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MAPPING IRRIGATED AGRICULTURAL LANDS USING REMOTE SENSING DATA: A CASE STUDY OF ORTACHIRCHIK DISTRICT, UZBEKISTAN

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Abstract

This paper presents a remote sensing-based approach for identifying and mapping irrigated agricultural lands in O‘rtachirchiq District, Tashkent region, Uzbekistan. A time series of the Normalized Difference Vegetation Index (NDVI) derived from Sentinel-2 imagery was used to calculate the maximum seasonal value (NDVImax) for each pixel. Irrigated areas were identified by integrating NDVImax with a cropland mask derived from the ESA WorldCover dataset. The resulting maps reveal the spatial distribution of irrigated lands and demonstrate the practical potential of satellite data for agricultural land monitoring and spatial planning.

Keywords: irrigated lands, remote sensing, Sentinel-2, NDVImax, cropland mask, mapping, O‘rtachirchiq District.

КАРТОГРАФИРОВАНИЕ ОРОШАЕМЫХ СЕЛЬСКОХОЗЯЙСТВЕННЫХ ЗЕМЕЛЬ НА ОСНОВЕ ДАННЫХ ДИСТАНЦИОННОГО ЗОНДИРОВАНИЯ (НА ПРИМЕРЕ ОРТАСИРЧИКСКОГО РАЙОНА)

Аннотация

В статье предлагается метод выявления и картографирования орошаемых сельскохозяйственных земель на основе данных дистанционного зондирования на примере Ортасирчикского района Ташкентской области. На основе временного ряда индекса NDVI, рассчитанного по данным Sentinel-2, была получена максимальная сезонная величина NDVImax для каждого пикселя. Выделение орошаемых земель выполнено с использованием маски пахотных угодий, полученной из набора данных ESA WorldCover. Полученные результаты отражают пространственное распределение орошаемых земель и демонстрируют потенциал дистанционного зондирования для мониторинга земельных ресурсов и территориального планирования.

Ключевые слова: орошаемые земли, дистанционное зондирование, Sentinel-2, NDVImax, маска пахотных земель, картографирование, Ортасирчикский район.

Introduction

Accurate identification of irrigated agricultural lands and knowledge of their spatial distribution are essential for effective water resource management, crop planning, and ensuring food security. In particular, under conditions of increasing water scarcity, monitoring the extent of irrigated areas is considered one of the key prerequisites for the sustainable development of agriculture [1], [2], [3].

Remote sensing technologies provide an opportunity to rapidly and cost-effectively assess land cover and crop conditions over large areas. Satellite systems such as Sentinel-2 and Landsat enable the monitoring of crop development and the discrimination between irrigated and non-irrigated areas using vegetation indices. Among them, the Normalized Difference Vegetation Index (NDVI) is one of the most widely applied indicators in agriculture, as it is directly related to biomass accumulation and photosynthetic activity of crops [4], [5], [6].

In recent years, the use of NDVI time series and its maximum value (NDVImax) has become a common approach for identifying irrigated lands. This method is particularly effective in detecting crop fields that achieve high biomass levels during the growing season because of irrigation. However, many studies apply global threshold values without adequately considering regional characteristics, crop types, and agro-climatic conditions, which can lead to over- or underestimation of irrigated areas in certain regions [7], [8].

Under the conditions of Uzbekistan, irrigated agriculture constitutes the backbone of the agricultural sector. The Presidential Decree of the Republic of Uzbekistan No. PF–6019 dated July 10, 2020, identifies the rational use of water resources and improvement of irrigated land productivity as priority tasks. Therefore, the introduction of modern, rapid, and cost-effective methods for the identification and monitoring of irrigated lands is of high relevance.

The objective of this study is to develop a methodology for identifying and mapping irrigated lands based on remote sensing data using the O‘rta Chirchiq district of Tashkent region as a case study, and to assess its practical applicability. Sentinel-2 satellite imagery was used to construct NDVI time series, and irrigated areas were delineated through the integration of NDVImax and a cropland mask.

Methodology

Study Area

The study area selected for this research is the O‘rta Chirchiq district of Tashkent region, which is specialized in agricultural production. The area has a well-developed irrigation system and is predominantly characterized by irrigated farming, with widespread cultivation of cereals, vegetables, and orchards. These characteristics provide favorable conditions for identifying irrigated lands using remote sensing techniques.

Data

The following datasets were used in this study:

- Sentinel-2 Surface Reflectance Harmonized satellite imagery (2024 growing season) for vegetation assessment and NDVI calculation [9], [10];
- ESA WorldCover (2021) land cover dataset for generating a cropland mask [11], [12];
- Administrative boundary of O‘rta Chirchiq district for spatial clipping and zonal analysis.

All data were processed using the Google Earth Engine (GEE) cloud computing platform and transformed into a unified spatial reference system.

Preprocessing

Sentinel-2 imagery was filtered to remove cloud and cloud-shadow pixels using the Scene Classification Layer (SCL). The filtered images were normalized to surface reflectance values (range 0–1) and composited using a median reducer over the growing season. A time series of NDVI was then constructed.

NDVI Calculation and Time-Series Analysis

Vegetation condition was assessed using the NDVI, calculated as:

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

where NIR is the near-infrared band (B8) and Red is the red band (B4).

For each pixel, the maximum NDVI value during the growing season (NDVImax) was extracted and used as an indicator of peak vegetation development.

Identification of Irrigated Lands

Irrigated lands were identified using the following logical framework:

1. Cropland areas were extracted using the ESA WorldCover cropland class.
2. Pixels with NDVImax values exceeding a defined threshold were classified as irrigated.
3. The final irrigated land mask was defined as:

$$I_{land} = (Cropland = 1) \cap (NDVI_{max} > T)$$

where T is a regionally calibrated threshold.

Threshold values ranging from 0.5 to 0.7 were tested, and the value yielding results closest to official statistics was selected. Irrigated area was calculated using the pixelArea() function in GEE and expressed in hectares and square kilometers. The proportion of irrigated land relative to total cropland was computed and presented in maps and tables.

Results

Spatial Distribution of NDVImax

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The spatial distribution of NDVImax across O‘rta Chirchiq district exhibited substantial variability. High NDVImax values were primarily concentrated in intensively cultivated areas close to irrigation canals, indicating well-watered crops and high biomass productivity. Low NDVImax values were associated with rainfed lands, built-up areas, and degraded zones. These patterns confirm the effectiveness of NDVImax as an indicator for irrigated cropland detection.

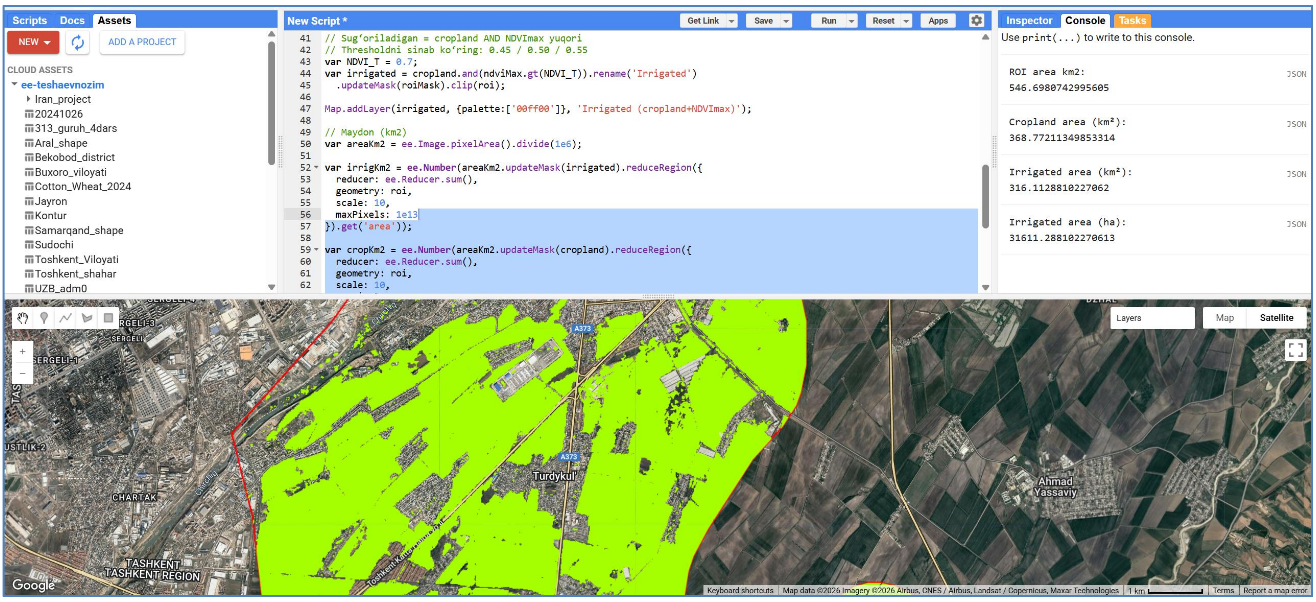

Figure 1. Illustration of irrigated cropland identification in Google Earth Engine.

Separation of Cropland and Irrigated Areas

Cropland areas extracted from ESA WorldCover were integrated with the NDVImax map to identify irrigated fields. The resulting irrigated areas were spatially clustered in flat terrain and near irrigation infrastructure. Elevated and drier areas exhibited significantly lower proportions of irrigated land.

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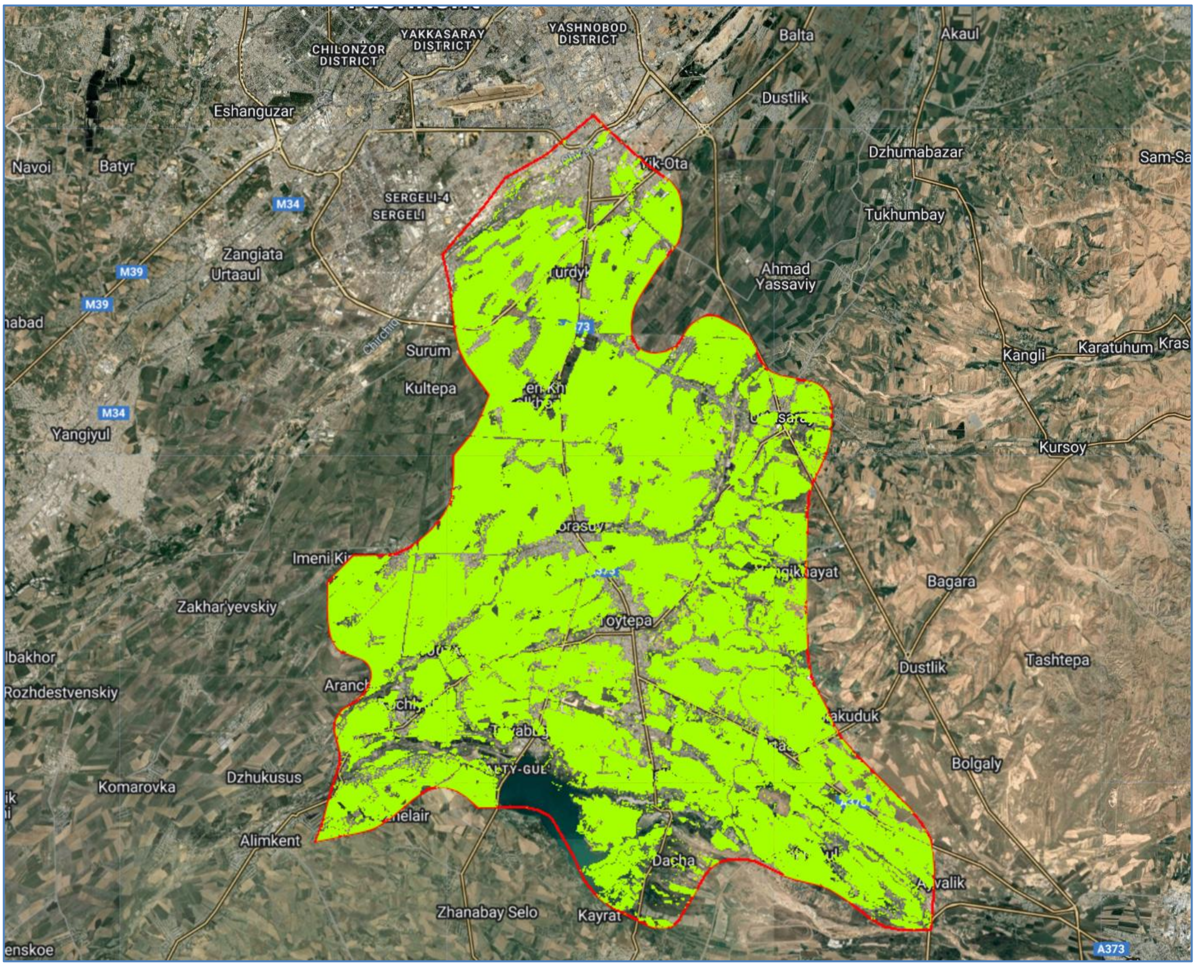

Figure 2. Irrigated areas in O'rta Chirchiq district identified using Sentinel-2 imagery.

Spatial Analysis

The spatial distribution of irrigated lands strongly corresponded to irrigation infrastructure, particularly main canals and water distribution networks. Areas classified as irrigated also showed higher vegetation density, reflecting adequate water supply.

Validation of Results

The sensitivity of the method was evaluated by testing different NDVImax threshold values. Higher thresholds reduced irrigated area estimates and retained only the most intensively irrigated fields. The threshold producing results closest to official statistics was selected, reducing the risk of overestimation and improving regional adaptability.

Conclusion

This study proposes a simplified yet operationally effective methodology for identifying and mapping irrigated agricultural lands using remote sensing data, demonstrated for the O'rta Chirchiq district of Tashkent region. The approach integrates Sentinel-2 NDVI time series, NDVImax, and a cropland mask derived from ESA WorldCover.

The results show that NDVImax is a sensitive and reliable indicator for distinguishing irrigated cropland. Integration with the cropland mask enabled accurate spatial delineation and area estimation of irrigated lands, with results consistent with official statistics.

Remote sensing thus represents a rapid, cost-effective, and scalable tool for irrigated land monitoring, supporting water resource management, agricultural planning, and policy development.

However, limitations exist. WorldCover data represent 2021 conditions and may not capture recent land-use changes. NDVImax does not account for crop-specific or management-related differences. Future research should integrate higher-resolution imagery, multi-year time series, and field data for improved accuracy.

Overall, the proposed methodology is transferable, adaptable, and suitable for application across other irrigated regions of Uzbekistan.

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