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Interactive web-based Geospatial eXplainable Artificial Intelligence for AI model output exploration

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Abstract. This case study presents a web-based Geospatial eXplainable Artificial Intelligence (GeoXAI) system demonstrated through a case study for wildfire susceptibility assessment. Addressing limitations in traditional GeoXAI tools, the system integrates XAI methods with open-source geospatial technologies. Using a Random Forest model, the system combines environmental, topographic, and meteorological features to provide global and local insights. SHAP values offer feature-level explanations, while the interactive platform enables users to visualize wildfire susceptibility, examine feature contributions, and correlate predictions with spatial patterns and distribution of feature values. This approach tries to enhance transparency in AI-driven environmental decision support systems, with a specific focus on the interpretability of model output.

Submission Type. Case Study, Software, Model

BoK Concepts. [GC3] Artificial intelligence (AI) in EO and GI, [WB6] Application development via Web services composition, [CV5] Map production

Keywords. Wildfire Susceptibility, Explainable Artificial Intelligence (XAI), GeoXAI, GIS, Random Forest

1 Introduction

Artificial Intelligence advancements have created new opportunities across domains due to AI's ability to handle complex data and discover intricate patterns. In geography, massive geospatial datasets from remote sensing, LiDAR, field surveys, and Volunteered Geographic Information (VGI), have enabled GeoAI applications ranging from predicting natural disasters such as floods (Lyu and Yin, 2023) and forest fires (Ghorbanzadeh et al., 2019; Piao et al., 2022) to urban planning (Kim et al., 2023) as well as leveraging location intelligence for logistics and supply chain management (Taghiyeh et al., 2023).

Despite these advances, explainability and transparency remain critical concerns. The European Parliament's Artificial Intelligence Act (Madiega, 2021) emphasizes that AI systems must provide interpretable outputs, allowing informed decisions. This principle falls under eXplainable Artificial Intelligence (XAI), with its geographical application known as GeoXAI (Roussel and Böhm, 2023; Xing and Sieber, 2023). Therefore, GeoXAI refers to systems that apply XAI techniques to interpret and understand the predictions made by AI models trained on geographic data through Geographic Information System (GIS) tools and methods.

Many scholars in environmental and GIS fields use XAI methods such as LIME[1] (Ribeiro et al., 2016) and SHAP[2] (Lundberg and Lee, 2017) to identify key factors in predictive models across domains such as flood (Seleem et al., 2022), wildfire (Abdollahi and Pradhan, 2023; Cilli et al., 2022), earthquake (Matin and Pradhan, 2021), site selection (Alqahtani et al., 2024), road traffic (Liua et al., 2024) and urban studies (Kim et al., 2023; Sun et al., 2023; Mueller-Kett, 2024; Li, 2022). These scholars primarily rely on plots and attribution maps to visualize explanations, but conventional XAI techniques often lack interactive cartographic maps and geovisualization techniques necessary for case-specific and local explanations (Das and Rad, 2020). This limitation is particularly problematic for natural disaster analysis, where geographic context is essential (Xing and Sieber, 2023). To address this, researchers like Maxwell et al. (2021) and Pradhan et al. (2022) advocate for interactive maps in GeoXAI, enabling users to explore local insights and interact with prediction outputs for better decision-making.

This paper addresses this research gap with an interactive Web GIS system using open-source geospatial technologies. Our wildfire susceptibility case study demonstrates the integration of geospatial data, machine learning, and explainability methods, allowing users to visualize AI pre-

[1]Local Interpretable Model-Agnostic Explanations
[2]SHapley Additive exPlanation

dictions, examine feature contributions, and obtain local interpretations within a geographic context.

1.1 Research Contribution

The primary contribution of this work is the development and implementation of a novel web-based GeoXAI framework that bridges the gap between AI models and human-interpretable spatial insights. Unlike existing approaches that often present interactive local GeoXAI outputs as abstract visualizations detached from their spatial context, our system:

1. Integrates SHAP-based explanations directly within a geospatial interface
2. Enables real-time, location-specific interpretations of model predictions
3. Correlates feature contributions with their spatial distributions
4. Facilitates interactive exploration of wildfire susceptibility factors

While previous studies have applied machine learning to wildfire prediction or used XAI methods for feature importance analysis, our work uniquely combines these approaches within an interactive web platform that maintains the geographic context critical for environmental decision-making.

2 Materials and Methods

This section outlines the methodology for developing a web-based GeoXAI system for wildfire susceptibility assessment and local explanation. It covers the study area, data collection, feature selection, implementation of a Random Forest model, SHAP computation for feature importance analysis, and the integration of GeoXAI for interactive geospatial interpretation.

2.1 Study Area and Inventory Dataset

The study encompasses Berlin and Brandenburg, Germany (43,010.4 km^2), an area prone to wildfires with 80 incidents recorded between 2015-2023 by the European Forest Fire Information System (EFFIS)[3] using MODIS sensor data. The prediction model considers wildfire susceptibility across this entire time period, modeling the probability of wildfire occurrence at specific locations based on environmental conditions.

2.2 Wildfire Contributing Features

Wildfire occurrence is influenced by climatic variables, topography, and vegetation properties (Naderpour et al., 2021; Wotton et al., 2010; Nami et al., 2018). This study considers three key categories: topographic attributes, meteorological variables, and vegetation indices.

- Topographic attributes were derived from OpenDEM platform and include elevation, aspect, and slope.
- Meteorological variables were obtained from the German Weather Service (DWD) and Landsat Collection 2, covering precipitation, drought index, global radiation, and Land Surface Temperature (LST).
- Vegetation indices, including NDVI, GNDVI, and NDMI, were calculated using Sentinel-2 imagery processed via *Google Earth Engine (GEE)*. The land cover dataset from the German Aerospace Centre (DLR) provided additional classification layers.

2.3 Random Forest Model

A Random Forest (RF) model was selected for its interpretability and robustness in high-dimensional settings. Key steps included:

- Merging environmental features and georeferencing using GeoPandas.
- Ensuring class balance by randomly selecting equal samples from fire and non-fire categories.
- Binary encoding of the target feature (burnt_area) with 1 for fire and 0 for non-fire.
- Splitting data into training and testing sets (80:20).
- Optimizing hyperparameters: max_depth = 10, min_samples_leaf = 1, min_samples_split = 2, n_estimators = 100.

Data preprocessing involved *GDAL* tools for CRS normalization, resampling, and format conversion.

The RF model generates a wildfire susceptibility raster (range 0–1) with 91% accuracy. It classified 197/208 non-burnt and 76/92 burnt areas correctly. Despite class imbalance (69% non-burnt), the model achieved strong precision (0.87) and recall (0.83) for burnt areas. While future work may incorporate oversampling or threshold tuning, this study emphasizes SHAP-based interpretability over pure predictive performance within the GeoXAI framework.

2.4 SHAP for Wildfire Prediction Interpretability

SHAP provides global and local interpretability, helping users understand overall model behavior and individual wildfire predictions. It quantifies each feature's contribution to the model's output, using Shapley values (Shapley, 1953) from cooperative game theory.

[3] https://forest-fire.emergency.copernicus.eu/

For global interpretation, SHAP averages feature contributions across all subsets (Lundberg and Lee, 2017), offering insight into which features most influence predictions. For local interpretation, it identifies the key drivers behind specific fire events, enhancing model transparency. In RF models, SHAP uses the *TreeExplainer* algorithm (Sharma et al., 2020) to determine feature contributions. It calculates the impact of each feature by comparing predictions with and without it at different nodes. Summing these contributions along the tree paths provides SHAP values, which are then averaged across all trees to determine each feature's final impact. In this case study, a Web-based GeoXAI framework was developed to enable user interaction with the RF model and local explanations using the SHAP Python package. This interactive system allows users to explore model predictions and feature contributions spatially, enhancing interpretability and decision-making capabilities.

2.5 User-Centered Design and System Architecture

The web-based GeoXAI system was designed with a focus on usability and performance for environmental decision-makers, ensuring that critical insights are both accessible and actionable. While developing the system, input from potential users—including wildfire analysts and GIS specialists—was considered to refine core functionalities. The architecture consists of:

1. Front-end interface: Crafted with modern web technologies (Vue.js, CSS3, JavaScript) and visualization libraries (Maplibre GL JS, D3.js), it offers an intuitive and visually rich user experience.

2. Middleware: Powered by FastAPI, a Python-based framework, it efficiently computes predictions and SHAP values on demand.

3. Database: PostgreSQL with the PostGIS extension stores and manages vector datasets efficiently.

4. Geospatial data server: GeoServer serves Cloud-optimized GeoTIFFs (COG) for smooth and scalable rendering.

To ensure the system effectively meets user needs, key requirements were identified based on common challenges faced in wildfire management. Color-coded susceptibility maps enable rapid risk assessment, while clicking the map reveals on-demand local explanations for swift interpretability. Dynamic visualizations of feature contributions boost model interpretability, and optimized response times—under 2 seconds—ensure real-time SHAP computations without interrupting workflows. By aligning these capabilities with user needs, the GeoXAI platform enhances transparency, interpretability, and efficiency in wildfire risk assessment.

2.6 Data and Software Availability

The source codes for both the RF model [4] and the web GIS application [5] are available on public GitHub repositories, and the application is accessible online [6]. All software and tools used are open-source, ensuring full reproducibility of the methods and analyses.

3 Implementation and Results

This section presents the outcomes of applying the proposed methodology within the GeoXAI web application, as outlined in Section 2. The application applies the detailed framework and technical architecture to provide a comprehensive analysis, interactive geo-visualization, and exploration of wildfire prediction model outcomes.

3.1 Training RF Model

We implemented the RF model using *Python 3.11* and *scikit-learn*. After data preparation with equal samples from fire and non-fire categories, we optimized the model using *GridSearchCV*. The model achieved strong predictive performance as evidenced by the 91% accuracy and 82% Cohen's kappa score on the test set. These metrics demonstrate the model's ability to distinguish between burnt and non-burnt areas beyond what would be expected by chance (Sasikala et al., 2017), particularly important given the class imbalance inherent in wildfire occurrence data. The trained RF model was used to predict the entire dataset, generating a forest fire susceptibility (FFS) map that visualized the likelihood of fire occurrence across the study area (Fig. 1). The model was saved in Joblib format,

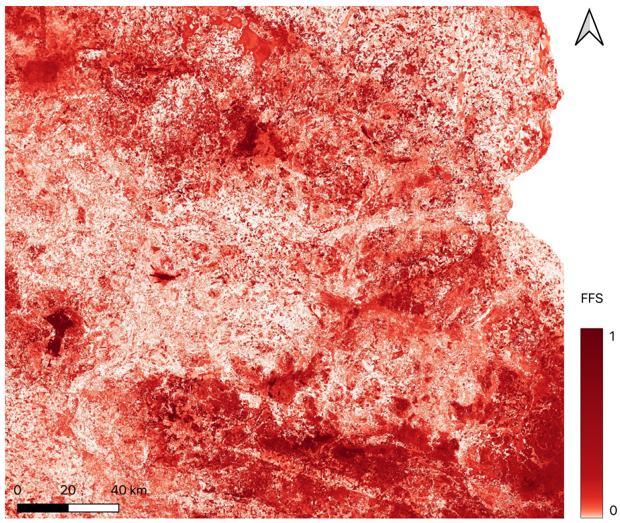

Figure 1. Wildfire susceptibility mapping using RF model

[4]https://github.com/QSafariallahkheili/FFS
[5]https://github.com/QSafariallahkheili/GeoXAI
[6]http://tv4-geo-xai.innowest-brandenburg.de/app/

enabling seamless user interaction through the GeoXAI web application for further analysis.

3.2 Local Explanation and Exploration

The GeoXAI interface offers an interactive environment for exploring the FFS map and understanding model predictions through local, interpretable explanations using SHAP values. The predictors are stored as COGs and hosted via a *GeoServer* instance. This architecture ensures efficient data delivery and spatial querying, which is essential for scalable, on-demand model interpretation.

The local explanation workflow is initiated when a user clicks on any location on the FFS map. This action triggers a client-side request that is sent to a dedicated API. The API performs several tasks sequentially:

1. Raster sampling: It extracts the pixel values for all predictor layers at the specified coordinates by querying the COGs.

2. Model inference: These values are passed to the trained RF model to generate class probabilities for "fire" and "non-fire."

3. SHAP value computation: SHAP values are computed in real-time to explain the contribution of each predictor to the local prediction.

4. Data packaging and response: The API returns probabilities for each class (fire, non-fire), SHAP values indicating each predictor's local influence, and raw raster values at the clicked location, enabling transparency and traceability

This backend workflow is tightly coupled with the frontend, which dynamically displays the results in response to user input. From a user experience perspective, this allows immediate interpretation of why a particular location is classified as high or low fire susceptibility.

The interface supports seamless zooming, panning, and interaction, enabling domain experts to iteratively explore regions of interest. Users can navigate between high-risk zones and areas with low susceptibility to identify patterns and anomalies in model behavior.

Performance evaluations confirmed consistent API response times ranging from 1.2 to 1.8 seconds per request, even under a moderate load. This level of responsiveness ensures smooth exploratory workflows, minimizing cognitive disruption and enhancing user engagement—particularly important in expert-driven spatial analysis tasks.

3.3 Interactive Visualization of SHAP Values

To make model explanations accessible and intuitive, the GeoXAI system visualizes local SHAP values using a fully interactive, D3.js-powered bar chart. This visualization is populated directly from the API response, offering a real-time, interpretable breakdown of predictor contributions at any selected location. Each bar in the chart represents one environmental predictor, with its length encoding the magnitude of its impact and its color indicating the direction—whether the feature increased (positive SHAP value) or decreased (negative SHAP value) the likelihood of fire. For instance, in Fig. 2, features like LST and DEM may elevate the fire risk locally, while global radiation and NDMI may reduce it. This granular view helps users distinguish between dominant and negligible factors in the model's decision-making process.

Beyond static interpretation, the visualization supports interaction. Users can:

- Hover over bars to reveal exact SHAP values and feature names

- Click on a bar to activate its spatial layer on the map, overlaying the selected predictor across the entire study area, complete with a dynamic color legend.

This dual linkage between the chart and the map (as shown in Fig. 3) supports spatial reasoning: users can examine how local predictor influence compares to broader spatial trends. A histogram widget complements this setup by displaying the distribution of the selected predictor across the full extent of the data, with a vertical marker indicating the clicked location's value. This contextual view helps users evaluate whether a predictor's value is extreme, typical, or anomalous. Together, the bar chart, histogram, and spatial overlay form a coherent and interactive explanation system. By integrating quantitative model outputs with geovisual analytics, the platform bridges the gap between statistical interpretation and geographic context. This enhances understanding not only of individual predictions but also of how environmental dynamics influence wildfire susceptibility across region.

4 Discussion

The fusion of machine learning, explainable AI (XAI), and interactive web GIS into our GeoXAI system offers a powerful yet complex approach to environmental decision support, revealing both opportunities and hurdles.

Since the model uses temporally aggregated inputs across 2015–2023, the system provides only static explanations. SHAP values reflect average feature contributions over the entire period, limiting the ability to explore temporal variation or trends in fire susceptibility. As a result, users cannot obtain year-specific or seasonally dynamic explanations—a key area for future development.

Our approach prioritizes interpretability over model complexity, briefly noting that RF was chosen for its reliable

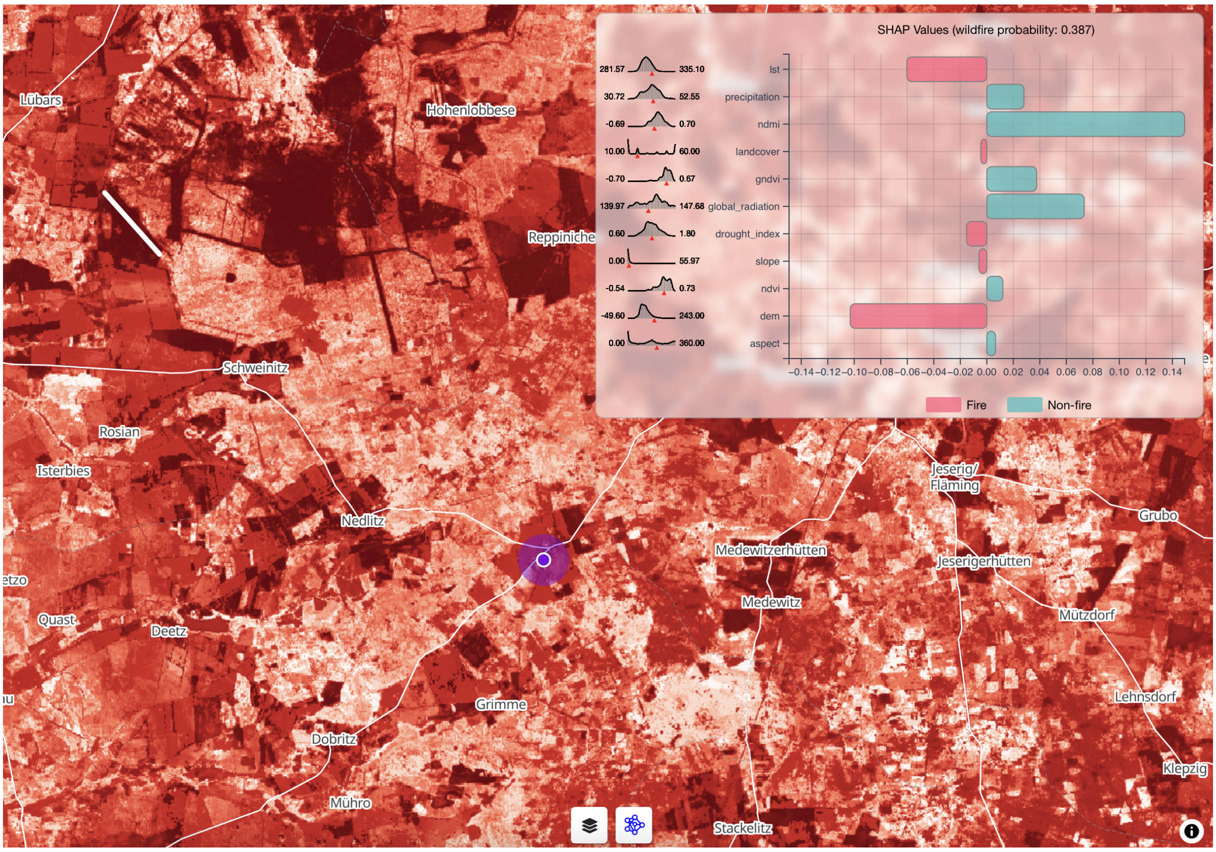

Figure 2. Interactive visualization of Local SHAP values of the features

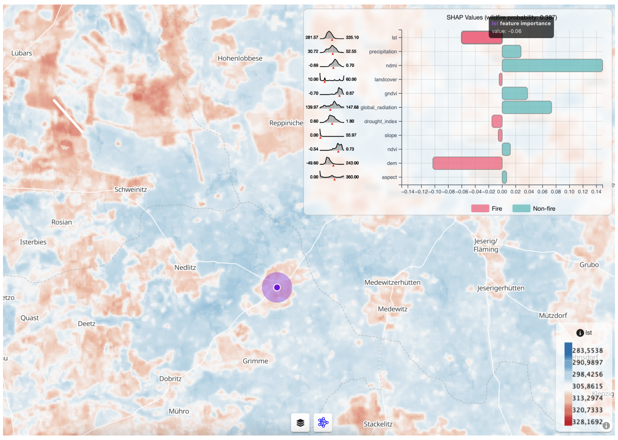

Figure 3. Interactive feature importance and spatial distribution of Land Surface Temperature (LST)

performance while enabling clear insights. The true emphasis lies in leveraging SHAP to unpack predictions, a vital capability in high-stakes wildfire management where understanding the ‘why’ behind susceptibility matters most. This focus on explainability revealed user engagement challenges during initial testing, as non-technical users struggled to grasp XAI concepts.

Performance poses another consideration. Generating SHAP explanations on the fly demands substantial computational power, and though our system leverages server-side caching and optimized algorithms to keep response times brisk, scaling up to larger regions or more elaborate models would call for further refinement. Together, these insights highlight how the GeoXAI system navigates the tension between technical capability and practical utility, paving the way for more transparent and effective environmental decision-making.

5 Conclusion

This case study presents a comprehensive assessment of model outputs, exemplified through wildfire susceptibility using a web-based GeoXAI system. By addressing limitations in traditional GeoXAI visualizations, we developed an interactive system combining open-source geospatial technologies with XAI methods.

The methodology integrates geospatial analysis with machine learning to deliver insights into wildfire risks. The key environmental factors derived from high-resolution data were processed using *GDAL* and *Google Earth Engine*, then incorporated into an RF model that demonstrated strong predictive performance for identifying areas susceptible to wildfire.

The GeoXAI system supports exploration at multiple scales, helping users understand both the global patterns of wildfire susceptibility and the specific local factors contributing to predictions at particular locations. This approach enhances transparency and trust in AI systems for environmental decision-making, demonstrating the potential of combining GeoXAI with machine learning to improve wildfire prevention and management strategies.

Future work will focus on incorporating temporal dynamics for more precise annual predictions, expanding the interface based on stakeholder feedback, and conducting user studies to evaluate the system's impact on real-world decision-making in wildfire management.

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