropping calendar for the rainfed agricultural practice follows the two seasons of rainfall, however, the rainfall of the 'Belg' season does not meet the crop water requirements of the crops and farmers use supplemental irrigation. Therefore, irrigation is practiced from October to June in the basin.

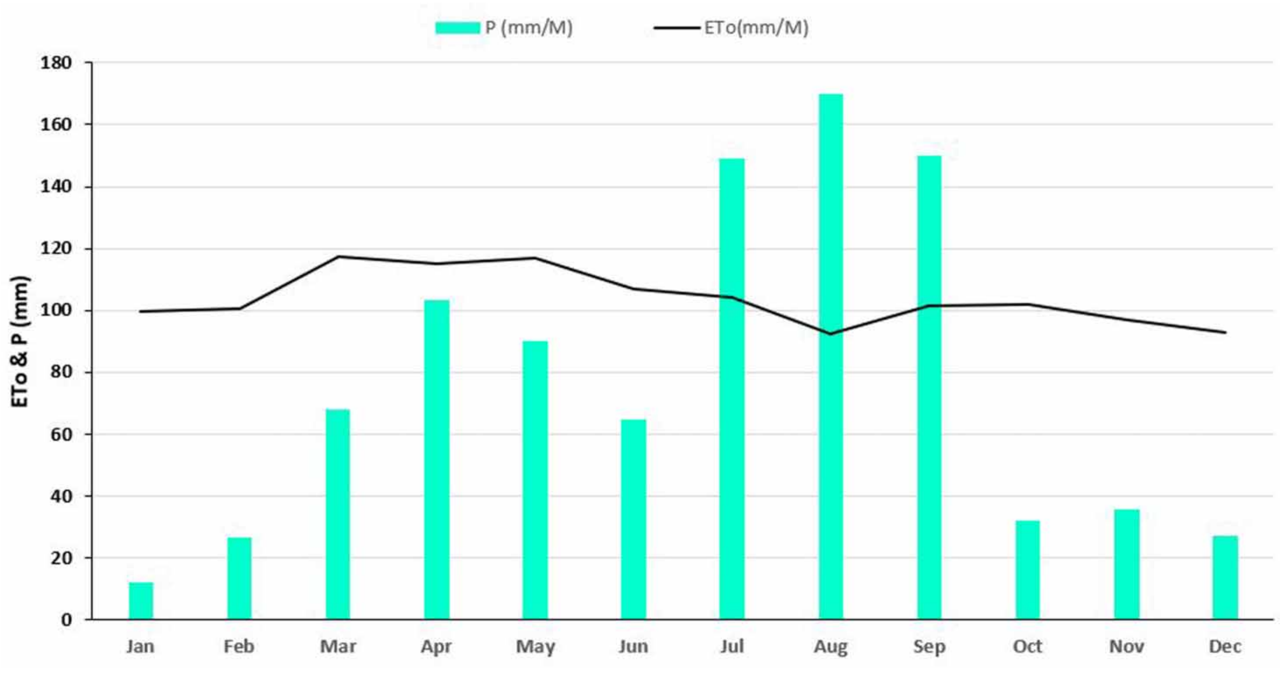

Figure 3 | Rainfall and ET_o of the RVLB.

3.1. Irrigated area mapping based on NDVI analysis

There is no specific NDVI value set for irrigated area classification, irrigated areas can have varying levels of vegetation density depending on the type of crops grown, growth stage, and the irrigation system efficiency. Therefore, based on the above factors and the NDVI trend analysis results, the threshold NDVI values were set to be 0.2–0.6. For this study, three years (2020–2022) Sentinel-2 images with fine temporal and spatial resolutions are used that enable the identification of individual plots in several grid cells. To calculate the NDVI of satellite images taken by Sentinel-2, Band 4 (red band) and Band 8 (NIR band) were used for the analysis. Figure 4 shows the peak NDVI values during 1–10 January, 2020, 2021, and 2022. Accordingly, as shown in Table 1, the current irrigated area in RVLB is 109,173 ha.

As shown in Figure 5, the trend of NDVI values spikes following the rainfall, and in most parts of the RVLB irrigation is practiced from October to February. At that time, the NDVI values from the imagery data analysis showed consistent greenness in the cultivated area even though there was no rainfall, greenness was observed due to irrigation. Supplemental irrigation is also practiced from March to May. Results go in line with reports from Chandrasekharan *et al.* (2018) as NDVI and rainfall in rainfed agriculture areas NDVI and pick rainfall overlap were used to identify the irrigation time.

3.2. Irrigated area mapping based on EVI analysis

The EVI is a vegetation index designed to improve the sensitivity of satellite sensors to changes in vegetation coverage. It is estimated using satellite imagery in the NIR, red, and blue spectral regions. EVI is used in irrigated area mapping to evaluate and track the strength and vitality of vegetation in irrigated areas. It is feasible to distinguish and identify irrigated areas from non-irrigated areas by comparing the EVI values over time in a given area. Due to improved vegetation growth and enhanced greenness brought about by irrigation, irrigated areas typically have higher EVI values. Compared to other vegetation indices, EVI offers a more accurate depiction of vegetation health since it considers both the canopy structure and chlorophyll content.

The EVI values set for irrigated area classification consider the type of crops, growth stage, and irrigation systems. Therefore, the threshold EVI values were set to be 0.20–0.60, as shown in Figure 6, which shows the peak NDVI values during 1–10 January, 2020, 2021, and 2022. Based on the image analysis using the EVI method, Table 1 indicated the current irrigated area in RVLB is 101,130 ha.

Figure 7 exhibits an identical pattern with a sharp peak in greenness around May and September followed by a rapid decline. While irrigated fields exhibit slightly larger EVI, possibly due to constant availability of moisture, the EVI value range 0.2–0.6 is observed consistently during October–May due to the irrigation practice. Findings go in line with previous studies (Zuo *et al.* 2023).

3.3. Irrigated area extract of the land use classification

Selection of training samples considered commercial farms, riparian farmers, irrigated areas around lakes, and center pivots. A signature file was created with the addition of training samples for other land use types, and the classification of the

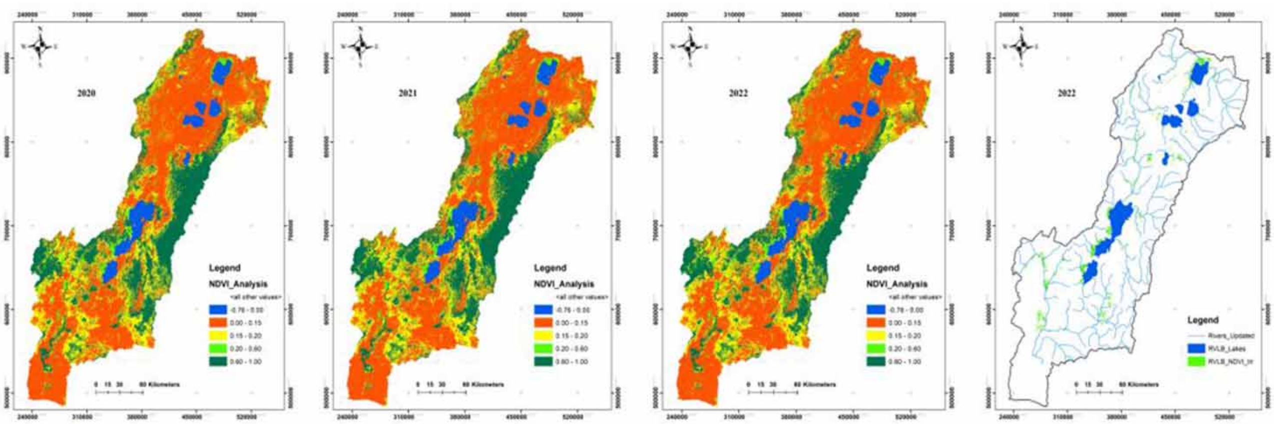

Figure 4 | RVLB-NDVI irrigated area map.

Table 1 | Irrigated areas computed by NDVI, EVI, and LULC analysis

	Irrigated area estimated (KM2)			
Major catchments	**NDVI-analysis**	**EVI**	**LULC**	**Mean**
Abijata	14.83	13.73	26.00	18.23
Bilate	132.13	122.39	131.70	121.13
Chamo	90.57	83.90	85.03	83.15
Dijo	29.26	27.10	27.56	29.12
Gelana	16.29	15.09	0.57	9.57
Gidabo	28.31	26.23	53.66	31.59
Hamessa	2.22	2.05	1.35	5.59
Hawassa	47.60	44.10	49.44	52.78
Katar	29.38	27.21	25.16	26.45
Meki	63.08	58.44	66.48	63.51
Langano	14.78	13.69	41.28	19.11
Segen	114.25	105.84	116.67	105.92
Serbela	51.21	47.43	76.73	63.66
Shalla	31.62	29.29	20.77	23.49
Weito	152.42	141.19	83.39	120.98
W_Abaya	163.79	151.72	137.14	140.62
Ziway_UG	109.99	101.89	92.54	99.90
Total area	1,091.73	1,011.30	1,035.47	1,014.81

NDVI = Normalized Difference Vegetation Index, EVI = Enhanced Vegetation Index, and LULC = Land use and Land Cover.

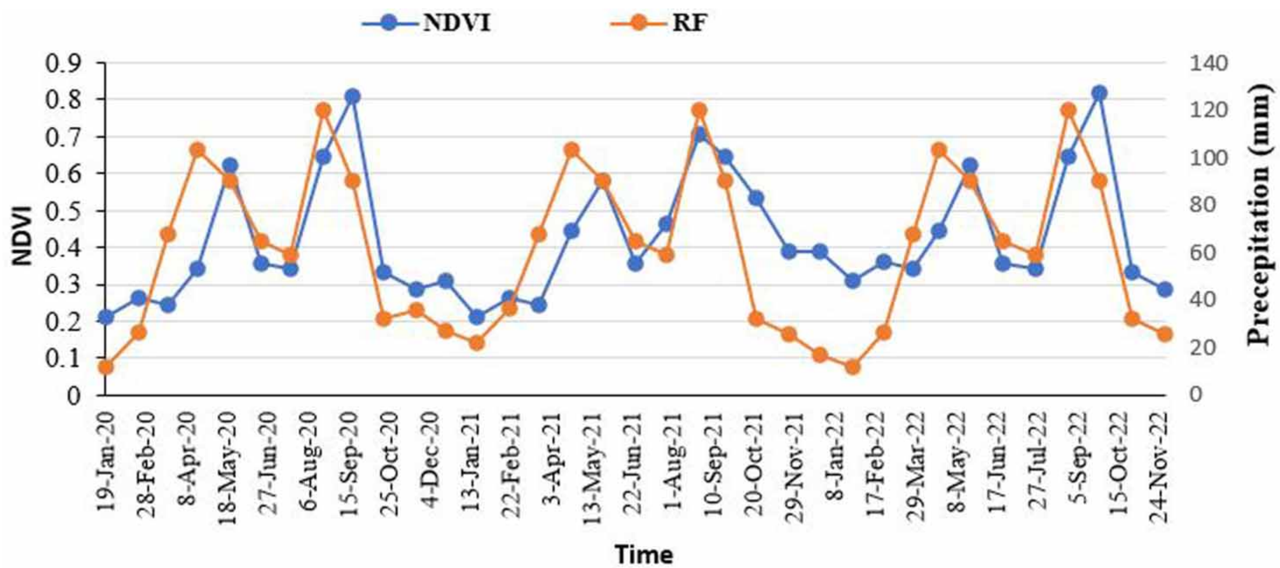

Figure 5 | NDVI annual time series vs. rainfall data.

remaining areas was done using the selected algorithm. The accuracy of the classification depends on the quality and number of training samples used, as well as the choice of the classification algorithm. Supervised land classification has been successfully used in many studies to identify irrigated areas and other land cover types (Hassan *et al.* 2016).

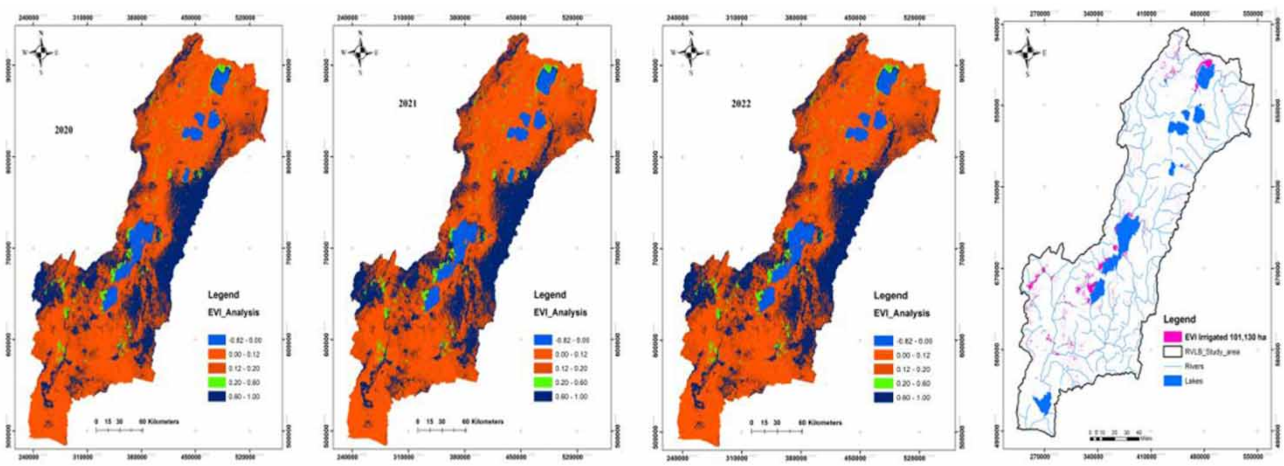

Figure 6 | RVLB-EVI irrigated area map.

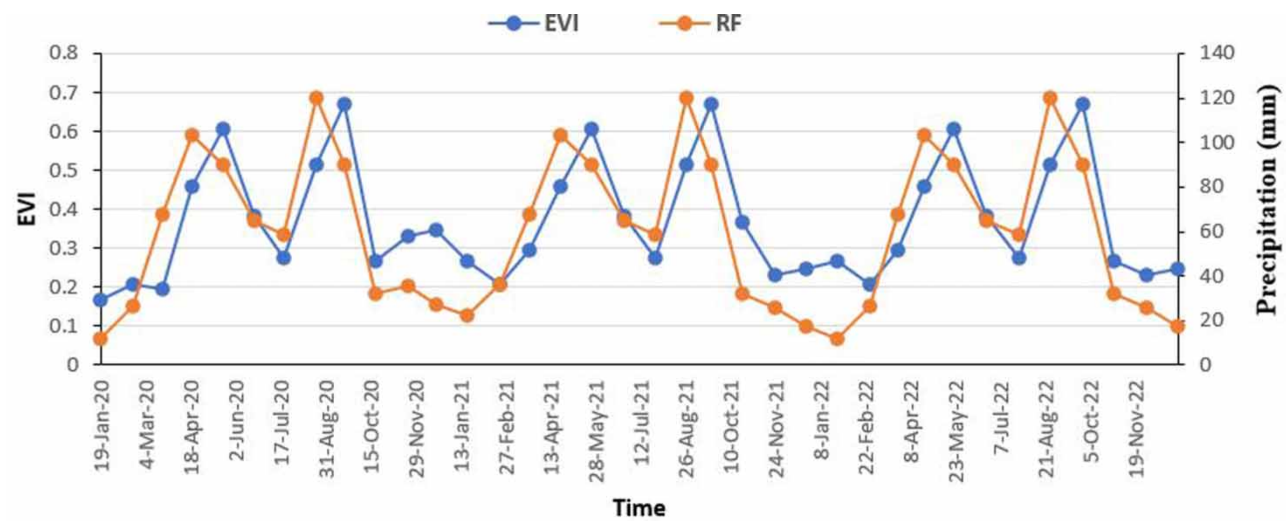

Figure 7 | EVI time series vs. rainfall data.

Polygon features representing the irrigated areas of the training samples for the irrigated area visible in high spatial resolution imagery data from the sentinel-2 imagery were used to create the training dataset for land classification. Accordingly, as shown in Table 1, the irrigated area's estimated area is found to be 103,474 ha (Figure 8), both the imagery data analysis approaches have relatively close results.

3.4. Intercomparison of outputs

Based on the validation sample points, the outputs of the irrigated area mapping methodologies were compared to each other, accordingly, the NDVI analysis was able to perform better in areas where vegetation is scattered or not denser, around Meki, Ziway, along the Bilate and Katar rivers. The EVI method was able to identify irrigated areas with highly denser vegetation with diverse crops and forest areas such as the Gurage mountains, around the Lake Abaya, Langano, Dijo, Segen and Weito catchments.

NDVI is more sensitive at lower vegetation levels because it is designed to capture the contrast between the red and NIR reflectance that is characteristic of green vegetation. When vegetation is sparse, there is a significant difference between the amount of red and NIR light reflected, resulting in a moderate NDVI value. As vegetation becomes denser, the difference

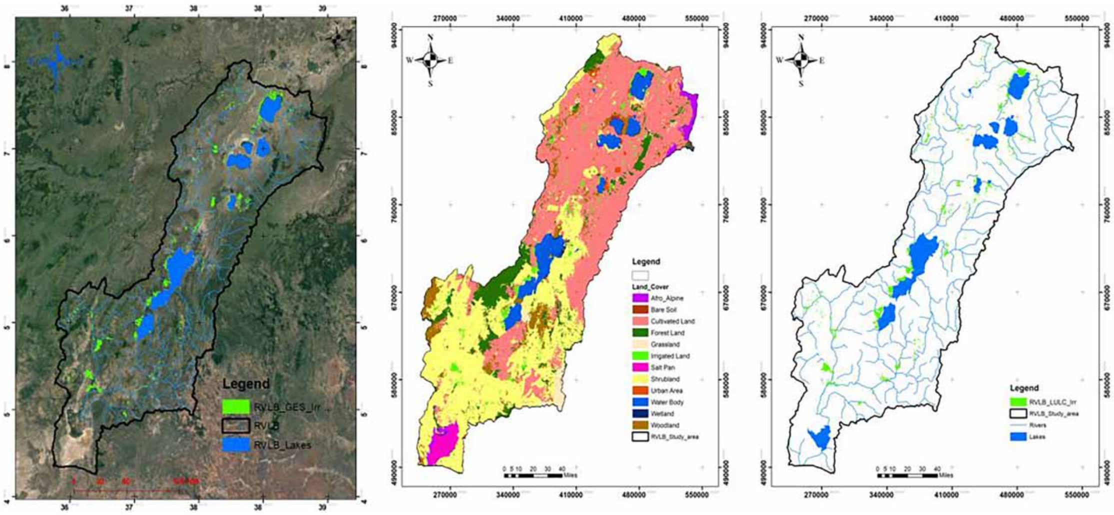

Figure 8 | RVLB-LULC irrigated area map.

between red and NIR reflectance decreases, making changes in NDVI less noticeable (Huang *et al.* 2021). Therefore, NDVI is a powerful tool for distinguishing areas with sparse vegetation from those with dense vegetation. The EVI is more sensitive to the NIR B2. As a result of the penetrating properties of the NIR band, EVI is more responsive to canopy structural variations, including the Leaf Area Index (LAI), canopy type, and canopy architecture. This sensitivity to canopy structure makes EVI particularly useful in areas with high biomass, where changes in vegetation structure over the growth season can be significant (Matsushita *et al.* 2007). Therefore, EVI tends to have stronger growth season peaks as it can capture these structural changes more effectively than NDVI. This makes EVI a powerful tool for monitoring vegetation in irrigated areas, where changes in canopy structure can indicate changes in water availability or crop health.

3.5. Accuracy assessment

Ground truthing for validation and accuracy assessment were conducted, and a systematic sampling technique was chosen for validation points; 996 sample points were selected in three years' time based on irrigated cluster areas considering the accessibility to water sources (lakes, rivers, and reservoirs), crop diversity, and cropping Calendar.

Evaluation metrics indicators were used to evaluate the performance of the irrigated area mapping techniques, as indicated in Table 2, the mean OA was 0.82, with a kappa coefficient of 0.76 and an F1-score of 0.86 with the highest and lowest OA observed in 2020 (0.86) and 2022 (0.76), respectively. The coefficient of determination (R^2) provides the portion of total variation explained between the ground truth data and remote sensing analyzed data. R^2 was 0.81, 0.86, and 0.94 in the

Table 2 | Accuracy assessment indicator

	Year			
Indicator	**2020**	**2021**	**2022**	**Mean**
R^2	0.81	0.86	0.94	0.87
Overall accuracy	0.86	0.85	0.76	0.82
Kappa coefficient	0.76	0.78	0.75	0.76
F1-score	0.84	0.85	0.83	0.84
Irrigated samples	151.8	203.6	163.8	173
None irrigated samples	178.2	147.4	151.2	159
Total samples	330	351	315	332

consecutive three-year evaluation, respectively, with a mean value of 0.87, which suggests a strong agreement between GT Irr and the multispectral remote sensing data analysis results. Results are in line with reports of previous studies (Xiang *et al.* 2020).

4. DISCUSSION

Satellite remote sensing offers tremendous potential for routine monitoring of irrigation due to the synoptic nature of the data and readily available archives of imagery. Various research and studies suggested that finer spatial and temporal resolution imagery of Sentinel-2 NDVI and EVI data is adequately efficient for identifying the irrigated land in a vast geographical location (Chance *et al.* 2017). As new methods for identification and estimation of existing irrigated land in the basin, remote sensing technologies have been applied and of course, integrated with other data acquisition techniques for the better and more reliable building of the dataset. High-resolution remote sensing analysis and mapping technique is used to identify the irrigated land covered. The data available at different spatial and temporal resolutions provide daily global coverage of observations to detect unique multitemporal, spectral vegetation signatures for mapping. The 'Sentinel-2' imagery data are currently available with enhanced vegetation sensitivity with minimal influence from the atmosphere, view and sun angles, clouds, and inherent non-vegetation influences of canopy, background, and litter.

Irrigated area information generated from NDVI, EVI, and LULC is 1,091.73, 1,011.30, and 1,035.47 km^2 respectively, comparing with FAO WaPOR portal report of LCC 2022 report on irrigated area (774.03 km^2), the results of this study are higher, and deviation is mainly due to the methodology difference and the resolution of the data used, the FAO WaAPOR report used a 100-m spatial resolution data. In comparison to NDVI, EVI, and LULC techniques, irrigated area is estimated for RVLB, and the multispectral remote sensing data analysis results from maps agreed with irrigated area mapping with respect to ground truthing with an R^2 of 0.81, 0.86, and 0.94 in the consecutive three years evaluation respectively with a mean value of 0.87. Xiang *et al.* (2020) and Zhu *et al.* (2014) have reported supporting the findings. Evaluation metrics indicators were also used to evaluate the performance of the irrigated area mapping techniques, the mean OA was 0.82, with a kappa coefficient of 0.76 and an F1-score of 0.86 with the highest and lowest OA observed in 2020 (0.86) and 2022 (0.76), respectively. The best irrigation patterns are seen in the Meki, Katar, Dijo, Bilate, Chamo, Hawassa, and West Abaya catchments, where comparatively big farms have similar irrigation patterns. However, the maps for the Gigabo, Gelana, and Weito catchments have shown inconsistent results.

5. CONCLUSION

Therefore, it can be concluded that the source data of Sentinel-2 had a fine spatial resolution (10 m $\times$ 10 m), which could explain the substantial precision in irrigated area mapping. We compared the spatial distribution of NDVI, EVI, and LULC with the spatial distribution of the historical precipitation or rainfall regimes to assess the consistency of the spatial distribution of irrigated areas in those three maps, assuming that irrigation would be practiced during the offseason and associated with peak NDVI and EVI values. Metrics indicators were used to evaluate the performance of the irrigated area mapping techniques and the coefficient of determination quantified the correlation in geospatial information, whereas the autoregression model identified the strength of the relationship between geospatial variables. These geospatial analysis techniques provide effective exploratory tools for comparing geospatial information derived from raster maps with differences in spatial resolution and classification methods. Further research is needed in the field of irrigation mapping to obtain a more realistic picture of water abstraction and accurate estimates of irrigated areas. Recent advances in the availability of remote sensing tools through the EU Copernicus system promise to improve irrigation mapping. In addition, better inventory and studies of irrigated areas are needed to improve global and regional water cycles and promote sustainable land use. Furthermore, in order to improve future attempts to regulate irrigation development in the RVLB, this study gives the spatial extent and distribution of currently irrigated areas. The findings of this study, along with additional research on potential irrigable area assessment, can help to advise policy-makers and investors about potential future irrigation development in the basin.

AUTHORS CONTRIBUTIONS

M.M. conceptualized, designed, performed the activities, analyzed the data, and wrote the manuscript. and B.B. contributed significant comments to improve the quality and language of the manuscript.

FUNDING

This research was funded by the Ethiopian Institute of Agricultural Research, Water Management Research Program.

ACKNOWLEDGEMENTS

The authors are grateful to the Ethiopian Institute of Agricultural Research for their financial support.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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First received 28 August 2023; accepted in revised form 11 November 2023. Available online 21 November 2023