Remote Sensing AI for Crop Planting in Wildfire Fuel Mapping

Paula Sánchez[1]*, Irene González[1], Carlos Carrillo[1], Ana Cortés[1], and Remo Suppi[1]

Computer Architecture and Operating Systems Department
Universitat Autònoma de Barcelona, Spain {paula.sanchez.gayet, irene.gonzalez.fernandez, carles.carrillo, ana.cortes, remo.suppi}@uab.cat

Abstract. Accurate wildfire prediction requires updated, high-resolution fuel maps that account for seasonal vegetation variations. The flammability of crops varies by season, affecting the behavior of wildfires. This study combines remote sensing indices and machine learning to dynamically update fuel models in cropland zones. Using Sentinel-2 data, the status of the cropland is classified as "planted" or "unplanted," achieving 80% accuracy. Applied to a 2019 wildfire in Catalonia (Spain), the updated fuel map closely matched the observed fire spread. The methodology outperforms traditional approaches and is efficient, allowing for real-time updates based on seasonal changes.

Keywords: Remote Sensing indices · Machine Learning · Seasonal fuel map · Wildfire · Cropland.

1 Introduction

To accurately forecast the behavior of a wildfire, having access to updated high-resolution fuel maps is crucial. However, obtaining maps that correspond to the specific year of a fire and accurately reflect the seasonal fuel characteristics of the affected area is often challenging. Fuel maps classify vegetation characteristics into fuel models, which are required for forest fire spread models. One of the most commonly used sets is the Scott and Burgan one [13] which includes the NB3 class for agricultural fields, treating cultivated land as a firebreak. However, depending on the season, some croplands can become highly flammable, contributing to fire spread. Current fuel maps lack this seasonal variability, so a tool to assess and update cropland flammability would enhance wildfire simulation accuracy. The availability of long-term open data, particularly from remote sensing instruments like Sentinel-2, has facilitated the creation of machine learning models to address information gaps in complex systems. Sentinel-2 provides periodic, high-resolution (10 m pixel) data, which is valuable for agricultural monitoring. This data provides new opportunities to collect more precise information about croplands to improve fuel map descriptions. In fact, this capability

* Corresponding author: paula.sanchez.gayet@uab.cat

ICCS Camera Ready Version 2025
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-97635-3_8

has already been used to monitor various crops, such as maize crop growth and rice field detection [2], and it has also been used to determine the extent of croplands [12]. This study proposes using remote sensing indices to train a machine learning model to determine if cropland is planted or unplanted. With remote sensing data updated every five days, this methodology allows fuel maps to be updated according to the current season.

2 Materials

The study conducted in this work focuses on the agricultural areas of Catalonia (Spain), using data from 2021, 2022, and 2023. Remote sensing indices from this period have been used as features to train an AI model, along with cropland data, such as the type of crop and the months they are planted or unplanted, to create the ground truth. The training data can be divided into two categories: *Crop Yield Data* and *Remote Sensing Indices Data*.

2.1 Crop Yield Data

Catalonia's DACC [5] collects crop data in the Unique Agrarian Declaration (DUN)[5]. Each year, all crop fields declared in DUN are available in a shapefile, where each crop field is represented as a polygon. In this study, only a subset of fields (polygons) was selected based on specific criteria. The selected fields met the following conditions: the same crop cultivated from 2021 to 2023, a minimum area of $100\,\mathrm{m}^2$, a single crop per year, and no interruptions like houses or structures. Polygons with invalid geometries, such as self-intersections, degenerated shapes, or other topological issues, were discarded. The selected crops included soft wheat, barley, oats, and corn.

2.2 Remote Sensing Indices Data

After obtaining crop yield data, remote sensing indices were processed using multispectral Sentinel-2 data (Level-2A product). The data was downloaded from 2021 to 2023 through the openEO API [1]. The vegetation indices—NDVI [3], MSAVI [3], GNDVI [6], and EVI [3]—were computed using bands 2, 3, 4, and 8 at a spatial resolution of 10 meters. These indices were selected for their widespread use in vegetation monitoring, and among them, preference was given to those without free parameters. To ensure Sentinel-2 data quality, the Scene Classification Layer (SCL) [11] was used to identify and exclude clouds and cloud shadows that make some pixels unreliable for analysis. These pixels were assigned NaN values, excluding them from the analysis.

3 Methodology

This section describes the proposed methodology to determine whether a cropland should be considered planted or not, consisting of the following 4 steps: *Image Segmentation and Preprocessing (ISP)*, *Data Cleaning (DC)*, *Model Development and Performance Evaluation (MDPE)* and *Fuel Map Updating (FMU)*. Subsequently, a more detailed explanation of these steps is included.

ICCS Camera Ready Version 2025
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-97635-3_8

3.1 Image Segmentation and Preprocessing (ISP)

After downloading all bands for the whole Catalonia area and for all available days in 2021, 2022, and 2023, the remote sensing indices were computed. For each cropland field, only the pixels from the remote sensing index that were entirely contained within the field boundaries were identified. A margin was intentionally left when selecting the pixels, as cropland fields are often not fully planted up to their borders. Figure 1 exemplifies this process using three pictures. The left picture shows the borderline of a given cropland with a white line. In the central image, the pixels used as a representation of the cropland are white colored and, finally, the right image illustrates the value of a certain remote sensing index for the representative pixels of the study field. For each remote sensing index, the median of the selected pixels was computed to reduce the influence of outliers and better represent the crop field, excluding anomalies caused by equipment, objects, or soil variability. Crop fields that contained only a single pixel (while accounting for edge constraints) were accepted as valid. However, fields with no interior pixels were excluded from the analysis.

Fig. 1: Steps for selecting representative pixels for a given cropland.

After evaluating the median of remote sensing indices for each cropland and day over the three years, a database was created with the following fields:

- **Crop ID**: This value corresponds to a unique identifier for each cropland.
- **NDVI, EVI, GNDVI, MSAVI**: Indices with a theoretical range between -1 and 1. In practice, bright (e.g., clouds) and dark areas (e.g., shadows) may produce anomalous values, which are treated as noise and discarded.
- **Crop**: This field describes the type of crop planted in the corresponding cropland. The possible values are *Soft wheat*, *Barley*, *Oats* and *Corn*.
- **Date**: A day corresponding to the date on which the data was recorded.
- **Planting status**: Will be 1 if the cropland is planted or 0 if it is unplanted.

To determine the planting status, fields have been selected where the typical crop cycles are known (see Table 1). For these fields, the months in which they are certainly planted and the months in which they are without crops (as no second crop is grown) are known. Transitional months (those involving planting, growth onset, or harvesting) were intentionally excluded from the table, as crop presence during these periods can be variable [8].

ICCS Camera Ready Version 2025
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-97635-3_8

Table 1: Planted and Unplanted months for selected crops in Catalonia [8].

Crop	**Planted Months**	**Unplanted Months**
Soft wheat	1, 2, 3, 4, 5	8, 9, 10
Barley	1, 2, 3, 4, 5	7, 8, 9, 10
Oats	1, 2, 3, 4, 5	8, 9, 10
Corn	6, 7, 8	11, 12, 1, 2, 3

3.2 Data Cleaning (DC)

Despite removing clouds and shadows from the SCL layer, some outliers may still exist. To address this, we consider that the selected crops follow planting cycles characterized by regular seasonal patterns. This seasonal signal creates wave-like time series data, which can be approximated by a sinusoidal curve. Therefore, the Fast Fourier Transform is used to clean the data effectively [9]. In remote sensing, such as with vegetation indices, it helps separate low-frequency patterns (e.g., seasonal vegetation growth) from high-frequency noise (e.g., interference from undetected clouds). A high-frequency filtering process is applied to detect and remove outliers for each crop in the dataset, filtering out high frequencies while keeping lower ones. An inverse Fourier Transform then reconstructs the "cleaned" data, removing unwanted fluctuations. By comparing the original and smoothed data, outliers are identified and removed.

3.3 Model Development and Performance Evaluation (MDPE)

The present study uses AI to classify cropland data from 2021 to 2023 based on planting status and four vegetation indices as predictive features. All variables were standardized to have a mean of zero and a standard deviation of one, ensuring a uniform contribution to the model. The dataset was split into 80% for training and 20% for testing. Multiple classification algorithms were evaluated, including *Logistic Regression*, *Decision Trees*, *Random Forest*, *XGBoost*, and *CatBoost*, with *CatBoostClassifier* chosen for its superior accuracy. The model's performance was evaluated using metrics such as *Accuracy*, *Precision*, *Recall*, and *F1-Score* [10]. The obtained results are shown in Table 2.

Table 2: CatBoost performance metrics.

Target	**Precision**	**Recall**	**F1-Score**
Unplanted	0.79	0.82	0.81
Planted	0.82	0.79	0.80
Weighted Avg	0.81	0.80	0.80
Accuracy	0.80		

3.4 Fuel Map Updating (FMU)

When a forest fire occurs, the pre-trained *CatBoost* model updates the fuel map to reflect the current cropland status. This process begins by identifying the area of interest, downloading the necessary satellite bands, and computing remote

ICCS Camera Ready Version 2025
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-97635-3_8

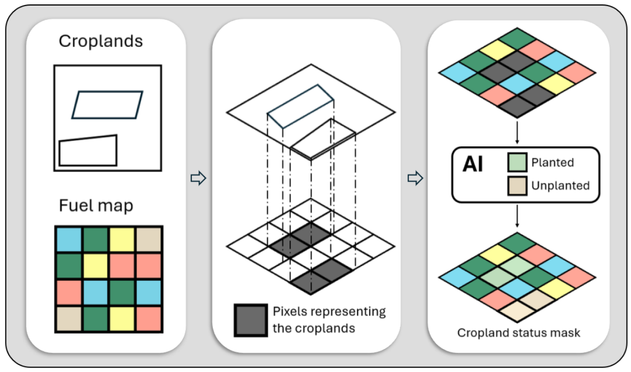


Fig. 2: Fuel map update process using the AI model to modify croplands status.

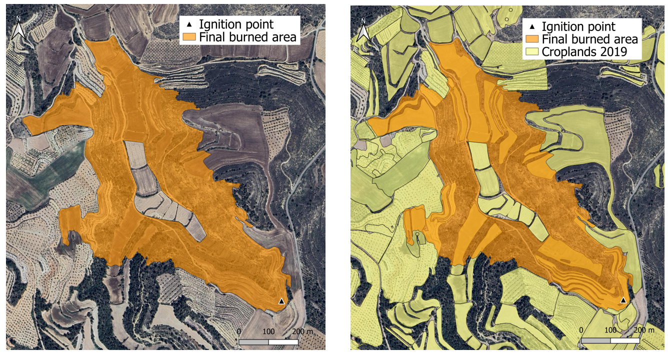
sensing indices. The analysis focuses on up to 5 days of pre-fire data, assuming optimal weather conditions. The median values of remote sensing indices are calculated for each agricultural field, following the procedure described in the *ISP* step. These median values will be used as input for the AI, which will classify the fields as either planted or unplanted. Unplanted fields are assigned the Burgan NB3 fuel model [13], acting as fire barriers, while planted fields are assigned the GR4 model[13], which represents 2-foot-deep vegetation in arid to semi-arid climates such as Catalonia. The pixels of the polygons that represent planted crop fields will be assigned this fuel model, which best represents the behavior of a forest fire in agricultural areas, overwriting the original fuel map data. It is important to note that in the pixels being overwritten, the original fuel map might have classified the area as NB3 (croplands, not-burnable) if it was correctly identified as cropland. It is also possible that the fuel map does not recognize the area as cropland, especially if it is an older fuel map where the area might have been classified as something else, like grass or shrub. Regardless of the previous classification, the new information will overwrite the data of the old pixel. This fuel map update scheme is illustrated in Figure 2.

4 Experimental Study and Results

4.1 Case Study

To evaluate the effect of updating cropland fuel data using an AI model, a real wildfire in Nalec, Catalonia (Spain), from June 2019, was selected as a case study. This wildfire was chosen because 60 % of the burned area was agricultural fields. Figure 3a shows the ignition point of the fire with a triangle (June 24 at 17:56) and the orange shape indicates the final burned area (June 24 at 21:05). To locate agricultural fields in the area, crops declared in the DUN of 2019 were used (see Figure 3b). Multispectral data from Sentinel-2 for June 17, 2019 (7 days before the wildfire occurred), was used. Wildfire simulations were conducted using FARSITE [4], with a LCP file from PREVINCAT [7]. While results depend on them, the methodology remains independent, ensuring broad applicability.

ICCS Camera Ready Version 2025
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-97635-3_8

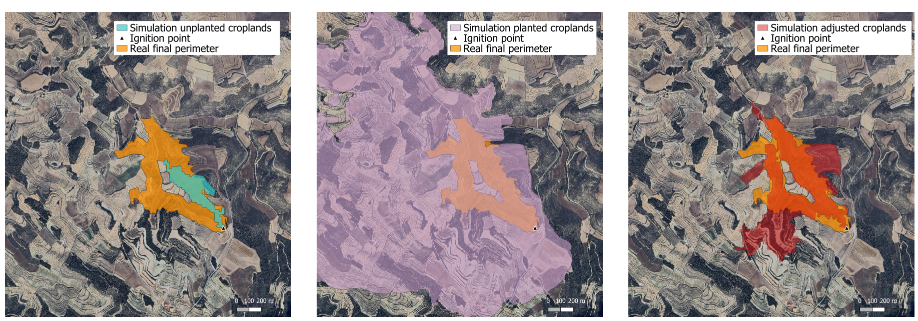


(a) *Nalec* fire. (b) Croplands in the fire area.

Fig. 3: Ignition point and final burned area 3a and croplands in the region 3b.

4.2 Experimental Results

This section presents the simulation forecasts for the study case when updating cropland status using the proposed AI model. To assess the impact of classifying cropland as planted or unplanted, two extreme scenarios were analyzed: all croplands planted (scenario P) and all unplanted (scenario UP). The scenario using the AI-updated fuel map is referred to as scenario AI. In all three simulations, only the fuel map was modified; all other input data remained unchanged. The simulation covered a total fire duration of 3 hours and 9 minutes. The orange area in all images indicates the real final fire perimeter.



(a) Scenario UP. (b) Scenario P. (c) Scenario AI.

Fig. 4: Wildfire simulation using scenarios: UP (a), P (b) and AI (c).

In Figure 4a (Scenario UP), the fire spread is significantly underestimated because unplanted croplands act as barriers, preventing the fire from advancing. This results in the simulated fire being confined to a much smaller area compared to the real perimeter (blue shape in Figure 4a). In contrast, Figure 4b (Scenario P) removes this barrier effect, leading to a substantial overestimation of the fire spread. The simulated area is much larger than the actual fire perimeter,

ICCS Camera Ready Version 2025
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-97635-3_8

extending beyond the available landscape data (LCP). Finally, Figure 4c (Scenario *AI*) shows the final burned area using the seasonal fuel map from the AI model. This simulation is the most accurate, as it incorporates detailed cropland information, distinguishing between planted and unplanted areas at the time of the fire.

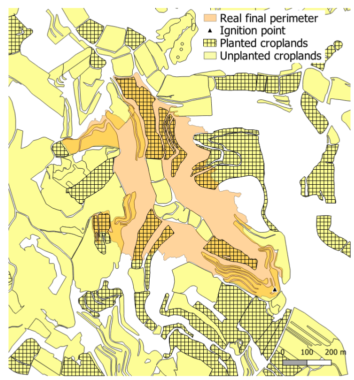


Fig. 5: Croplands in the fire area classified as planted or unplanted by the AI.

Figure 5 presents a zoomed-in view of the fire area and includes information about the croplands classified by the AI model as planted or unplanted. This is the classification used to update the fuel map for Scenario *AI*. The white areas in the figure are non-cropland areas, therefore, the AI model does not update the fuel information associated with them. It is worth noting that the "hole" in the real burned area corresponds to areas identified by the AI model as unplanted cropland, which aligns with the fire behavior that avoids burning this zone. Additionally, the AI model correctly classifies the croplands to the "head of the fire" (north) as unplanted, consistent with the firefighter report describing these areas as non-burnable. Furthermore, most of the croplands that fall within the real final perimeter are accurately marked by the AI model as planted, demonstrating its ability to capture the conditions that facilitated the spread of the fire.

5 Conclusions

This study emphasizes the importance of integrating remote sensing data into fire behavior modeling to improve wildfire spread predictions. The results demonstrated the impact of cropland status (planted vs. unplanted) on fire dynamics. For that reason, an AI system has been proposed to train a *CatBoost* model, which uses several remote sensing indices as training features along with seasonal information about crop planting status extracted from the DUN database. The AI model was tested on the *Nalec* fire, being capable of identifying unplanted crops, aligning with firefighter reports, and confirming the model's potential as a reliable tool for managing wildfires. This methodology is fast and easy to implement, making it suitable for near-real-time applications.

ICCS Camera Ready Version 2025
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-97635-3_8

Acknowledgments

This work is part of the project CPP2021-008762 financed by the Spanish Ministry of Science and Innovation, and European Union-*NextGenerationEU*/PRTR. It has also been granted by MCIN AEI/10.13039/501100011033 under contract PID2020-113614RB-C21 and PID2023-146193OB-I00, and by the Catalan government under grant 2021 SGR-00574. We thank *CTFC* for its guidance.

References

1. openEO API. `https://openeo.org/`, accessed on 24 January 2025
2. Ali, A.M., Savin, I., Poddubskiy, A., Abouelghar, M., Saleh, N., Abutaleb, K., El-Shirbeny, M., Dokukin, P.: Integrated method for rice cultivation monitoring using sentinel-2 data and leaf area index. The Egyptian Journal of Remote Sensing and Space Science **24**(3, Part 1), 431–441 (2021). https://doi.org/10.1016/j.ejrs.2020.06.007
3. Antunes Daldegan, G., Gonzalez-Roglich, M., Noon, M., Zvoleff, A.I.: Assessing the performance of NDVI, 2-band EVI and MSAVI vegetation indices for land degradation monitoring across variable biomass cover at global scale. In: AGU Fall Meeting Abstracts. vol. 2020, pp. SY003–0008 (Dec 2020)
4. Finney, M.A.: FARSITE: Fire Area Simulator-model development and evaluation (1998). https://doi.org/10.2737/rmrs-rp-4
5. Generalitat de Catalunya: Mapa de cultivos - sigpac (2023), `https://agricultura.gencat.cat/ca/ambits/desenvolupament-rural/sigpac/mapa-cultius/`, accessed: 2025-01-26
6. Gitelson, A., Kaufman, Y., Merzlyak, M.: Use of a green channel in remote sensing of global vegetation from eos-modis. Remote Sensing of Environment **58**, 289–298 (12 1996). https://doi.org/10.1016/S0034-4257(96)00072-7
7. González-Olabarria, J., Piqué, M., Busquets, E.: Cartografia de vegetació per la simulació d'incendis forestals. Servidor PREVINCAT (2019)
8. Ministerio de Agricultura, Pesca y Alimentación: Calendario de siembra, recolección y comercialización 2014-2016 (2016), disponible en: `https://servicio.mapama.gob.es/tienda/`
9. Oberst, U.: The fast fourier transform. SIAM J. Control and Optimization **46**, 496–540 (01 2007). https://doi.org/10.1137/060658242
10. Powers, D., Ailab: Evaluation: From precision, recall and f-measure to roc, informedness, markedness & correlation. J. Mach. Learn. Technol **2**, 2229–3981 (01 2011). https://doi.org/10.9735/2229-3981
11. Sanchez, C., Mena, F., Charfuelan, M., Nuske, M., Dengel, A.: Assessment of sentinel-2 spatial and temporal coverage based on the scene classification layer. In: 2024 IEEE International Geoscience and Remote Sensing Symposium. p. 4099–4103. IEEE (Jul 2024). https://doi.org/10.1109/igarss53475.2024.10642213
12. Savitha, C., Talari, R.: Mapping cropland extent using sentinel-2 datasets and machine learning algorithms for an agriculture watershed. Smart Agricultural Technology **4**, 100193 (2023). https://doi.org/10.1016/j.atech.2023.100193
13. Scott, J.H., Burgan, R.E.: Standard fire behavior fuel models: a comprehensive set for use with rothermel's surface fire spread model. Tech. rep., U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station (2005). https://doi.org/10.2737/rmrs-gtr-153

ICCS Camera Ready Version 2025
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-97635-3_8