International Journal of Computational and Experimental Science and ENgineering (IJCESEN)

Vol. 11-No.2 (2025) pp. 2505-2514
http://www.ijcesen.com

ISSN: 2149-9144

Research Article

Evaluating Soil Fertility Degradation Due to Crop Residue Burning: Implications for Sustainable Agriculture

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Article Info:

DOI: 10.22399/ijcesen.1676
Received : 11 February 2025
Accepted : 05 April 2025

Keywords :

Soil fertility,
Crops residues burning,
NBR,
dNBR NDVI GEE FIRMS.

Abstract:

Crop burning is an age-old issue that is practiced by farmers mostly for clearing the fields. This practice causes environmental pollution ranging from reducing soil fertility to human health. This study utilized multi-geospatial processing platforms: Google Earth Engine (GEE) and Fire Information for Resource Management System (FIRMS) to derive Normalized burn ratio (NBR), and pre/post-fire ΔNBR for 2015 and 2023 to identify burnt fields and changes in burning practices. Further, the study relied upon on-field data to assess soil properties pre/post-fire date of 2023 in selected fields within Babil governorate. Overall, the study found that the leveraging of cloud-based geospatial platforms performed well in detecting burnt fields with a noticeable decrease in fire hotspots of 2023 when compared to 2015. The results of pre/post burning analysis soil samples showed that soil nutrients are declined. Among the measured soil properties, Nitrogen and soil organic matter are highly declined in average of 30% for nitrogen and 45% for O.M. While the average of decreasing in CEC and CaCO3 ranged from 5 to 15%. A slightly increased are observed for pH, salinity, Ca, Na, Mg, and Potassium. Open wheat field burning depletes soil organic matters and nutrients contents and away all the essential that make the topsoil healthy. The fire severity classification results indicated a dominant of low severity class over all selected Wheat-cultivated fields with value ranged from 22 to 86% of the burned area. A low correspondence was observed for low to moderate severity class with accuracy of 47.58%, suggesting high misidentification of these classes. Moreover, the study findings confirmed the effectiveness of utilizing multi- processing platforms approaches to overcome the misidentification of residue burnt fields.

1. Introduction

Burning of agricultural residues is a serious problem in modern agricultural practices. It is often considered necessary in the crop management process due to a lack of time between harvest and sowing of the new crop [1]. As crop residue constitutes a significant part of soil organic carbon, recycling crop residue is beneficial for improving soil health and provides a route to conserve natural resources [2]. Crop residues management requires significant labour and equipment costs, crop residues burning is such a common, effective, time saving and inexpensive way, Although, an effective residues management has the key role to put a large quantity of burned crop residues in alternative sustainable use [3,4]. Almost of Iraqi farmers tend to burn residues across their fields to simplify the preparation practices for the next cultivation. This practice encompasses a long-term risky impact on the soil depending on its type. Soil health is closely related to sustainable agricultural crop productivity. Destruction of crop residues causes a decrease in soil organic carbon, soil degradation, biological degradation, fertility loss, and leads to the release of greenhouse gases. However, many studies referred to decrease in soil nutrients, inducing soil erosion, decimate soil microbes, destroy soil organic matter, and degrade water holding capacity as main impacts of burning [5-8]. Agarwal et. al. observed a significant increase in soil pH leading to alkalinity as the organic matter and levels of nitrogen (N) and carbon (C) in the top layer of the soil profile (0-15 cm) are decreased [9]. However, despite the benefits of burning crop residues in controlling diseases and pests, the resulting heat elevates soil temperatures to over 40 degrees Celsius [10]. This elevated soil temperature is detrimental, causing the death of approximately 50% of beneficial soil organisms critical for maintaining soil fertility [11]. Air pollution is the other risky impact of the open agricultural residues burning, as such practice releases a large amount of smoke in a short amount of time hence ends in long-term effects on the human health. Biomass burning affects in climate through releasing greenhouse gases and other pollutants that contribute to the climate change in the longer term [12,13]. In Iraq, mostly in Babil governorate, such agricultural practice is a widespread implemented and poorly documented. This gap emphasizes the necessitate for a broad spatiotemporal study.

Remotely sensed imagery studies take advantage of the fact that spectral response is one of the most reliable methods to estimate the burned areas of interest. The advance in this technology and data processing platforms offer a helpful tool to environmental monitoring. Google Earth Engine (GEE) and NASA's Fire Information for Resources Management System (FIRMS) represent a promise tool to depict and mapping crops residue burning and assessing burn severity with high efficiency and accuracy. In recent years, several fire indices have gained substantial attention for mapping burned areas [14-16].

Cloud-based platforms provide valuable method to determine changes in burning density around area of interest under period of study. According to Mathur and Srivastava [17], the burning density events / Km2 area/ year in 2009 was much larger than burning events in 2001. They detected significant increasing in soil pH and the electrical conductivity (EC) with decreasing in soil permeability, content of nitrogen, and shifting in microorganisms' population. Generally, fertility is an aspect that many scientists are deeply involved in. However, for soil fertility assessment in some areas, particularly in the study regions where post-harvest burning is widely used to clear the field from debris, there are very few studies. Up until now, there has also been a lack of studies carried out to assess the change in soil fertility after crop residue burning activities. Many scientists emphasize the reduction in crop yield, air pollution, and airflow, but concerns regarding soil fertility are not well mentioned. Besides this, nowadays the world is facing the problem of food scarcity, and land is not enough to feed the billions of the rising population, mainly in low-income socio-economic conditions.

In Iraq, the burned areas were not detected, nor have they been identified. With intellectual curiosity and concern for managing soil health, this paper was an attempt to assess the influence of crop burning on soil properties. Furthermore, this study assumes that a multi- platforms combining approach can provide dependable data on duration and extending of burning occurrence, considering the country-specific needing for a proper crop residue management to reduce the environmental footprint from agricultural sector. The primary objective of this study is to:

- Evaluate soil fertility pre/post burning practices.
- Describe patterns, duration and frequency of crop residue burning in Babil governorate.
- Evaluating the effectiveness of rapid processing data platforms (GEE and FIRMS) in estimating the fire severity and extent and overcoming the limitations of lacking data for such studies.

2. Materials And Methods

2.1 Study Area

In Iraq, Babil classified as the most prominent cultivated governorate with 512 thousand hectares divided into four administrative districts: Al-Hilla, Al-Mahaweel, Al-Musayyib and Al-Hasmiyah. The governorate famous in cultivation of rice, maize, barely, wheat, cotton, and sesame, as well as various vegetables. A large amount of these crops' residues are burned annually across farms [18]. The governorate exhibits a flat topography and characterized by low annual rainfall ranging from 50 to 200 mm and high temperatures that can raise to 50 degrees Celsius in summer.

2.2- Field Data

Field data were collected from two district across Babil governorate include: Al-Kifil, and Al-Hashmiyah in 2023 to validate burned spatial extent outputs. To ensure a representative coverage, the pre-burning visits during 15th April to 15th May, and post-burning visits during June 2023 was planned to select the ground fields based on their a widespread prevalence with residues burning practices. A total of 100 soil samples were selected from each of randomly distributed fields in each district. The burned (post burning) and un-burned (pre-burning) soil in this system were analyzed in terms of fertility (available nitrogen, phosphorus, and potassium). We examined CEC, pH, salinity, $CaCO_3$, Na, Ca, Mg and soil organic matter along with document the pre, post- fire observations. Sample points coordinates and visual observed indicators were recorded to document burn severity characteristics.

2.3 Remote-Based Data Sources and Platforms

This study is based on the utilization of cloudy-based processing platforms, where Google Earth Engine (GEE) was used to facilitate deriving large-scale indices like NDVI and NBR. The free accessible data sources like Sentinel-2 and MODIS were accessed through GEE and utilized for Land cover classification and burned area mapping. This study chooses two timeframes, where 2015 was selected to stand for a baseline for depicting burned areas before recent adopted residues management. while 2023 was selected to reflect the current residues managing if any. The comparative study period (2015-2023) was selected to identify the changes and tendency of residues management and the shortcoming in agricultural residues overseeing in Babil governorate.
Fire Information for Resource Management System (FIRMS) was used to detect burned areas. NASA's FIRMS is an essential platform for fire monitoring that operational since 2006, facilitating near real time fire detection utilizing data from MODIS and VIIRS satellites. Moderate Resolution Imaging Spectrometer (MODIS) is the mostly product used by the scientific community, with information in 36 spectral bands from visible to thermal infrared region of spectrum. MODIS sensor on board NASA's Terra and Aqua satellites provides senses in near - daily temporal resolution and moderate spatial resolution at 250, 500, and 1000 m at global scales [19].

2.4 Fire Detection Techniques

Normalized Difference Vegetation Index

The Normalized Difference Vegetation Index (NDVI) is an extensively utilized remote sensing index to measure vegetation density, growth rate, and stress level.
This index analyses the reflectance of vegetation in the near-infrared and red parts of the spectrum. Healthy vegetation reflects a large amount of NIR and absorb most of red part of visible spectrum. In general, NDVI is calculated by using this equation [20].

$$\mathrm{VI} = \frac{(\mathrm{NIR} - \mathrm{RED})}{(\mathrm{NIR} + \mathrm{RED})} \qquad (1)$$

The calculated values usually range between -1 and +1, whereas water, built-up areas, and soil range from -1 to 0, and dense vegetation has values of 0.5 to +1. NDVI was computed in GEE by processing Sentinel-2 level - 1C imagery for April to June across 2015 and 2023. NDVI pixel-by-pixel comparison values were performed for 2015 and 2023 to identify areas with loss or burned vegetation, which typically have significant decreasing in NDVI values.

Normalized Burn Ratio.

The Normalized burn ratio (NBR) represents the most used index in fire monitoring due to its sensitivity to distinguishing between burned and unburned areas. NBR was derived from near-infrared (NIR) and shortwave infrared (SWIR) bands of satellite imagery. The methodology for calculating the Normalized Burn Ratio was applied according to Miller & Yool [21] with the following formula.

$$\mathrm{NBR} = \frac{(\mathrm{NIR} - \mathrm{SWIR})}{(\mathrm{NIR} + \mathrm{SWIR})} \qquad (2)$$

Where NIR is the reflectance value in the near-infrared band, SWIR is the reflectance value in the shortwave infrared band. The normalization process involves scaling the NBR values to a specific range, often -1 to 1. To map fire extended and severity, ΔNBR was derived to categorize burn severity into high, moderate and low severity. This calculation based on the capturing the differences between pre- and post-fire according to the following formula:

$$\Delta\mathrm{NBR} = \mathrm{NBR}_{\mathrm{postfire}} - \mathrm{NBR}_{\mathrm{prefire}} \qquad (3)$$

NBR postfire and NBR prefire are the difference in NBR values between two different time periods. Applying ΔNBR values was used to classify areas into different categories, such as burned, recovering, or unchanged. This threshold is a valuable way to identify areas that have undergone significant changes in two different times of period and assess the fire severity [22],. NBRs were composited from April to June of 2023. This period was selected to encompass the winter crop harvest and the associated burning of residues in the study region.

Fire Hotspot Detection.

Fire spatial distribution and intensity change was detected in baseline year 2015 to recent 2023. The active fire data from Fire Information for Resource Management System (FIRMS) were analyzed to map burned areas in hotspots with different confidence levels. The freely downloaded from NASA/LANCE/FIRMS data provides real time

MODIS active fire locations as web fire Mapper, email alert, shape files, and MODIS subset formats. According to the quality of identification, the algorithm classifies all fire pixels into low, nominal, or high confidence. This study adopted only nominal to high-confidence with values ranged between 70-100% within the study region.

2.4 Land cover classification

Remotely sensed data from Sentinel-2, level -1C from the Copernicus Programme that developed by European sensed data were used to classify the study area land cover into four categories: vegetation, bare land, built-up area, and water. The scenes of interest cover the study area during April of 2015 and 2023, were downloaded from Copernicus Open Access Hub. All collected images were pre-processed to reduce the atmospheric irradiance caused by different aspects, the study applied correction according to Soenen et al. [23]. The collected imageries set was computerised to distinguish LULC in ArcView 10.8 with Supervised classification tool.

2.5 Validation and Accuracy Assessment

Land Cover Classification Accuracy.
This study adopted two different approaches to assess the accuracy of LULC classification and fire detection. Regarding LULC classification accuracy, a set of total 250 reference ground control points were randomly generated from visual interpretation of high-resolution of Google Earth Pro image over Babil governorate. As the most used method in accuracy assessment, Kappa's coefficient was computed from the following formula.

$$\text{Kappa coefficient} = \frac{(\mathrm{T} \times \mathrm{C}) - \mathrm{G}}{\mathrm{T}^2 - \mathrm{G}}$$

Where: T is the test pixels, C is the correctly classified pixels, G is the sum of multiplied total value. The following formula was used to calculate the overall accuracy:

$$T = \frac{\sum D_{ii}}{N}$$

Where: T is the overall accuracy, ∑D_ii is the total number of correctly classified pixels and N is the total number of pixels in the error matrix [24].

Burn Severity Validation.
Field visits for the collected districts: Al-Kifil, and Al-Hashmiyah were conducted immediately after burning events. The reliability of ΔNBR classification was assessed by using ground observations. A confusion matrix was constructed to compare ΔNBR -derived burn severity classification with field observed data. The validation was computed to assess the model's ability to identify specific classes in terms of Producer's and User's accuracy, we utilized the following equations to compute them [25].

$$\textbf{Producer's Accuracy} = \frac{\textbf{Correctly classified points for a class}}{\textbf{Total ground-truth points for that class}} \times \mathbf{100} \text{ ---------------(4)}$$

$$\textbf{User's Accuracy} = \frac{\textbf{Correctly classified points for a class}}{\textbf{Total Classified points for that class}} \times \mathbf{100} \text{ ------------------------ (5)}$$

These measures were used to ensure that no real burned area was missed, and reducing the bias of labelling unburned area as burned one [26].

3. Results And Discussion

3.1 Land Cover Classification

The major LULC classification of Babil governorate involved two steps: Firstly, supervised classification based on the training reference points for different land cover categories were derived from sentinel RGB composition. Secondly, A collection of S2L2 sentinel images from the same period were computed by using Google Earth Engine (GEE) cloud-based platform (figure 1)[26, 27] United Nations. Vegetation landscapes are typically complex, encompassing various types of vegetation cover that pose a challenge when attempting to classify them. The using of suitable algorithm with minimal time of processing and acceptable classification accuracy and supervised classification are crucial to overcome the challenges of mapping vegetated area.

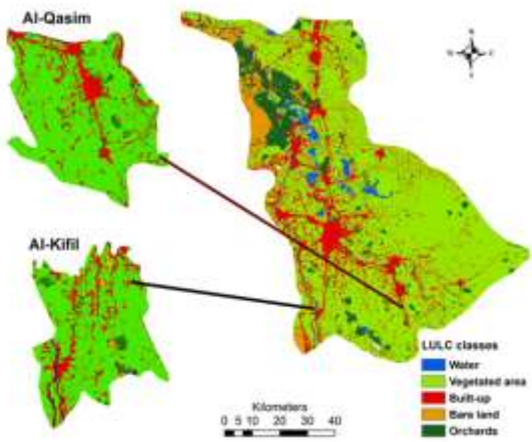

***Figure 1**. Maps of LULC 'COPERNICUS/S2_SR' images for Bail governorate, Al-Qasim, and Al-Kifil districts in 2023.*

Pixel-based approach from GEE was used to enhance classification accuracy [28]. The overall classification accuracy was 87.54%, and kappa coefficient of 79.63%, indicating high reliability of land cover classification (table 1). A noteworthy declining of vegetated areas in 2023 in comparison with 2015. The decline of vegetated areas has been supported by numerous prior studies [29-32]. These studies attributed such declines to the increased frequency of drought events and anthropogenic activities, including randomized patterns of urban expansion and the reduction of irrigated agricultural areas due to water scarcity.

Table 1. *Classification validation of LULC for Babil governorate in 2023.*

Category	Water	Vegetation	Built-up	Bare soil	Total	Correct sampled
Water	46	0	0	4	50	46
Vegetation	0	92	0	17	109	92
Built-up	0	0	41	6	47	41
Bare soil	0	10	2	32	44	32
Total	46	102	43	59	250	211
Overall accuracy		**87.54%**		**Kappa coefficient**		**79.63%**

3.2 Temporal Changes in Fire Hotspots

This study relied upon FIRMS to identify fire hotspots changes between 2015 and 2023, where data from FIRMS identifies all pixels with actively burning fires as "fire pixels" while the other pixels are classified as non-fire, cloud, missing data, or unknown pixels. To confirm whether the burned area prolonged from 2015 to 2023, Table 2 shows results of nominal to high-confidence (70-100%) hotspots for both Al-Qasim and Al-Kifil districts. A noticeable shifting in total fire hotspots in 2023 when compared to 2015 with alike change in both studied districts with percentage of 21.3 and 22.1% for Al-Kifil and Al-Qasim, respectively. In term of changing, this shifting well aligned with decreasing of cultivated area across the study region (figure 2). The findings, revealing a slightly reduction in average brightness, reflecting shorter or less complete burning periods. Results of fire intensity indicator (RFP), indicating a significant drop of burning intensity hence the results showed a dominant of low intensity class over both studied districts. Al-Qasim district showed higher drop in FRP with percentage of 20.3% than 5.5% in Al-Kifil. The observed decrease in fire detection metrics (total number of hotspots and fire intensity RFP), suggesting crop cultivation diminish among farm owners and increase the tendency of shift agricultural into urbanized areas due to neighbourhood effect [33].

Table 2. *Fire hotspots metrics for both districts over two timeframe 2015 and 2023*

Metrics	Al-Kifil			Al-Qasim		
	2015	2023	Average of change %	2015	2023	Average of change %
Total Fire Hotspots	80	63	21.3	86	67	22.1
Average Brightness (K)	282.5	278.3		295.4	291.4	
Fire Radiative Power (FRP)	101.7	96.13	5.5	118.6	94.5	20.3

We employed a combination of Normalized Difference Vegetation Index (NDVI) figure 2, and land use/land cover classification to detect the alteration in vegetation cover and contrast between vegetated areas and the other surrounding land covers. This approach was adopted to overcome the limitations associated with field sampling at the district level within our study area. The using of high spatial resolution imaging from Sentinel-2 satellites noticeably enhanced the detection of cultivated areas over the studied periods of 2015 and 2023 (figure 2). The spatial pattern of cultivated areas over the study years, reflect a vegetation considerably decreased in 2023. On-site visit data was combined with temporal NDVI to identify this reduction in accurate manner, and to overcome the deficiency of lacking historical data.

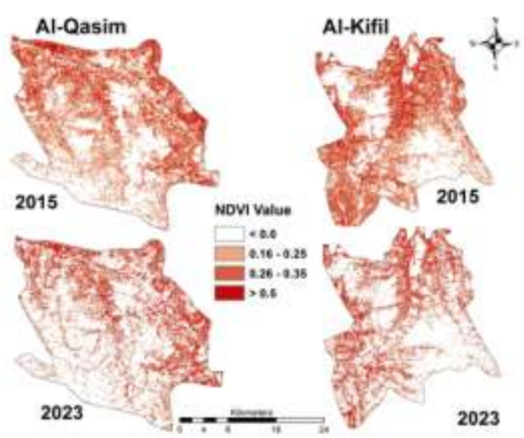

Figure 2. *Maps of NDVI computed from 'COPERNICUS/S2_SR' images for Al-Qasim and Al-Kifil districts in 2015 and 2023*

The another reason behind the declining of fire hotspots in 2023 (table 3) is the fact that crop residues burning is anthropogenic activity. Whether the residues of a particular farm are burned or not depends on the choices made by the farm's owners. As a rapid and effortless way to prepare land for the next planting season, farmers burn crop residues immediately after harvesting [18]. Hence such activity is extremely different from forest fire in terms of spatial and temporal extent, as open crop residues burning can generate a large amount of smoke in a short period of time. Such practices pose additional challenges in burning area determination due to the sensitivity of the satellite-based algorithms to small fires and the time of burning that usually start according to the farmers time schedule [25]. That may generate a bias in the estimate of the burned farm area and detection of active fire.

3.3 Soil Properties Alteration

Most of the studied fields have at least some soils that may be more susceptible than most districts soils to harmful consequences from burning. The results of soil analysis showed direct effects of burning on most of soil characteristics (table3). Overall results indicated that the selected fields of Al-Qasim district have higher values of all studied soil metrics than Al-Kifil fields. Burning the crop residue results in a sharp decline in essential nutrients such as nitrogen and phosphorus in both selected districted, where a noticeable decreasing in available soil N from 87.22 to 60.33 mg/g in Al-Kifil, and from 92.15 to 71.56 mg/Kg in Al-Qasim post- burning of crop residue. Alike, soil available P depleted from 45.82 to 30.18 mg/Kg in Al-Kifil and from 55.84 to 33.14 mg/Kg in Al-Qasim fields. Organic matter, which acts like a sponge in the topsoil, declined from ~ 0.45 to ~ 0.23%. The valuable soil organic matter components are lost in greater heat, and even the remaining ashes after the burning are not able to replace the degraded soil quality. Soil organic matter is an essential property for soil that is susceptible to management practices, so soil organic matter is progressively lost through oxidation. The proportional contribution to cation exchange capacity from organic matter is approximately four times higher than clay. Thus, the decline in organic matter due to the burning of crop residues will significantly affect the increase or decrease in the fertility of affected soil. Soil organic matter is related to soil pH, nitrogen dynamics, and soil management, and more specifically, soil microbial diversity. As the higher the quantity of organic matter, the more nutrients and moisture it will retain. Burning of these materials thus becomes an element that slightly increase the pH of the soil (more alkaline) in response to the increment of basic cations, K^+, Ca^{2+}, Na^+ due to ash deposition [34]. Burning of overdeveloped materials leads to excessive Na^+ led to obvious increasing in soil salinity. The process of burning has a great effect on soil nutrient content due to its volatilizing effects on nutrients, especially nitrogen and phosphorus. Post-burning analysis showed severely declined in available soil nitrogen, phosphorous, and soil organic matter with percentages from 30 to 67%, and slightly reduction in CEC with percentages from 19 to 30% [35]. While, almost of the rest soil metrics exhibited alike of increasing changes in both studied districts. Nutrient dynamics following burning influenced by several factors include the physical and chemical properties of the soils, local environmental conditions, burning intensity, and the residual properties associated with burning [36]. It is thus important to cover better management practices for maintaining or increasing nutrient stocks in soils against the likely preference of farmers to remove non-usable organic matter by burning. Retaining nutrients, and perhaps greater soil carbon content, would increase the sustainability of cropping systems.

Table 3. *Changes in Soil Metrics Induced by Crop Residue Burning: Comparative Analysis Across Districts*

Metrics	Al-Kifil					Al-Qasim				
	Pre-burning		Post-burning		Change %	Pre-burning		Post-burning		Change %
	Min	Max	Min	Max		Min	Max	Min	Max	
N mg/Kg	13.25	87.22	5.01	60.33	-62 to- 31	20.55	92.15	7.73	71.56	- 67 to -22
P mg/Kg	3.8	45.82	1.9	30.18	-50 to -34	2.93	55.84	1.28	33.14	-56 to -40
K (meq/L)	13.87	44.92	14.01	50.11	1 - 11	13.85	49.66	14.88	59.45	1 to 19
EC (dS/cm^3)	1.43	1.81	1.64	2.4	14 - 32	1.23	2.11	1.91	2.83	55 to 34
pH	7.1	7.3	7.3	7.8	3 - 7	7.1	7.5	7.6	8.0	7 to 6
Na (meq/L)	10.87	11.64	11.97	13.65	10 - 17	10.09	11.61	12.87	14.35	15 - 23
Ca+Mg (meq/L)	50.01	54.08	52.23	57.17	4 - 6	54.36	59.12	56.34	63.18	4 - 7
O.M (%)	0.13	0.45	0.09	0.21	- 30 to - 53	0.11	0.42	0.08	0.28	-27 to 33
CEC (Meq/100g)	33.87	41.98	26.31	29.21	-22 to -30	33.58	39.74	27.31	29.78	-19 to -25
$CaCO_3$ (%)	4.12	36.01	3.92	32.12	-5 to -11	3.98	35.14	3.74	32.17	-6 to -8

3.4 Burn Severity Analysis

This study adopted complementary approach by using several multispectral burn indices NBR, dNBR to map burned areas. As each index supplies different information, a combination of multiple indices will enhance detecting of burning in agricultural area. NBR shows the overall distinguishing burned from unburned areas, where high values of 0.777 indicate the healthy vegetated areas while the negative values of -0.669 highlight areas affected by crop residues burning (figure 3). The efficiency of NBR map is very limited for actual burned areas estimation due to the high spatial variability of active fires in the total burning period, and the area of the burned farm. Hence the underestimation is caused by the small, burned areas, while the large, burned areas result in overestimation [37].

The efficiency is also affected by the time of satellite pass, which is crucial to detect the active fire, so the NBR map does not represent the actual burning patterns. Large number of active fires could be missed as agricultural burning remains for few hours compared to forest fires that remains for several days.

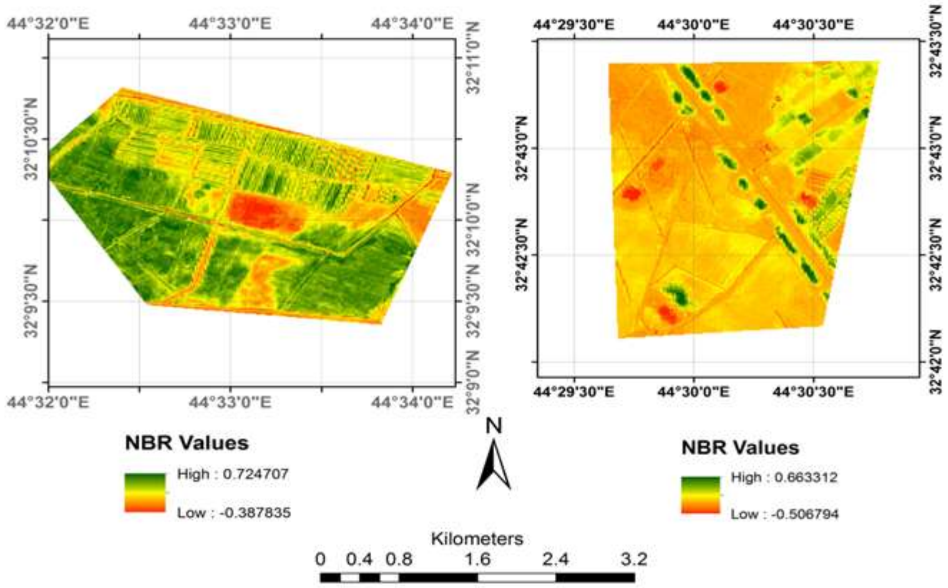

Figure 4. *NBR map estimated over selected wheat fields the studied districts during May, 2023.*

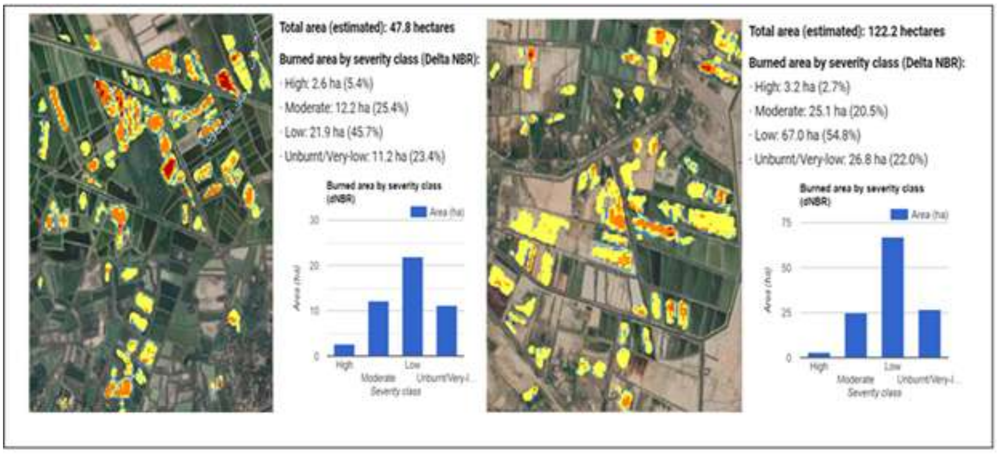

Figure 4. *dNBR generated from FIRMS data for the selected farms within Al-Musayiab, Al-Kifil, and Al-Hashmyia districts.*

Pre-burning field visits during 20th to 30th May, 2023 were planned to select some field locations, which can be later used as a base to analyse the extent and severity of burning practices in Al-Kifil, and Al-Qasim districts. The Fire Information for Resource Management System (FIRMS) was used to analyze dNBR and burning severity class (Figure 4). The results showed that the low severity class is the most dominant in both selected districts with values of 45.7%, and 54.8%, while the percentage of areas with high severity class are 5%, and 2.7% of burned area in Al-Kifil, and Al-Qasim, respectively. The data were further compared using Sentinel-2A/B satellite images and accuracy assessment to ensure the dependability of burn severity categorization. The producer's accuracy was 73.12%, indicating the effectiveness in detecting areas of high severity burning class, and the User's accuracy was also high with value of 70.08% emphasise that most pixels were correctly categorized as high severity burns. The detection of moderate burns class was relatively reliable with values of 63.14% and 61.23% for producer's and user's accuracy, respectively. The spectral overlap caused some misidentification of moderately burns and unburned pixels. At the same time, the low-severity burns achieved the lowest value of producer's accuracy (47.58%) signifying the spectral confusion with bare soil and leading to reduce classification accuracy. The fragmented pattern of agricultural fields exacerbates the complexity of burns pixels classification which are often smaller than the spatial resolution of using sensor. This misidentified could convincingly be expected for a

small fire due to the confused ambiguous of water and land pixels near fire pixels [36]. As a rapid burned area classification FIRMS offers promise available real time data for crop residues burning detecting especially soon after fire, but further data are required to help decision making regarding crop residues management. Both active fire data and ground onsite knowledge are needed to accurately detect of crop residues fire as confirmed by several studies [38-42].

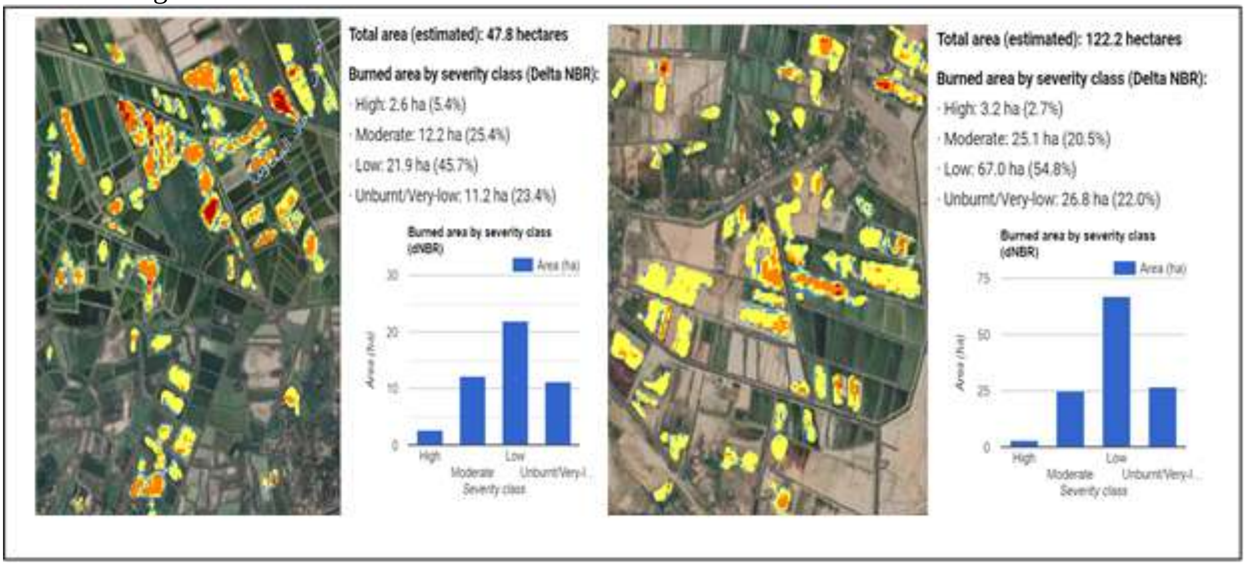

***Figure 4.** dNBR generated from FIRMS data for the selected farms within Al-Musayiab, Al-Kifil, and Al-Hashmyia districts.*

These results highlighted the complexity of accurately detecting small, fragmented fire areas. The multisensory approach proved effective in using GEE, FIRMS, Sentinel-2, and ground-truth data in enhancing the reliability of distinguishing burned from unburned areas. Furthermore, the results addressed spatial biases in using single data resources or algorithm.

4- Conclusion

This study integrated Google Earth Engine (GEE) and NASA's Fire Information Management System (FIRMS) with Sentinel-2 and ground-truth data to detect residue burning activities over two timeframe 2015 and 2023, and soil fertility dynamics under such practices. The results detected a noteworthy reduction in fire hotspots in 2023 compared to 2015, aligning with the reduction in vegetated areas in the last 8 years. The conventional practices of burning crop residues influence soil fertility, resulting in sharp loss of main soil available nutrients (nitrogen and phosphorous), soil organic matter, and CEC. In the studied regions, burning contributes to increased soil salinity, pH, and availability of Na+, K+, Ca+2, and Mg+2. The complementary results of land cover classification and NDVI attributed this declining trend in vegetated areas to the urbanization and drought, while the implementation of sustainable residue managing practices were low probability to reduce fire hotspots. According to our results, the fragmented patterns and small size of farms are the main factors that limit the efficiency of using burning indices. Results of Delta NBR classified fire severity into three classes: low severity burns, which was the dominant class over all studied districts with low producer's and user's accuracy. While moderate and high severity burns were low to rare with high values of producer's and user's accuracy. These findings confirmed the importance of the field data and multi-sensor imagery approaches to accurately generate and categorize the spatial extent and severity class of burned areas. In conclusion, this study contributes to filling the gaps in detecting spatial and temporal residue burning particularly in small farms. The future research needs to develop machine learning models to overcome the misclassification or bias detection, especially in small burned farms. This study sets the groundwork for monitoring approach and making a basic national database that contributes in the future sustainable development and environmental conservations.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The authors team of this research like to express their sincere gratitude to the College of Environmental Sciences at Al-Qasim Green University for supporting this research. We are also grateful to Google Earth Engine and FIRMS for granting their powerful cloud computing platforms, which were essential in enabling data analysis.
- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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