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Symbiotic Artificial Intelligence and satellite imagery for rapid assessment of war-induced agricultural damage in Ukraine

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Abstract: This study aims to enhance damage detection methods for the agricultural sector in Ukraine, which has been severely affected by ongoing conflict. While existing approaches, such as the method by Kussul et al. (2023), are among the best for monitoring damage, they are limited by the use of static threshold coefficients that can lead to inaccurate results, particularly false positives. To address these issues, we introduce a new approach using Symbiotic Artificial Intelligence (SAI), which integrates human oversight with machine learning to enable real-time adjustments to detection sensitivity based on field-specific characteristics. The proposed SAI-based method was tested using high-resolution satellite imagery from MAXAR for fields in Donetsk and Kherson. Results demonstrated a significant reduction in false positive rates, from 8.5% to approximately 1%, while maintaining a high rate of correctly identified undamaged areas. However, a slight decrease in true positive detections was observed, indicating a necessary balance between false positive reduction and sensitivity to actual damage. The SAI method effectively minimized false detections at field boundaries and other non-damage-related anomalies. This approach showcases the potential of combining human expertise with AI to improve accuracy and adaptability in damage detection. While the results are promising, further research should focus on automating the adjustment of detection thresholds for broader application, such as developing regression models to optimize field-specific coefficients.

Keywords: remote sensing, Symbiotic Artificial Intelligence, human interaction, agricultural field anomaly detection, agricultural damage

1. Introduction

Ukraine, a major global agricultural producer, is facing severe disruptions due to ongoing conflict, which has profoundly affected its agricultural sector and food supply chains. Monitoring and accurately assessing damage to agricultural fields amidst such conflict presents significant challenges due to restricted access and threats to human safety in affected regions.

Satellite-based remote sensing offers a practical solution, enabling field monitoring from space. Satellite data is widely utilized in the agricultural sector for various applications, offering unique insights into crop health, yield predictions, and damage assessments. For instance, Sentinel-2 and MODIS satellite images have been effectively used to predict crop yields, as seen in studies by Becker-Reshef et al. (2010), Shammi and Meng (2021) and Aslan et al. (2024). These satellite-based models provide reliable yield forecasts, essential for food supply chain planning. Remote sensing data is also valuable for calculating cultivated areas, with studies like those by Zhu et al. (2019) using high-resolution imagery to delineate agricultural land and improve monitoring accuracy. Additionally, satellite data aids in detecting the impacts of natural disasters on agriculture. For instance, Garzón and Valánszki (2020) assessed damage from hail using satellite imagery, while Gitelson et al. (2019) and Wu et al. (2023) explored satellite-based drought impact assessments on crop health.

Key studies specifically addressing damage detection using satellite imagery in conflict or disaster zones include: Mueller et al. (2021) applied machine learning to MODIS and Sentinel-2 data to monitor destruction in conflict zones, showing how satellite imagery can accurately capture agricultural and environmental damage. Avtar et al. (2021) highlighted remote sensing's role in international peace and security, demonstrating how satellite images help assess the impact of armed conflicts on agricultural areas, specifically in post-conflict reconstruction planning. Goswami and Nayak (2022) focused on the use of AI-enhanced satellite data for optimizing agricultural resilience, showing how satellite images reveal the extent of crop damage post-disaster, informing recovery strategies. Eklund et al. (2017) analyzed land use changes in conflict zones affected by ISIS occupation, using Landsat data to observe declines in agricultural activity, emphasizing remote sensing's value in damage assessment. Butsic et al. (2015) investigated the environmental effects of warfare in the Democratic Republic of Congo, using Landsat to track deforestation linked to conflict, highlighting the indirect impacts on agriculture and resource availability. Alvarez (2003) explored the impacts of Colombia's conflict on forest conservation and agricultural land use, utilizing satellite imagery to show shifts in land use and environmental degradation.

Existing methods for detecting agricultural damage, while effective in certain contexts, often face limitations in accuracy or fail to provide regularly updated data, sometimes focusing only on specific areas. For instance, Duncan and Skakun (2023) utilized a U-Net-based deep neural network with ultra-high spatial resolution satellite imagery, successfully detecting even small craters. However, their research was confined to a limited region in Donetsk Oblast. Meanwhile, Kussul et al. (2022) conducted bi-weekly analyses across all of Ukraine throughout 2022, employing an NDVI-based change detection approach. Despite its wide application, this method lacked sufficient reliability in accurately identifying damage.

The most promising approach for detecting damage to Ukraine's agricultural fields has been developed by Kussul et al. (2023). This methodology leverages free Sentinel-2 satellite imagery combined with a random forest classifier to identify damaged fields, complemented by anomaly analysis of spectral bands and vegetation indices to detect localized damage. While effective, this approach relies on static threshold coefficients, which may not adapt well to the unique characteristics of each field, such as variations in vegetation, soil type, and landscape features. As a result, the method can be overly sensitive in some areas, mistaking natural variations for damage, or insufficiently sensitive in others, missing actual war-induced damage. This lack of adaptability can lead to both false positives and false negatives, compromising the accuracy of damage assessment. The key limitation lies in the rigidity of autonomous AI systems, which can result in frequent errors without human oversight to adjust and refine the model's behavior.

To address these challenges, this study proposes an enhanced method based on Symbiotic Artificial Intelligence (SAI) – a collaborative AI framework that integrates human supervision to modify model parameters in real time. SAI's flexibility enables dynamic adjustment of sensitivity settings based on the specific features and anomalies of individual fields, substantially reducing false-positive rates. Although applications of human-AI collaboration in agricultural damage assessment are still emerging, similar approaches in other sectors have shown significant success. For example, in medical diagnostics, combining human expertise with AI has improved disease detection accuracy (Hussain, W., 2024). Additionally, in organizational decision-making, human-AI integration has enhanced problem-solving capabilities. Calabrese et al. (2023) demonstrated the effectiveness of human-AI collaboration in examining the relationship between sustainable development and industry, while Taggio et al. (2024) highlighted the potential of SAI for Earth observation applications. These studies underscore the growing momentum behind SAI research and its broadening scope. We hypothesize that SAI could serve as an effective tool for overcoming the limitations of Kussul et al. (2023) method in detecting agricultural damage. Specifically, we believe that integrating human expertise to dynamically set threshold coefficients, paired with AI-driven anomaly detection, will help reduce false positives and improve overall accuracy in damage assessment.

2. Materials and methods

2.1. Kussul et al. (2023) damage detection methodology

This study expands upon the methodology developed Kussul et al. (2023) utilizing Sentinel-2 satellite data to assess the damage to agricultural lands from military actions in Ukraine, integrating the latest approach based on symbiotic artificial intelligence (SAI). Kussul et al. (2023) highlighted the spectral bands B2 (blue) and B3 (green), as well as vegetation indices such as NDVI (Normalized Difference Vegetation Index) and GCI (Green Chlorophyll Index), as particularly effective for identifying damage in satellite imagery. Through comprehensive analysis, they determined that bands B2 and B3 offer high sensitivity for this purpose. Specifically, B2 is effective in detecting lighter areas that indicate white craters resulting from shelling, while B3 is useful for highlighting darker areas, such as burn marks or disrupted soil. This combination of spectral characteristics allows for distinguishing damaged regions from undamaged agricultural areas.

The study also established standard threshold coefficients k for each spectral band and index to facilitate consistent damage detection across various areas and time periods (Table 1).

Table 1. The coefficient k for different spectral bands and indexes Kussul et al. (2023)

index or spectral band	coefficient k
NDVI	0.5
GCI	1
GCI(1)	−0.7
B2	−0.7
B3	0.4

Detection of damage using spectral bands involves identifying anomalous pixel values within a field based on the following formula:

$$\mathrm{Band_{dam}} = \begin{cases} 1, \text{if } \mathrm{Band_{mean}} - \mathrm{Band} > \mathrm{k} \cdot \mathrm{Band_{stdDev}} \\ 0, \text{if } \mathrm{Band_{mean}} - \mathrm{Band} \geq \mathrm{k} \cdot \mathrm{Band_{stdDev}} \end{cases} . \tag{1}$$

In this formula, Band represents the pixel values in the B2 and B3 spectral bands of the Sentinel-2 satellite, $\mathrm{Band_{mean}}$ is the average band value within the field, $\mathrm{Band_{stdDev}}$ is the standard deviation of the band's pixel values within the field, and k is the threshold coefficient. Band B2 is used for recognizing light areas, while band B3 is sensitive to dark craters. To calculate NDVI and GCI for damage analysis, the following formulas are used:

$$\mathrm{NDVI} = \frac{(\mathrm{NIR} + \mathrm{RED})}{(\mathrm{NIR} - \mathrm{RED})}, \tag{2}$$

$$\mathrm{GCI} = \frac{(\mathrm{NIR})}{(\mathrm{GREEN} - 1)}. \tag{3}$$

For Sentinel-2 data, the band assignments are: GREEN = B2, BLUE = B3, RED = B4, and NIR = B8. To detect damage in agricultural fields using GCI (suitable for areas with low vegetation) and NDVI (used for fields with high vegetation), the analysis follows these formulas:

$$\mathrm{Index_{diff}} = \mathrm{Index_{filtred}} - \mathrm{Index_{real}}, \tag{4}$$

$$\mathrm{threshold} = \mathrm{Index_{diff_{mean}}} + \mathrm{k} \cdot \mathrm{Index_{diff_{stdDev}}}, \tag{5}$$

$$\mathrm{Index_{an}} = \begin{cases} 1, \text{ if } \mathrm{Index_{diff}} - \mathrm{k} \cdot \mathrm{threshold} < 0 \\ 0, \text{ if } \mathrm{Index_{diff}} - \mathrm{k} \cdot \mathrm{threshold} \geq 0 \end{cases} . \tag{6}$$

Separate damage masks are generated for dark crater ($\text{Index}_{\text{black}}$) and light crater ($\text{Index}_{\text{white}}$). These masks are then combined to produce a comprehensive damage map that highlights all affected pixels within the field:

$$\text{Damage}_{\text{Index}} = \text{or} \begin{array}{l} \text{Green}_{\text{dam}} \cdot \text{Index}_{\text{black}} \\ \text{Blue}_{\text{dam}} \cdot \text{Index}_{\text{white}} \end{array} . \tag{7}$$

The coefficient k in this context is critically important as it determines the algorithm's sensitivity to damage detection. Increasing this parameter raises the threshold for identifying damages, making the algorithm more conservative and potentially reducing the number of false positive detections (Fig. 1), but it may also lead to missing some truly damaged pixels. Conversely, decreasing this parameter makes the algorithm more sensitive, increasing the risk of false positives but ensuring better detection of smaller or less obvious damages Shelestov et al. (2023).

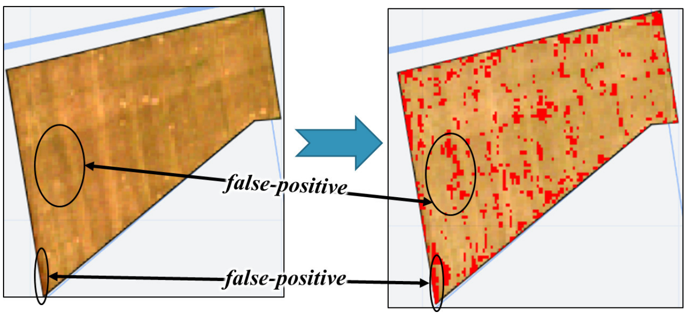

Fig. 1. An example of false-positive results of the method of Kussul et al. (2023) caused by static threshold coefficients

Adjusting the k coefficient is therefore essential for fine-tuning the model's accuracy and ensuring reliable damage identification across agricultural fields.

2.2. SAI for improving the method of Kussul et al. (2023)

This study introduces the application of symbiotic artificial intelligence (SAI), guided by human input, to refine the threshold coefficients in the methodology proposed by Kussul et al. (2023). The goal is to adapt these thresholds according to vegetation density and geographical context to improve the accuracy of crater detection in satellite imagery. Regional variability plays a crucial role; for example, the landscape characteristics of the Kherson region differ markedly from those of the Luhansk region. Applying a uniform set of standard coefficients across different regions can negatively impact identification precision.

By allowing human experts to adjust threshold coefficients, Kussul et al. (2023) method can be tailored to specific regions, seasons, and the unique attributes of individual satellite images. This flexibility enhances the reliability and accuracy of damage detection, ensuring that the methodology remains effective across diverse environments and conditions. Figure 2 presents the proposed algorithm that integrates SAI into Kussul et al. (2023) method, aiming to achieve more precise and adaptable results in satellite-based damage detection.

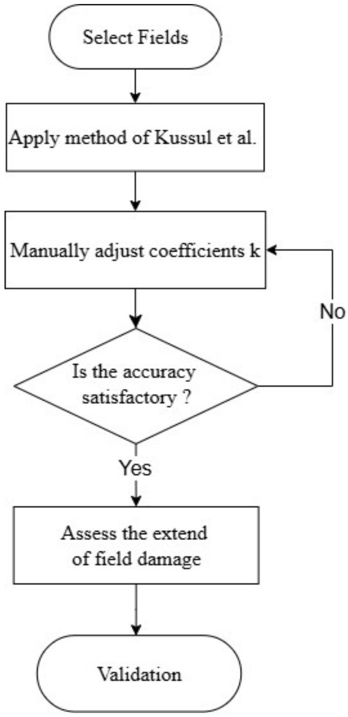

Fig. 2. The scheme of the proposed improvement using the SAI algorithm of damage detection in agricultural fields by the method of Kussul et al. (2023)

The process begins by selecting the target field for analysis. This field is then used to search for craters using the anomaly detection method developed by Kussul et al. (2023) with default threshold coefficients. These coefficients serve as initial settings for the detection algorithm. Next, we manually adjust these threshold coefficients to improve the accuracy of the detection. After making adjustments, we run Kussul et al. (2023) damage detection algorithm again. This iterative process involves visually assessing the changes in damage detection based on satellite imagery. We repeat this cycle of adjustment and evaluation until we achieve satisfactory results. Once we have established the optimal threshold coefficients for each index and channel, the overall extent of damage is then quantified. For validating the proposed method, we plan to use MAXAR data (Bennett et al., 2022; Sticher et al., 2023) that are closest in date to the Sentinel-2 satellite imagery. The selected areas for this study are the Kherson and Luhansk regions, as they have been most impacted by military activity. Given that MAXAR data are commercial and acquiring them involves considerable expenses, we propose using Google Earth Pro, which provides open-access MAXAR data composites. Utilizing MAXAR satellite imagery, craters resulting from shelling will be manually digitized, creating a 10 m resolution crater mask that serves as a reference for validation. The validation process will compare two methods – the SAI-enhanced approach and the original method Kussul et al. (2023) – by calculating the pixels corresponding to the resultant damage mask and analyzing them with the following formulas:

$$Damage_{\text{validation}} = \frac{damaged\ \ shelling_{\text{Symbiotic AI}} - damaged\ \ shelling_{\text{default coef}}}{Actual\ \ positives} \cdot 100\%, \tag{8}$$

where TP is the number of correctly detected damage pixels, TN is the number of correctly undetected damage pixels, FP is the number of damaged pixels that were not detected by mistake, FN is the number of undamaged pixels that were mistakenly detected as damaged, *Actual positives* is the number of pixels indicating damage to the field according to Maxar data, *Actual negatives* is the number of undamaged pixels to the field according to Maxar data $damaged\ \ shelling_{\text{Symbiotic AI}}$ is the number of pixels indicating damage to the field according to the proposed method based on SAI, $damaged\ \ shelling_{\text{default coef}}$ is the number of pixels indicating damage according to the method Kussul et al. (2023). Figure 3 illustrates the research fields in the Kherson and Luhansk regions where the validation will be conducted.

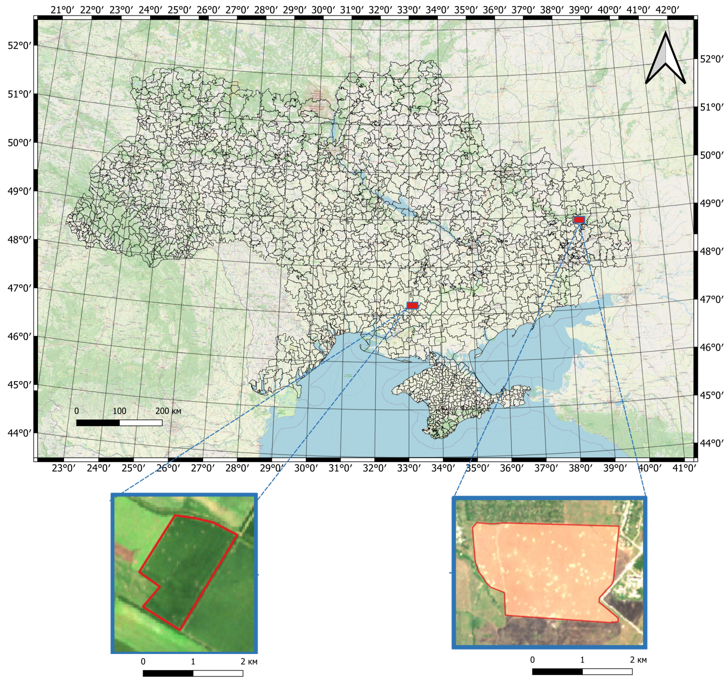

Fig. 3. Research area

These regions were chosen for their differing landscape properties, which significantly impact the accuracy of damage detection. The application of symbiotic artificial intelligence is therefore justified for enhancing the method’s adaptability and precision in these diverse terrains.

3. Results and discussion

According to the results of our study, the modified method based on Symbiotic Artificial Intelligence (SAI) with human-guided parameter adjustment significantly improved the accuracy of method Kussul et al. (2023). Figure 4 shows the accuracy results of applying the method Kussul et al. (2023) and the proposed method based on SAI.

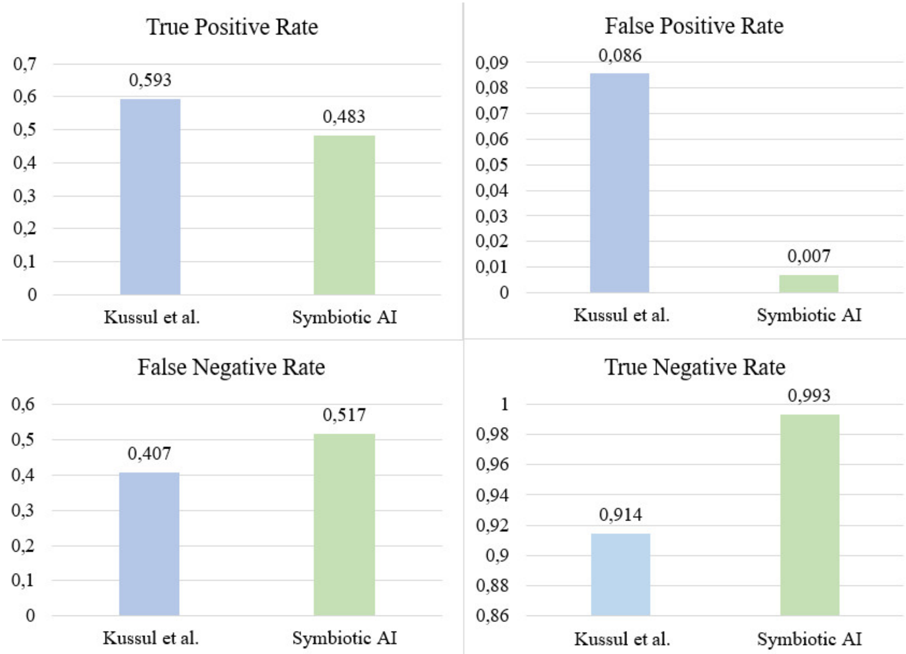

Fig. 4. Comparison of the accuracies of method with standard coefficients Kussul et al. (2023b) and the method with Symbiotic AI

Figure 4 compares the effectiveness of two methodologies in detecting agricultural damage due to military activity: (1) Kussul et al. (2023) method using static coefficients and (2) the proposed SAI-based approach with adaptive coefficients. The graph illustrates how the SAI method reduces the FPR by approximately 8%, from 8.6% to around 0,7%, highlighting its improved accuracy in identifying undamaged pixels while acknowledging an increase in false negatives due to coefficient adjustments (from 40.7% to 51.7%). Thus, the SAI model's dynamic coefficient adjustments significantly lower the FPR compared to Kussul et al. (2023) method, resulting in fewer undamaged areas mistakenly flagged as damaged. However, this improvement in precision comes with an increased FNR, meaning some true damages may go undetected. This trade-off has practical implications. Lower FPR enhances the model's utility in focusing resources on genuinely damaged areas, essential in resource-limited recovery efforts. However, the higher FNR could mean that some affected areas remain unidentified, potentially delaying interventions in those regions and impacting crop recovery planning. To mitigate this, future improvements could include adaptive thresholds or automated re-checks for high-risk zones, balancing FPR and FNR based on specific application needs. Thus, while the SAI model's reduced FPR streamlines damage assessment, adjustments may be needed to ensure comprehensive coverage in real-world applications. Visualization of the results is presented in Figure 5.

Fig. 5. Spatial Detection of Military-Induced Damage in Agricultural Fields in Luhansk and Kherson Regions

Figure 5 showcases two methods applied to detect field damage from military actions: (a) Kussul et al. (2023) method in Luhansk with static coefficients, (b) SAI method in Luhansk with adaptive thresholding, (c) Kussul et al. (2023) in Kherson, and (d) SAI method in Kherson. The SAI method, with dynamic coefficients, reduces false identifications, especially along field boundaries, demonstrating enhanced accuracy around craters and minimizing anomalies that do not indicate damage. In analyzing the detection results for the Kherson and Luhansk regions (Fig. 5), distinct environmental characteristics reveal how regional differences affect the model's accuracy. From Figure 5(a,b) we can see, that field in Kherson region is characterized by relatively flat terrain and dense agricultural vegetation during the growing season, Kherson's high vegetation density increases reflectance variability, making it challenging for the model to differentiate natural vegetation changes from actual damage. The SAI model's dynamic coefficient adjustments mitigate some of these challenges by adapting sensitivity based on field conditions, though occasional misclassifications persist due to the complex vegetation. However, the model accurately detects large-scale damage, indicating reliable performance in areas with strong visual contrasts. Figure 5(c,d) demonstrates that field in Luhansk region differs with more varied terrain, sparser agricultural vegetation, and a significant presence of forested areas. The reduced agricultural vegetation density and increased forest cover allow the model to detect damage patterns more clearly, as the lower natural variability in open fields minimizes false positives. The forested areas, however, introduce complexity, as tree cover can obscure certain ground-level changes, potentially leading to missed detections (higher FNR) in small or shaded damaged zones. Nevertheless, the SAI model achieves improved accuracy here, as adjustments to coefficients better distinguish between undisturbed forested areas and cratered soil typical of conflict-impacted landscapes. These regional differences highlight the need to tailor detection thresholds to environmental conditions. In regions like Kherson with dense agriculture, conservative adjustments reduce false positives, while in areas like Luhansk with more forest cover and lower agricultural density, increased sensitivity improves detection accuracy. Adapting the SAI model to account for these regional characteristics can significantly enhance its overall reliability across diverse landscapes. Looking toward future applications, the proposed model's potential for automating the coefficient adjustment process could significantly enhance its scalability and effectiveness across extensive agricultural areas in Ukraine. To achieve this, we plan to train a regression model based on the coefficients collected during the initial assessments. This regression model will analyze field-specific variables, such as vegetation stage, geographical characteristics, and spectral responses, enabling it to predict and adapt threshold coefficients dynamically for diverse conditions. By automating this adjustment process, the model will no longer require manual fine-tuning, making it feasible for large-scale implementation and ensuring consistent accuracy across varied agricultural landscapes. This automation will streamline the damage detection process, offering a robust tool for ongoing monitoring and rapid assessment in Ukraine and potentially in other regions affected by similar conditions. Our future research will focus on building a regression model to automate the selection of optimal threshold coefficients for agricultural damage detection, leveraging the insights gained from this study's Symbiotic AI-based coefficient adaptation. This regression model will be designed to dynamically determine thresholds based on environmental variables (e.g., vegetation density, soil type, and regional climate), improving the model's adaptability to various landscapes.

4. Conclusion

In this study, a novel method based on symbiotic artificial intelligence (SAI) guided by human intervention was implemented to enhance the accuracy of war damage detection, improving upon the existing approach developed by Kussul et al. (2023). The innovative aspect of this method lies in its ability to modify coefficients, allowing for the adjustment of the model's sensitivity according to the unique landscape and vegetation characteristics of specific fields. This flexibility makes it particularly useful for adapting to varying environmental conditions, ensuring that the damage detection process remains robust across different terrains.

A detailed comparison between the proposed SAI-based method and the original Kussul et al. (2023) method was conducted. The findings demonstrated that the SAI-enhanced method significantly reduces the false positive rate by 8%, thereby improving the precision of war damage identification. This improvement is crucial for minimizing incorrect damage assessments, which can lead to more accurate decision-making in post-conflict recovery efforts. However, the analysis also highlighted an increase in false negatives due to coefficient adjustments, rising from 40.7% to 51.7%.

The developed SAI method currently requires ongoing manual calibration of dynamic coefficients. This manual process, while effective on a smaller scale, presents challenges when scaling up to larger areas due to the significant time and labor involved. To address this limitation, future research will focus on automating this process by developing a regression model capable of determining the threshold coefficients automatically for each field. To support this automation, a comprehensive dataset will be collected using the method established in this study, laying the groundwork for more efficient and widespread application.

The automated regression model is expected to streamline the adaptation process, enabling the method to maintain high accuracy without manual intervention. This advancement would significantly enhance the practicality and scalability of the SAI-based approach, making it a more viable solution for extensive war damage assessments. Ultimately, the improvements outlined in this research have the potential to support better resource allocation and contribute to the efficient recovery and rehabilitation of affected agricultural sectors.

Author contributions

Conceptualization: O.P., S.D.; writing original draft: O.P.; methodology: S.D.; formal analysis: O.P., S.D., P.M.; validation: O.P.; writing – review and editing: O.P., S.D., P.M.; supervisor: A.S.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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