





Wildfire Impact and Forest Flux in Penjween, Iraq: A Remote Sensing-Based Deforestation Assessment (2010–2020)

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Abstract

Increased severity of environmental issues such as climate change, land use, and frequency of wildfires has started causing concerns on a global scale. This research is intended to identify forest wildfire, deforestation, and the carbon exchange process in the Penjween District of the Sulaymaniyah Governorate in Northern Iraq using Remote Sensing Technologies. Three models were employed to evaluate forest cover changes from 2010 to 2020, including the Normalized Difference Vegetation Index (NDVI) and Radar Vegetation Index (RVI), and satellite-based fire alert data. Through NDVI analysis, a notable change in land cover was observed, where there was a decline of ‘barren land’ from 500,000 hectares in 2010 to < 200,000 hectares by 2018, while the shrub and grassland areas increased from 400,000 to 650,000 hectares. The data obtained through RVI showed a strong signal of vegetation (0.9) in Spring 2015. This was followed by declining value trends that RVI data represented. These trends indicated the presence of droughts, changes in land use, and the frequency of land burns. An assessment of burnt areas using MODIS data revealed increased wildfire activity from 2014. Almost two hundred fire incidents had been observed by the year 2020 fires were recorded. July accounted for 113,962 hectares burned. Spatial fire frequency maps showed chronic fire zones, which are likely tied to humans and arid conditions. In any case, the Penjween forests continue to act as a net carbon sink. They release 5.68 ktCO₂e/year but are absorbing 1.03 ktCO₂e/year of the carbon dioxide from the atmosphere.

Keywords: Matrix gene, inflammatory biomarkers, RT-PCR

Keyword: Remote Sensing; Wildfire Impact; NDVI and RVI; Carbon Flux; Penjween Forests.

I. Introduction

The world has experienced increasing wildfire prevalence as summers become hotter and drier. Under the current climate change predictions, these wildfires are anticipated to grow stronger, threatening forest ecosystems, their flora, fauna and severe damage to infrastructure (Bargali et al., 2024; Chiva and Sala, 2025; Pausas and Keeley, 2019; Veloso et al., 2025), In addition to climate factors, deforestation and land-use change, both legal and illegal, have significantly increased wildfire risk (Huang et al., 2025; Lewis et al., 2015; Salar, 2019). Globally, human activity remains a major driver of fire incidents, especially in areas experiencing rapid environmental transformation so the complex interplay of climatic, ecological, and human factors, need to implying the proactive management for fire risk (Park et al., 2025). Iraq, particularly the North Region, has witnessed substantial ecological changes over the past two decades. Between 2000 and 2010, the country experienced a severe deterioration in drought conditions, progressing from normal to exceptional levels (Hameed et al., 2018). These climatic shifts have been accompanied by an increasing frequency and intensity of wildfires within forests globally, especially during the hot and dry seasons (Kelley et al., 2025; Rahimi et al., 2020; Rasul et al., 2021). Forest fires lead to drastic ecological consequences, including shifts in vegetation density, species composition, soil surface degradation, increased erosion, and altered runoff patterns (González-Pelayo et al., 2024; Smith et al., 2011; Wu et al., 2015). Additionally, they



release large quantities of greenhouse gases, particularly CO₂, into the atmosphere (Zhao et al., 2025). where climate change and the increased frequency of La Niña Phenomena, particularly recurring droughts, have attracted the attention of researchers to address them and develop potential remedies by relying on the research aspect (Gabash et al., 2024). In the Sulaymaniyah Governorate, which includes the Penjween area, the average annual increase in burned areas has reached approximately 188.7 km² in recent years. Monitoring fire frequency in Penjween has traditionally relied on field observations and local assessments, which, while valuable, are limited in scope. In the past decade, however, remote sensing (RS) technologies have proven instrumental in tracking fire activity and assessing vegetation health on a broader scale. Tools such as the Normalized Difference Vegetation Index (NDVI) have enhanced our ability to quantify forest changes and evaluate fire risk (Apraku et al., 2023; Chen et al., 2024). NDVI is the most common way to quickly find places with plants, figure out how disturbed a forest is, and track changes in land cover over time (Hsu, 2025). The objectives of this study are threefold: first to determine the spatial extent of forests and assess their changes over time in the Penjween area using Geographic Information Systems (GIS) and remote sensing; second to apply remote sensing tools for monitoring vegetation dynamics through NDVI-based change detection; and finally to provide data and resources that support sustainable forest management and fire risk mitigation in northern Iraq.

II. Materials and Methods

Penjween is a picturesque district in the Sulaymaniyah Governorate in northern Iraq. The coordinates for the Penjween are approximately 35.62366°N and 45.94954°E, as shown in Fig 1. Penjween is considered the best place for eco-tourists and attracts thousands of tourism groups due to dense forests, mountains, springs and the landscape surroundings and close attachment to the Iran border (Karim et al., n.d.). But wildfires and deforestation have significantly impacted Iraq, particularly in the northern and northeastern regions, including the Iraqi Kurdistan Region, over the past decade. Between 2010 and 2019, the country experienced an average annual increase of approximately 71.7 km² in burned areas, with a notable surge in 2019 when burned areas expanded by around 1,363 km² compared to previous years.

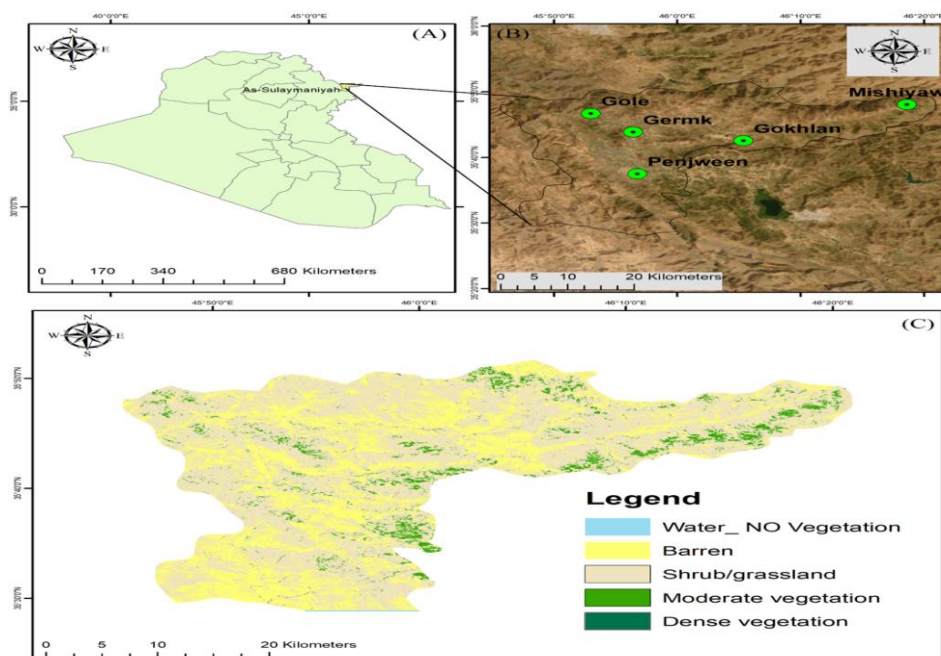


Fig. 1: A) Location of study area B) Satellite image of study area C) Normalized Difference Vegetation Index

Deforestation and wildfires in the area of study can be assessed with the help of satellite data from MODIS (Moderate Resolution Imaging Spectroradiometer), Copernicus (Global Monitoring for the Environment and Security with its Sentinel satellites), as well as Landsat Image Seven. With the help of satellite images, scientists can measure and calculate several indices which show the changes in vegetation cover in the area of interest. Indices are amongst the most powerful tools that can be used for environmental monitoring, and are described in detail below.

Normalized difference vegetation index (NDVI):

The NDVI (Normalized Difference Vegetation Index) methodology relies on the principle that healthy vegetation exhibits low reflectance in the visible spectrum of the EMS (electromagnetic spectrum) due to the absorption by chlorophyll and other pigments, while demonstrating high reflectance in the NIR due to internal reflection by the mesophyll spongy tissue of green leaves (Nath and Acharjee, 2013). To identify changes in vegetation in the study area, covering over ten years, five intervals were selected between 2010 and 2020. For classification and NDVI (Normalized Difference Vegetation Index) calculations, Landsat image seven was chosen as the source data. In Landsat seven, $NDVI = (Band\ 4(Near\ infrared - Band\ 3(red)) / (Band\ 4(Near\ infra-red) + Band\ 3(red)))$ as equation below

$$NDVI = \frac{(NIR-RED)}{(NIR+RED)} \dots\dots\dots Equation\ 1$$

Because it is reliable, adaptable, and simple to understand, it is a commonly used metric for assessing the density and health of vegetation on Earth. The NDVI value was categorized into five classes based on (Rahmi et al., 2024). Also, the value of NDVI has a strong relationship with drought. High NDVI mean extremely wet conditions, while the low NDVI value indicates extreme drought, which may signal changes like the loss of forests or significant disturbance (Hsu, 2025)(Table 1).

TABLE 1: Description and classification of vegetation cover based on NDVI standard values
(Aquino and Oliveira, 2012)

NDVI_Class	Range	Vegetation class	Color (Map)
0	0-≥0.2	Water or non-vegetation	Blue
1	<0.2-≥0.4	Barren-built area	tan
2	<0.4-≥0.6	Shrub/grassland	yellow green
3	<0.6-≥0.8	Moderate vegetation	Green
4	<0.8-≥1	Dense vegetation	Dark green

Radar Vegetation Index (RVI)

Monitoring vegetation dynamics is essential for understanding environmental changes, assessing land degradation, and informing natural resource management. In this context, the Radar Vegetation Index (RVI) serves as a valuable tool for evaluating vegetation health and changes, making it particularly useful for effective forest cover monitoring and management. RVI, a measure of randomness of scattering, has been suggested as a way to track the amount of vegetation development, especially when time series data are



available (Kumar et al., 2013). The values range between 0 and 1. Higher RVI values typically indicate denser vegetation, while RVI values near 0 indicate sparse vegetation or bare soil conditions (Szigarski et al., 2018). Synthetic Aperture Radar (SAR) is now frequently combined with optical data for agricultural survey, with its ability to image in all weather conditions (Chang et al., 2025). One widely used SAR-based metric is the Radar Vegetation Index (RVI). It quantifies vegetation structure and density based on polarization backscatter data and is expressed for dual-polarized Sentinel-1 imagery based on Equation 2 as follows:

$$RVI = \frac{4.\sigma_{vh}^0}{\sigma_{vv}^0 + \sigma_{vh}^0} \dots \dots \dots \text{Equation 2 by (Pan et al., 2023)}$$

Where: σ_{vv}^0 = backscatter coefficient for vertical transmit and vertical receive polarization, and σ_{vh}^0 = backscatter coefficient for vertical transmit and horizontal receive polarization.

With the integration of Google Earth Engine (GEE), with calculations and time-series analysis of RVI over wide areas using Sentinel-1 SAR data, the RVI is obtained. This enables monitoring of vegetation changes over time across remote and ecologically important landscapes in the study area.

Burned Area Indices (BAI)

Areas impacted by fire are identified and mapped using indices generated from remote sensing. By analyzing variations in reflectance brought on by fire, they assist in identifying vegetation that has been burned. Calculated BAI using red and near-infrared (NIR) bands as shown in Equation (3). BAI highlights burned regions because burned surfaces reflect differently than healthy vegetation.

$$BAI = \frac{1}{(NIR-0.06)^2 + (RED-0.1)^2} \dots \dots \dots \text{Equation 3 by (Martín et al., 2005)}$$

Where: BAI is the burned area index, NIR is the near infrared wave band, and RED is the red band.

The data provided and displayed in the Global Wildfire Information System (GWIS), derived from the Global Fire methodology. Glob Fire uses the MODIS burned area product (MCD64A1) to define wildfire events and compute the burnt area of each event (Artés et al., 2019). The MODIS data integrated in GEE and used for depicting the median day of burning in the whole of Iraq is shown in Figure 2.

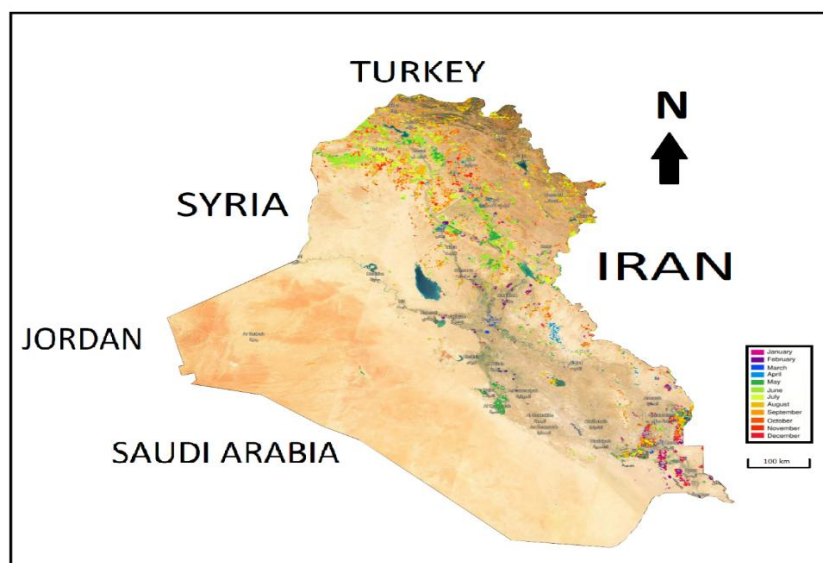


Fig. 2: Median day of burning area in Iraq



Forest-related carbon flux

Forest ecosystems play a vital role in the global environmental balance. They constantly exchange water, energy, carbon, and other biochemical with the atmosphere, and are particularly important for absorbing atmospheric carbon dioxide as result of photosynthesis, while emissions primarily generated by deforestation, wildfires, and soil respiration. Continuously mapping these ecosystems provides essential data for quantifying and understanding environmental changes at all levels (Szigarski et al., 2018; Zhang and Zhang, 2025). The process of transferring carbon between the atmosphere and Forest cover plays an essential role in the carbon sink and carbon source (release). One important measure of how ecosystems act as carbon sinks or sources is Net ecosystem exchange (NEE), utilized to measure the CO₂ exchange between the atmosphere and terrestrial ecosystems (Wu et al., 2025). Calculation of Net Ecosystem Exchange (NEE) as shown in the following equation

$$NEE = C_r (\text{Carbon release}) - C_s (\text{Carbon sink}) \dots\dots\dots \text{Equation 4 by (Baldocchi, 2003)}$$

Where: Carbon sink (uptake) is the process of uptake of CO₂ from the atmosphere during photosynthesis and stores it in roots, leaves, and soil, while Carbon release is the release of carbon dioxide into the atmosphere that occurs as a result of respiration, decomposition, and disturbances like logging, deforestation, and wildfires. If NEE A negative indicates a carbon sink (absorbing more CO₂ than releasing). Understanding forest-related carbon flux is essential for climate models, REDD+ programs (Reducing Emissions from Deforestation and Forest Degradation), and sustainable forest management strategies.

Ground truth collection

The accuracy assessments of the resulting maps were checked using 47 ground truth samples collected from the field in the study area in order to check the reliability of the three models' results, which include NDVI, RVI, and burned area BAI.

III. Results and Discussion

NDVI

The value of NDVI shows variation from 2010 to 2020, as shown in Figure 3. The barren land decreased from more than 500000 hectares in 2010 to less than 200000 hectares in 2018, which is a great indication of increased vegetation cover. The shrub-grassland area increased from 400000 hectares in 2010 to 650000 hectares in 2018, indicating an increase in farming and plantations. Also, moderate and dense vegetation increases, but within a very restricted area, as shown in Figure 4.



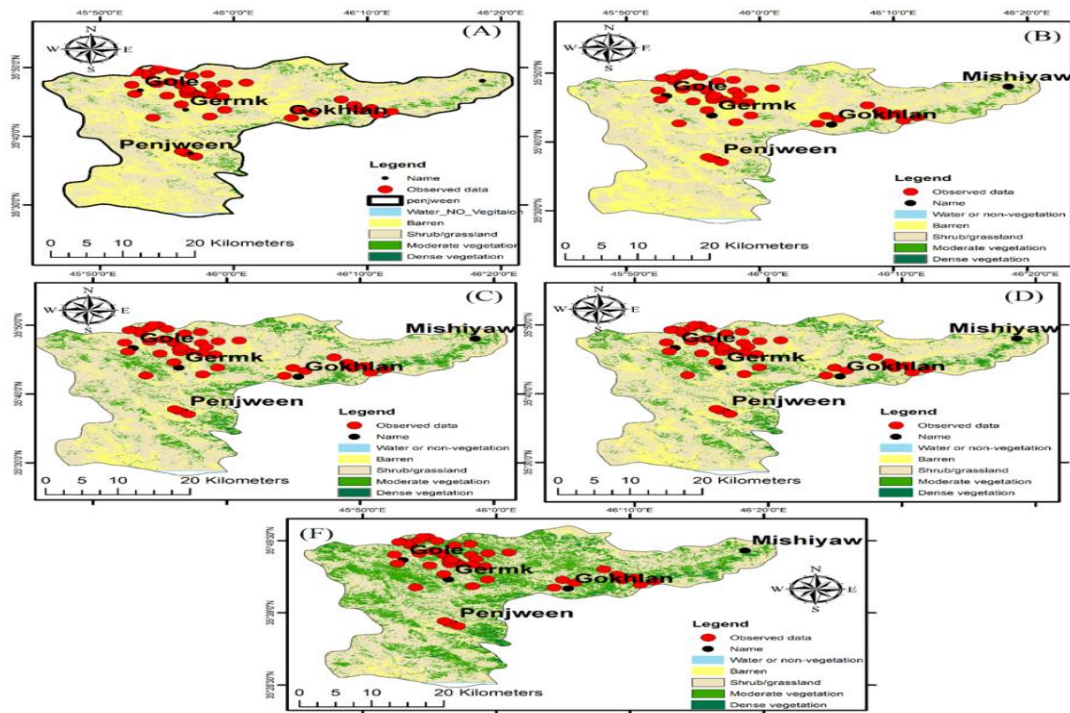


Fig. 3: NDVI change using change detection cover between 2010-2020 (A) 2010 (B) 2012 (C) 2014 (E) 2016 (F) 2018

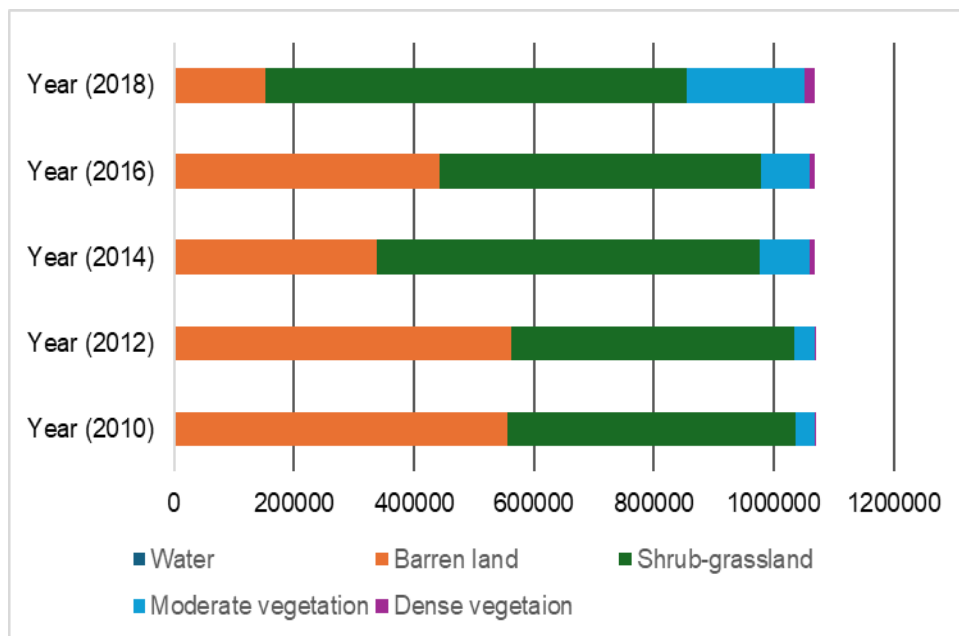


Fig. 4: Landover change based on NDVI from 2010 to 2020.

According to the variation in the vegetation cover of the Penjween area, the Vegetation Classes changed based on ground truth data observation (47) points, as shown in Table 2. Class 2 (Grass/Bush Land) increased from 13 field observation points in 2010 to 24 points in 2018, Class 3 (Moderate Vegetation) increased from 3 points of ground observation in 2010 to 6 in 2018, Class 4 (Dense Vegetation) increased from 0 in 2010 to 6 in 2018 based on ground truth observations and at the same time Class 1 (Barren Land) dropped from 23 in 2010 to 4 in 2018.

TABLE 2: Vegetation classes in Penjween area according to NDVI from (2010-2018)

Land Cover Class based on (NDVI)	2010	2012	2014	2016	2018	Ground truth Field observation in 2025
0 – No vegetation	8	8	8	8	7	8
1 – Barren land	23	20	8	9	4	11
2 – Grass/bush land	13	13	21	22	24	14
3 – Moderate vegetation	3	6	8	6	6	8
4 – Dense vegetation	0	0	2	2	6	6
Total Point (ground truth/)	47	47	47	47	47	47

The increasing correlation coefficient (R^2) values in recent years strongly hint at a degree of stability or predictable change in land cover types, as shown in Table 3.

TABLE 3: The R^2 (coefficient of determination) values between the observed data and each year's land cover

Year	R^2 Value
2010	0.446
2012	0.581
2014	0.716
2016	0.757
2018	0.716



The RVI time-series for the Penjween area

The RVI show significant fluctuation values over the study area as shown in Fig.5. The high RVI values (around 0.9) are observed in spring 2015, which may be related to an exceptionally productive growing season, possibly linked to favorable rainfall or land cover conditions. In mid-2016 onward, RVI values show increased fluctuation with lower seasonal peaks, possibly reflecting land use changes, deforestation, increased bare land or drought stress as shown in Figure 6 and Figure 7. The RVI seems to have stabilized at moderate values (0.7) between 2017 and 2018, but the increased frequency of lower spikes could indicate fragmented or degraded vegetative cover, possibly as a result of climate or human-caused factors. These results demonstrate the capability of SAR-based RVI monitoring for identifying vegetation patterns and potential land degradation in mountainous areas Fig. 7.

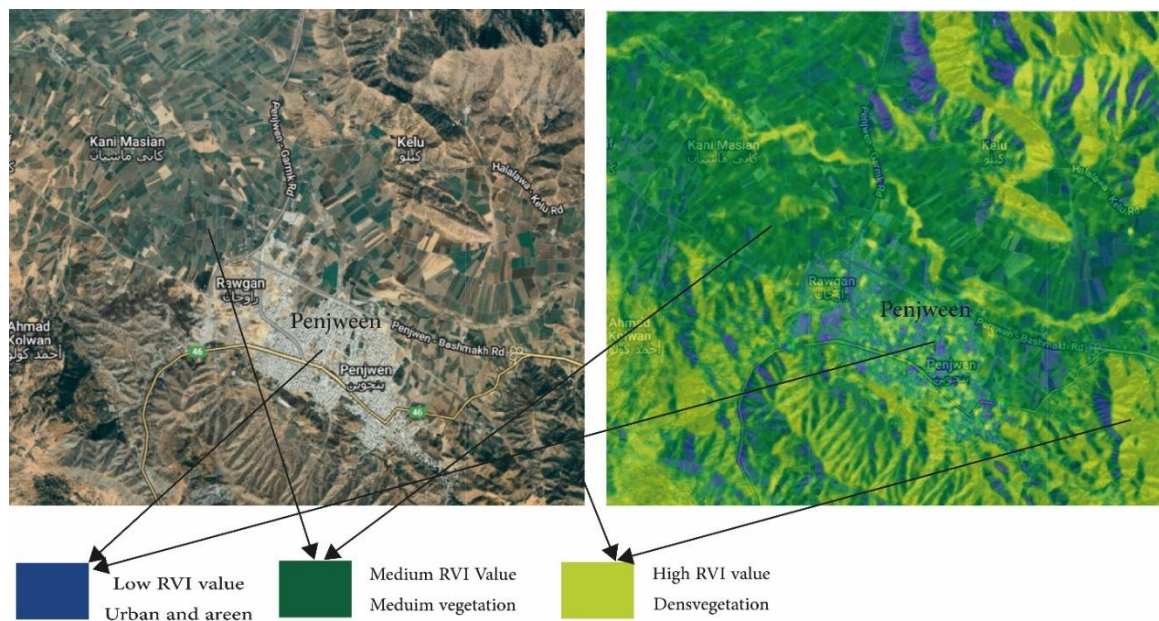


Fig. 5: Radar Vegetation Index (RVI) Analysis of Penjween Region for Land Cover Classification

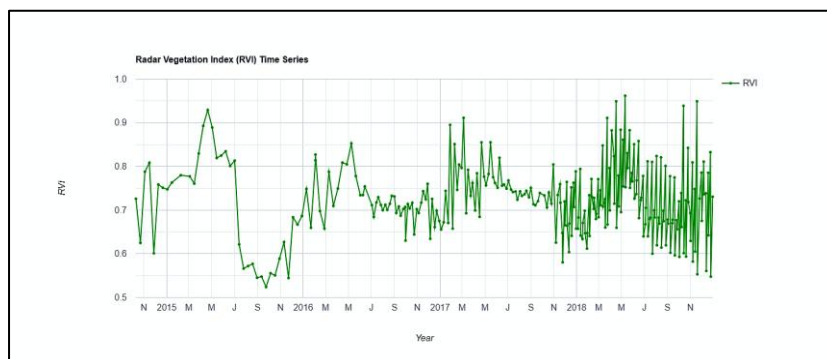


Fig. 6: Radar vegetation index time series change

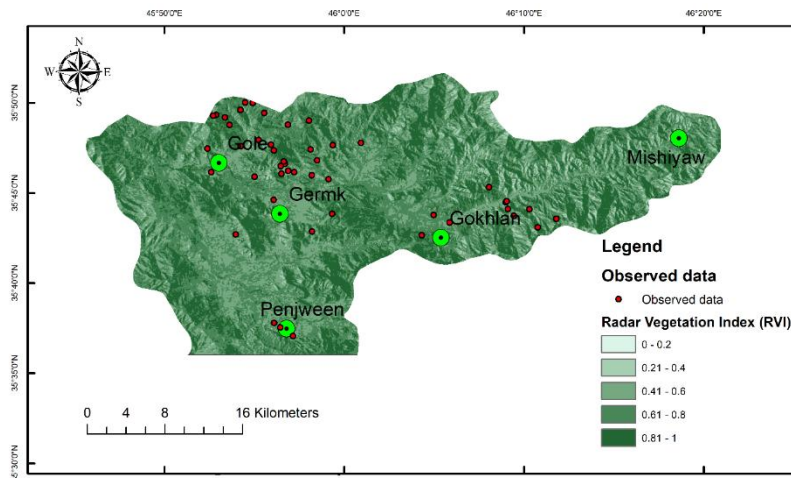


Fig. 7: Spatial distribution of Radar Vegetation Index (RVI)

Burned Area Indices:

Burnt area data generated in the GWIS product is based on the combined use of thermal abnormality from MODIS and Visible Infrared Imaging Radiometer Suite(VIIRS). The spatial resolution of the active fire detection pixel from MODIS is 1 km for delineating single fire circumferences, which are then used to determine the burnt area. Based on MODIS satellite data indicating a fire alert, there is a clear upward trend in fire numbers from 2010 to 2020, as shown in Fig. 8. The number increased in 2020, to close to 200. In 2019, there was a relatively high number, slightly less than 2020, while 2013, 2012, and 2011 had the lowest numbers, all below 50, as Fig. 9 illustrates. Fire numbers generally increased over time, particularly after 2014, as shown in Fig 9.

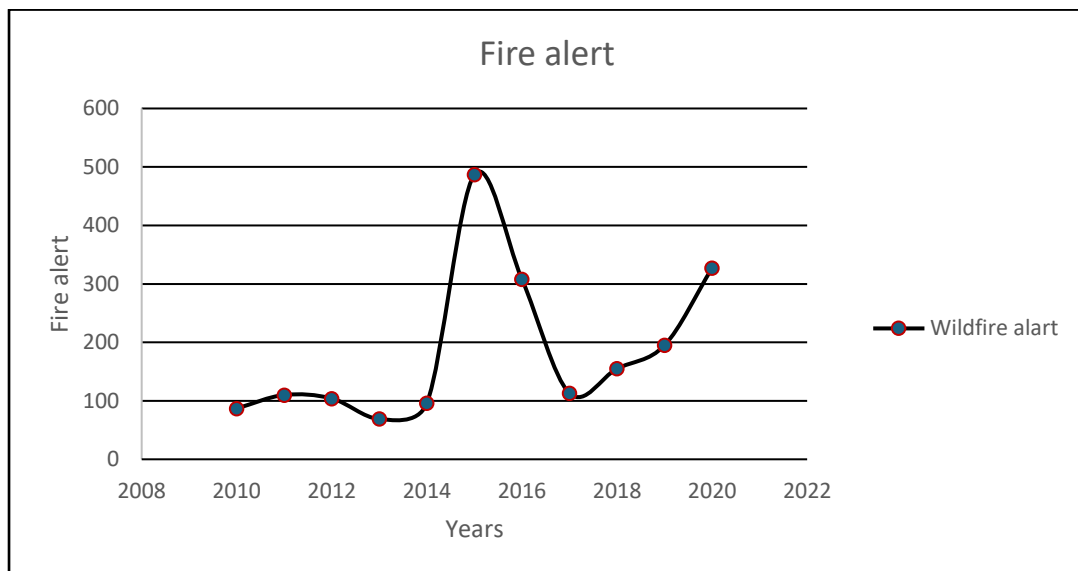


Fig. 8: Fire alert from 2010-2020

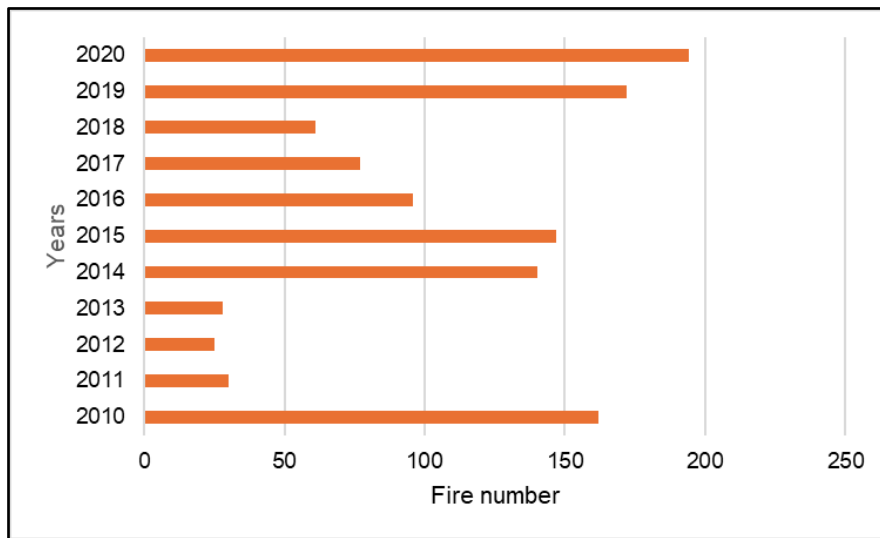


Fig. 9: Wildfire Incidents by Year (2010-2020)

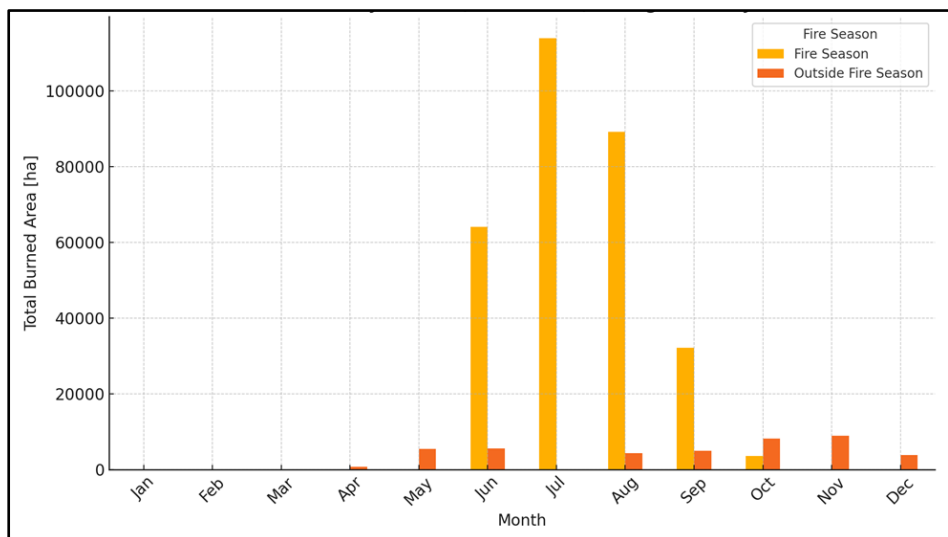


Fig. 10. Total burned area by month (2010-2020)

Fig. 10 above shows the total burned area each month from 2010 to 2020, categorized by Fire Season and Outside Fire Season. It is clear that the summer months, which are considered the fire season and usually last from June to September, have the highest levels of fire activity. Most of the burned area occurs during fire season, peaking in July (113,962 ha), followed by August (89,169 ha) and June (64,054 ha). There is a decrease in September (32,156 ha). Outside this season (fire season), burned areas are much lower, with May (5,431 ha) being the highest level. Fires are not spread at random. There is a clustered pattern for fire that may correspond to ecological zones, terrain (valleys, forest, etc.) or land use (such as farmland).

Fire frequently:

The fire frequency ranges from 1 Occurrence (dark purple) to 18 Occurrences (bright green-yellow) as shown in Fig. 11. Low Fire Frequency Zones: Purple/blue areas experienced only 1–4 fires, indicating less frequent burning or better fire management. Areas with 10 or more occurrences (green to yellow) represent chronic fire zones, probably as a result of human activity, dry vegetation and repeated lightning strikes.



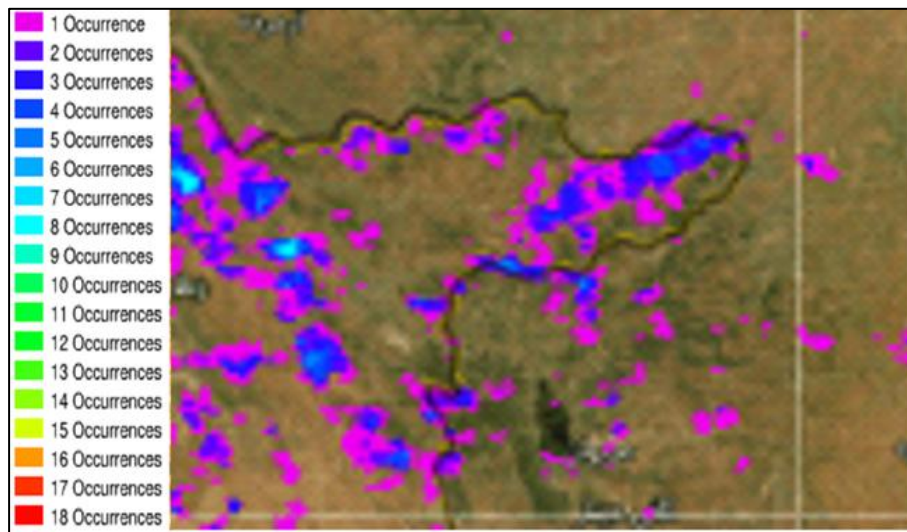


Fig. 2 :The frequency of fires in Penjween over a period (2010–2020)

Forest-related Carbon flux:

Forests in Penjween, As-Sulaymaniyah, Iraq, between 2010 and 2020, they are emitted 5.68 tCO₂e/year and sank -1.03 ktCO₂e/year from the atmosphere. This means the forests released 5.68 metric tons of CO₂ equivalent per year into the atmosphere, which gives strong evidence that emissions usually come from wildfires, degradation of vegetation cover (deforestation, changes in land use in the study area), and organic matter decomposition. From the result, the amount removed is much larger (1,030 t/year), so the forest is acting as a net carbon sink, meaning the Net Ecosystem Exchange (NEE) indicates a carbon sink (absorbing more CO₂ than releasing), as shown in the fig. (12).

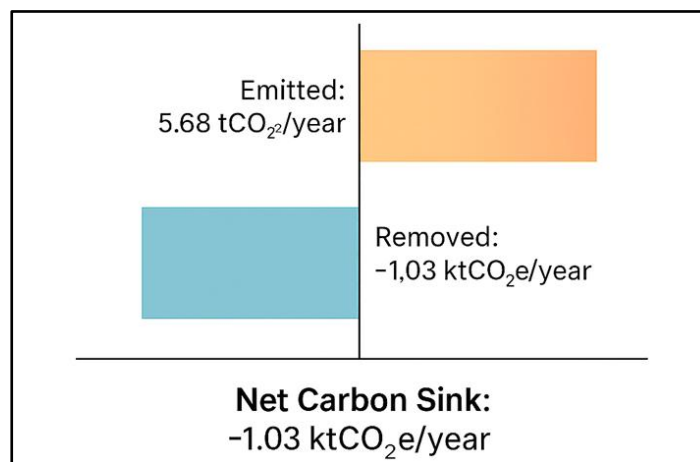


Fig. 12: NEE balance between emitted CO₂ and sink CO₂ in the Penjween area

IV. Conclusions

Forest loss has become a growing environmental concern in Iraq, driven by factors such as climate change, unsustainable land use, and increasing wildfire frequency. NDVI showed significant changes in vegetation cover between 2010 and 2020, particularly Barren land decreased dramatically from over 500,000 hectares in 2010 to less than 200,000 hectares by 2018, while shrub and grassland areas expanded from 400,000 to

650,000 hectares. These changes indicate a positive shift toward re-vegetation ($R^2=0.716$). SAR-based RVI monitoring, with values peaking around 0.9 in 2015 and stabilizing near 0.7 by 2017–2018, effectively reveals vegetation dynamics and signs of land degradation in mountainous regions. Fire incidents based on BAI increased significantly after 2014, peaking at 200 events recorded in 2020 and over 113,000 hectares burned in July alone. Penjween forests remain a net carbon sink, removing approximately 1.03 ktCO₂e/year. Overall, the integration of NDVI, RVI, and BAI indices demonstrates the power of remote sensing in monitoring environmental change, identifying vulnerable areas, and informing sustainable land management strategies. These findings highlight the complex interactions between vegetation recovery, wildfire disturbance, and climate-related stressors.

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