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Integrating remote sensing and machine learning to evaluate environmental drivers of post-fire vegetation recovery in the Mount Kenya forest

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Abstract
In recent decades, the increasing frequency and severity of wildfires have been linked to climate change and human activities. Understanding the dynamics of post-fire vegetation recovery (PVR) is therefore critical for forest ecosystem restoration and management. The present study analysed burn severities and investigated the impact of environmental variables on post-fire recovery (PVR) in the Mount Kenya Forest Ecosystem (MKFE). The Random Forest (RF) regression model was employed to predict PVR and identify factors that significantly contribute to PVR in the Mount Kenya Forest ecosystem. Landsat satellite imageries from 2011 to 2021 were used to classify burn severity into seven classes based on the differenced Normalized Burn Ratio (dNBR) index. Climate data, soil organic carbon, and topographic variables were integrated into the RF model to predict trends in PVR. The RF model achieved excellent accuracy with a coefficient of determination (R^2) of 0.9013 and a Root Mean Square Error (RMSE) of 0.0280 on the training dataset, and R^2 of 0.8753 and RMSE of 0.0406 on the validation set. The model further revealed a strong positive relationship between temperature and Land Surface Temperature (LST), as well as vegetation recovery. On the other hand, topographic variables demonstrated a strong negative relationship with vegetation recovery. The combined influence of topographic and temperature condition variables highlights the heterogeneous nature of recovery processes, hence the need for spatially targeted management strategies. These findings have significant implications for adaptive management strategies in tropical montane ecosystems facing increasing wildfire risks.

Keywords Post-fire vegetation recovery (PVR), Land surface temperature, Burn severity, Random forest model, Remote sensing, Mount Kenya forest ecosystem

1 Introduction

Wildfires significantly disrupt terrestrial ecosystems, altering vegetation cover, soil properties, and hydrological cycles [1]. Wildfires can lead to considerable ecological changes, including alterations in species composition, loss of biodiversity, and changes in soil properties. Wildfires also notably disrupt human activities, with consequences for the local economy and communities [2]. High-severity fires often result in more pronounced shifts in forest structure compared to low-severity fires [3, 4]. These disturbances often have long-term consequences for biodiversity and ecosystem services, particularly in regions where natural resources are crucial for human livelihoods. Communities located in fire-prone areas often face the threat of displacement due to evacuations and property loss during wildfire events [5].

Globally, wildfires have a significant impact on tropical montane forests [6, 7]. Forest fires have affected regions, including the Amazonia Basin [8], the Congo Basin [9], and the Indonesian tropical mountains [7]. Wildfire trends have increased in recent decades in both intensity and frequency [10]. Climate change is expected to increase the frequency and intensity of wildfires globally, potentially outpacing the recovery capabilities of many ecosystems [11]. Mount Kenya Forest Ecosystem (MKFE) stands out as a critical water tower supplying approximately 40% of the country's water while supporting agriculture, hydroelectric power production, and biodiversity conservation [12]. However, the region has recently experienced numerous fire occurrences. For instance, a fire incident in 2005 burned approximately 3000 hectares of moorland region [13]. Similarly, in 2009, approximately 2,500 hectares of moorland area were affected. In 2011, an expansive area of 3600 hectares of upper montane forest was reported to have burned [12]. In 2012, a fire incident led to the destruction of over 10,000 hectares of the ecosystem (Downing et al., 2017). Another fire destruction also occurred in February 2019, affecting over 80,000 hectares. Fires in MKFE have been exacerbated by human activities, including illegal logging, agricultural encroachment, and poaching, which have historically strained the mountain's ecological balance [12, 13].

Post-fire vegetation recovery (PVR) is essential for restoring ecosystem functions and maintaining ecosystem services in regions such as MKFE [14]. Remote sensing has significantly advanced PVR monitoring, enabling efficient and timely evaluations across extensive and previously inaccessible areas [15]. Satellite-based indices, including the Normalized Burn Ratio (NBR) and its derivative, the difference Normalized Burn Ratio (dNBR), are commonly employed to evaluate fire severity and monitor vegetation recovery [16]. These indices utilize changes in spectral reflectance to quantify vegetation damage and regrowth following a fire event, allowing for a detailed analysis of ecosystem resilience [12].

Remote sensing offers substantial benefits and helps overcome the challenges encountered in responding to emergencies, such as wildfires. The technology offers a continuous record of earth observation data from any part of the globe and can be acquired at relatively low costs [17]. This helps to enhance the efficiency of various organization's initiatives with limited resources dedicated to fire management. Environmental agencies in Kenya, such as the Kenya Wildlife Service (KWS) and the Kenya Forest Service (KFS), lack spatially explicit fire data, which hinders effective monitoring and decision-making. Thus, remote sensing offers a viable solution by providing detailed and continuous coverage, enabling the reconstruction of fire histories and the monitoring of recovery dynamics over time [12]. Satellite imagery and aerial surveys can provide valuable data on burn severity, recovery rates, and changes in land cover, aiding in the development of effective management strategies [18]. Furthermore, the integration of machine learning algorithms with remote sensing data is also becoming increasingly common, allowing for more accurate predictions of fire behaviour and post-fire recovery dynamics [19].

Much research has focused on the use of vegetation indices to monitor PVR without assessing the role of environmental variables in this process. Environmental variables, such as temperature, elevation, and land surface temperature (LST), influence key recovery determinants, including evapotranspiration rates, soil moisture, and vegetation regrowth, but are often overlooked in traditional recovery models [16]. This omission limits the models' ability to capture the complexities of recovery in heterogeneous ecosystems, such as Mount Kenya. Mount Kenya's ecological complexity adds another layer of challenge to monitoring PVR. The mountain's vegetation zones, which include lower montane forests, bamboo, upper montane forests, Ericaceous bushlands, and alpine vegetation, respond differently to fire disturbances. For instance, lower montane forests show higher resilience compared to the fire-intolerant bamboo and upper montane forests [12]. Moreover, cloud cover and the lack of high-resolution datasets pose additional challenges to monitoring PVR in tropical montane environments [16].

While previous studies have explored burn severity and vegetation recovery, few have integrated machine learning models with multi-variable environmental datasets to predict recovery trajectories in tropical montane forests. To address these gaps, this study proposes the development of a comprehensive PVR model that integrates LST and other key variables. By leveraging satellite imagery and state-of-the-art machine learning models, the study aims to enhance our understanding of PVR dynamics and provide actionable insights for managing post-fire recovery in the MKFE. Integrating LST into PVR models is a novel approach to understanding recovery dynamics and addressing the challenges posed by climate variability [16]. Therefore, the overarching objectives of the study are to (i) Classify and map the study area into different burn severity classes, (ii) Evaluate the relationship between LST and other variables in post-fire vegetation recovery using the Random Forest machine learning model, and (iii) Analyze vegetation recovery potential in the ecosystem based on the key environmental variables. Importantly, the study aligns with national and global priorities for conserving Kenya's water towers and mitigating the impacts of climate change. Its findings will offer valuable insights for policymakers and conservation practitioners, contributing to more effective forest management and restoration strategies.

2 Materials & methods

2.1 Study area

The study was conducted in the Mt. Kenya Ecosystem in central Kenya. The region spans 30 km wide by 50 km long, centred on latitude 0° 10' 48 "S and longitude 37° 18' 0 "E (Fig. 1). Mount Kenya is characterized by a diverse range of ecosystems that vary with elevation, from tropical forests at the lower levels to alpine meadows and glaciers at the summit. This vertical gradient supports a wide array of flora and fauna, making the region a biodiversity hotspot [20]. The Mt. Kenya ecosystem is vital to Kenya's socioeconomic well-being, serving as a critical water source for millions of people and key sectors, including agriculture, hydroelectric power, and urban water supply [21]. From

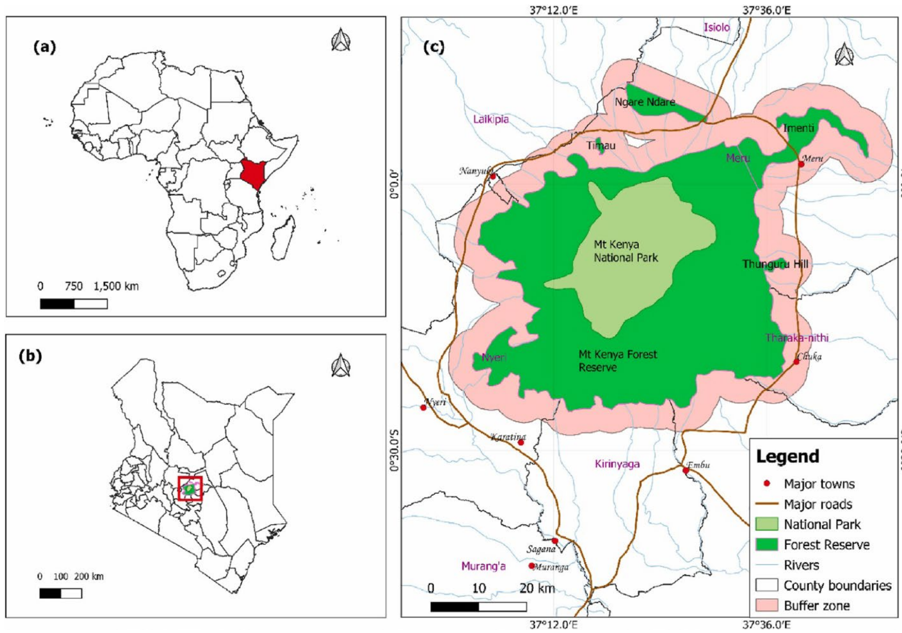


Fig. 1 Map of the study area. **a** Location of Kenya in Africa; **b** Location of Mount Kenya Ecosystem in Kenya; **c** Map of the Mount Kenya Ecosystem

an ecological perspective, Mt. Kenya's forests play a crucial role in carbon sequestration and maintaining regional climate stability [22].

Climatically, Mt. Kenya experiences a bimodal rainfall pattern, with the long rains occurring between March and May and the short rains from October to December. The region's climate is influenced by its elevation, with temperatures decreasing substantially at higher altitudes [23]. However, the region is under threat from human activities, including deforestation, land-use changes, and encroachment [24]. These activities have heightened the risk of forest fires, with significant implications for biodiversity, soil stability, and water resources. The mountain's diverse ecosystems, socio-economic importance, and vulnerability to climate change and anthropogenic pressures make it a compelling site for research, particularly in understanding the effects of environmental changes, such as post-fire vegetation recovery and land cover dynamics.

2.2 Data and data sources

For this study, Landsat imagery was utilized to derive key indicators such as the NBR, dNBR, and LST, which were used to assess burn severity and post-fire vegetation recovery. The data span the years 2011 to 2021, with Landsat 7 ETM + providing imagery for 2011 and 2012, and Landsat 8 OLI/TIRS imagery used from 2013 onwards.

Satellite images and SRTM data were obtained from the USGS Earth Explorer platform. Pre-processing included applying cloud and snow masks, followed by extraction and clipping of images from 2011 to 2021 to the study area. To ensure radiometric consistency across sensors, this study utilized Landsat Collection 2 Surface Reflectance (SR) products, which are atmospherically corrected and processed to provide harmonized surface reflectance values. These products minimize inter-sensor variability between Landsat 7 ETM + and Landsat 8 OLI by applying standardized calibration and correction procedures, making them suitable for multi-temporal and cross-sensor analysis.

To calculate NBR, bands 4 (0.77–0.90 μm) and 7 (2.09–2.35 μm) for Landsat 7 ETM + and bands 5 (0.85–0.88 μm) and 7 (2.11–2.29 μm) for Landsat 8 OLI/TIRS (Near-infrared and Shortwave infrared, respectively) were used. Healthy vegetation reflects high levels of NIR and absorbs SWIR due to its moisture content. This results in high positive NBR values (Table 1). Burned areas exhibit reduced near-infrared (NIR) reflectance (due to vegetation loss) and increased short-wave infrared (SWIR) reflectance (due to exposed soil or charred material). This results in low or even negative NBR values. 2011 was designated as the pre-fire year, while the remaining years were considered post-fire years. The difference between pre-fire and post-fire NBR values (dNBR) was then used to classify the severity of burns according to the USGS burn severity thresholds. Burn severity is estimated by first calculating the NBR for pre- and post-fire images. NBR was determined using Eq. 1.

$$\mathrm{NBR} = (\mathrm{NIR} - \mathrm{SWIR})/(\mathrm{NIR} + \mathrm{SWIR}) \tag{1}$$

The difference in the above index for prefire and postfire was then obtained from Eq. 2

$$\mathrm{dNBR} = \mathrm{NBRprefire} - -\mathrm{NBRpostfire} \tag{2}$$

Thresholds for dNBR values were used to classify the area into seven burn severity classes as recommended by USGS: unburned, low, moderate-low, moderate-high, high, very high, and extreme severity. This was done in the Raster Calculator in QGIS, where the values were reclassified to values 1 to 7 to represent the classes. Subsequently, maps for the post-fire years were created in the layouts.

For LST, band 6 (Thermal Infrared): 10.40–12.50 μm was used for Landsat 7 ETM + while bands 10 (Thermal Infrared Sensor 1): 10.60–11.19 μm and 11 (Thermal Infrared Sensor 2): 11.50–12.51 μm for Landsat 8 OLI/TIRS) were used in the LST calculations. The thermal band data was scaled to temperature (Kelvin), and the mean LST for the entire year was calculated. The SRTM dataset provides high-resolution elevation data, which is critical for understanding terrain characteristics and their influence on ecological processes. For this study, SRTM data were utilized to analyse the topographic variability within the study area, which plays a role in post-fire vegetation recovery. QGIS software was used to derive aspect and slope values from the digital elevation model (DEM) data.

Monthly temperature data (minimum, maximum, and mean temperature data) and monthly precipitation data were downloaded directly from worldclim.org. The database provides ready-to-use raster files at a spatial resolution of approximately 1 km. Raster calculations were conducted to obtain the desired variables, which were mean annual

Table 1 Description of the burn severity classes and their ranges according to the USGS

Class	dNBR Range	Description
Unburned	dNBR Range (< −0.1)	Areas unaffected by fire.
Low Severity (Regrowth)	dNBR Range (−0.1 to 0.1)	Low impact or areas experiencing regrowth.
Low Severity (Burned)	dNBR Range (0.1 to 0.27)	Minor fire effects.
Moderate Severity	dNBR Range (0.27 to 0.44)	Moderate vegetation and soil burn.
High Severity	dNBR Range (0.44 to 0.66)	Significant vegetation and soil impact.
Very High Severity	dNBR Range (> 0.66)	Severe vegetation and soil damage.
Increased Greenness	Negative dNBR values (< −0.1)	Areas showing increased vegetation (e.g., post-fire recovery or seasonal changes).

maximum temperature, mean annual minimum temperature, mean annual temperature, and mean annual precipitation sum. The soil organic carbon dataset provides critical information on the amount of organic carbon present in the soil, which directly impacts vegetation growth and recovery by influencing soil fertility, water retention, and nutrient availability. Understanding the soil organic carbon in the context of fire recovery provides insights into carbon sequestration rates, which can help quantify the potential for long-term recovery in terms of carbon storage. The data was obtained from the Africa Soil Information Service (AFSIS), which provides high-quality soil data at 250 m resolution for various regions across Africa. The KFS provided field data that was used to validate the spatial extent and burn dates of burn areas derived from satellite data.

Additionally, the MCD64A1 fire product was obtained from the Google Earth Engine (GEE) Catalogue to supplement the field-observed data from KFS. The product detects burned areas using algorithms that analyze the spectral and temporal characteristics from MODIS data. It identifies changes in vegetation and surface properties caused by fire, specifically targeting areas where biomass burning has occurred. The product detects burned areas by analyzing changes in MODIS Surface Reflectance Bands and Thermal Anomalies from the MOD14/MYD14 Active Fire Product. Figure 2 summarizes the workflow employed in this study.

2.3 Analysis of vegetation recovery using the RF model

Random Forest is a supervised machine learning algorithm that is used for solving classification and regression problems. The model integrates multiple decision trees and an aggregation technique during training and averages their outputs to produce robust predictions [25, 26]. It is particularly suited to this study due to its ability to handle

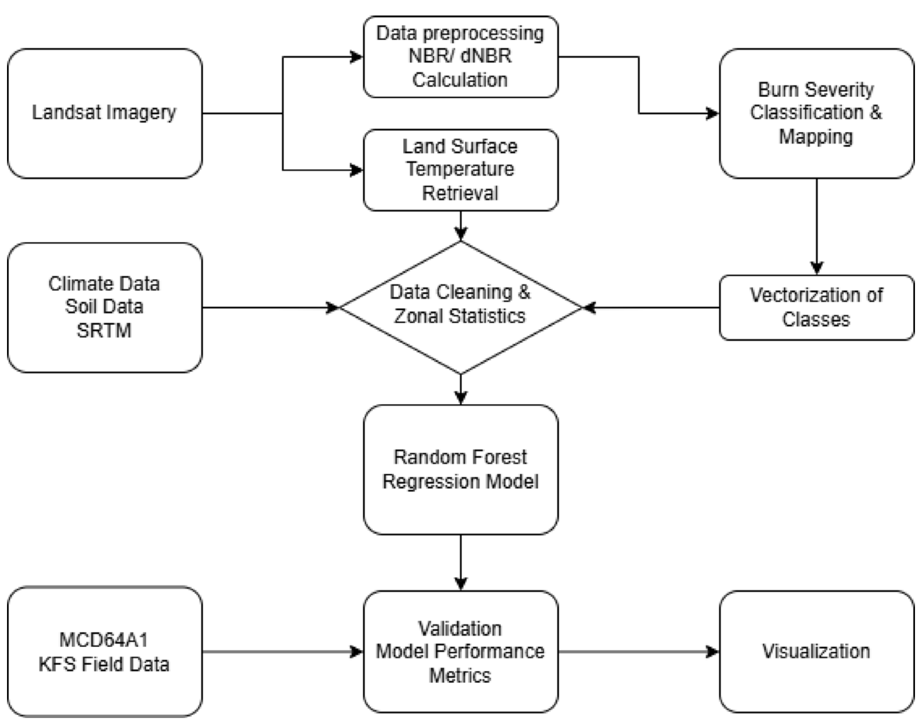


Fig. 2 Overall workflow for PVR analysis. NBR-Normalized Burn Ratio; dNBR-differenced Normalized Burn Ratio; SRTM-Shuttle Radar Topography Mission; KFS-Kenya Forest Service; MCD64A1-Moderate Resolution Imaging Spectroradiometer (MODIS)

high-dimensional data and complex, non-linear relationships between variables [25, 27, 28]. The model was used to predict NBR values representing vegetation recovery for the years 2012–2021, with 2011 as the pre-fire baseline. The baseline was chosen based on the successive fire incidences in 2011 and early 2012, which is essential in providing a reference for estimating long-term (decadal) recovery effects. The burn severity (dNBR) estimate was the dependent variable, whereas LST, maximum temperature, minimum temperature, mean temperature, precipitation sum, soil total organic carbon, elevation, aspect, and slope were the explanatory variables. The model was parameterized using 100 trees (ntrees). This is a commonly used baseline that provides an optimal balance between predictive accuracy and computational efficiency. This choice was driven by several considerations. Using 100 trees ensures model stability by averaging predictions across multiple decision trees, thereby reducing variance and enhancing generalization. Although increasing the number of trees can improve accuracy, it also increases computational cost. The selection of 100 trees was found to offer robust performance without significantly prolonging training time. Cross-validation results showed that 100 trees yielded satisfactory RMSE and R^2 scores, with diminishing returns observed for further increases in the number of trees. Thus, 100 trees were chosen to balance model performance and computational feasibility effectively. For the mtry parameter, we took the default value, which is the square root of the number of features available. Each tree splits the dataset recursively based on a feature and a threshold that minimizes prediction error. This process continues until a stopping condition is met (e.g., reaching the maximum depth or achieving the minimum number of samples per leaf). At each node, a random subset of features was considered for splitting, ensuring diversity among the trees and preventing overfitting.

2.4 Model training and evaluation

The dataset used for training and testing the RF model's performance was divided into an 80:20 ratio. The training dataset was resampled using bootstrapping, creating multiple subsets for training individual trees. This step ensured that each tree saw a slightly different view of the data. A systematic search across hyperparameter combinations was conducted to find the best values for n_estimators and max_depth. For evaluation, K-fold cross-validation was applied to ensure the model's performance was generalized well across different subsets of the data. Metrics such as the root mean square error (RMSE) and the coefficient of determination (R^2) were used to quantify the accuracy and explanatory power of the model. Additionally, a feature importance analysis was conducted to determine importance scores and identify the predictors that contributed most to explaining post-fire vegetation recovery.

2.5 Statistical analysis

Other statistical analyses performed include time-series trend analysis, Analysis of Variance (ANOVA), honestly significant difference test (Tukey's HSD), and correlation analysis. Time series analysis was employed to visualize the temporal trends in vegetation recovery within the study area. ANOVA analysis was conducted to determine the variation in burn severities across different burn severity classes. The analysis is crucial in revealing significant burn severity classes, which is useful in establishing appropriate measures based on the levels of burn intensity in the study region. Tukey's HSD is used

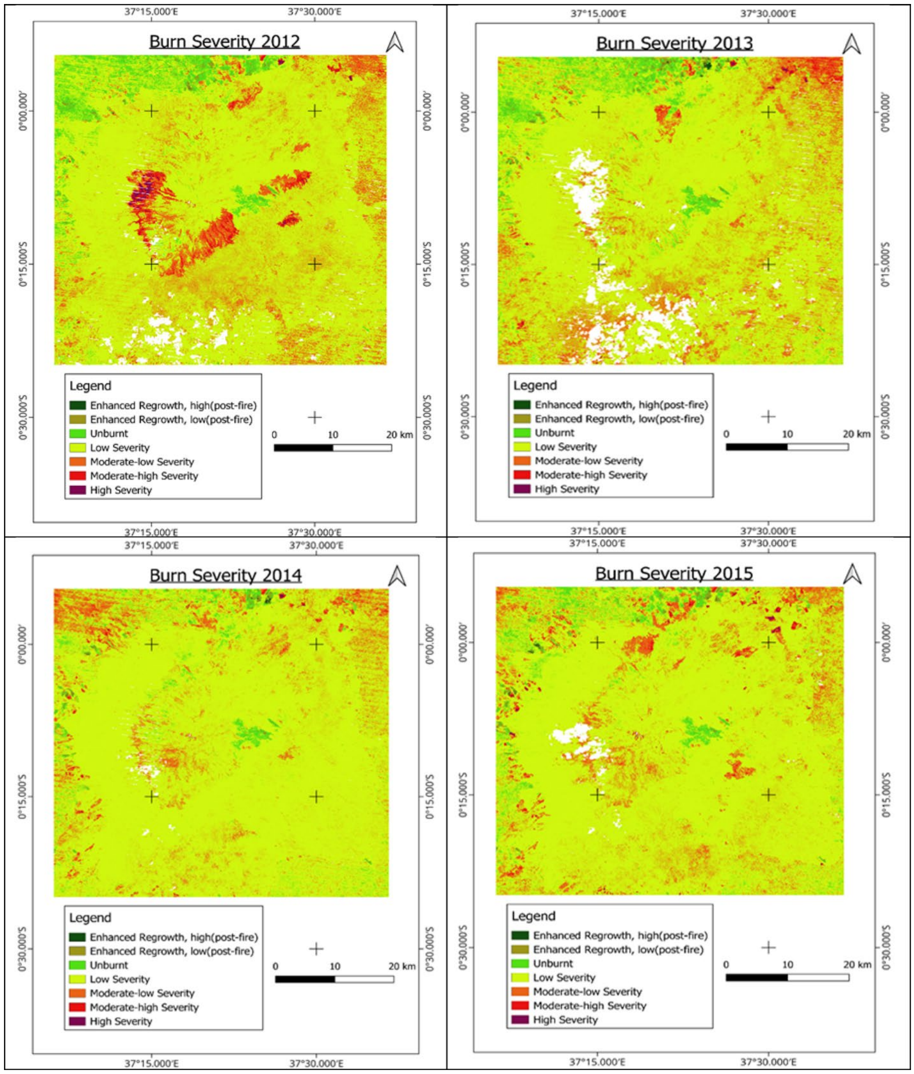


Fig. 3 Spatial distribution of burn severity classes in the Mt. Kenya Ecosystem from 2012 to 2021, highlighting temporal trends in recovery patterns

to test for differences among sample means to determine significance. The correlation analysis was conducted to measure the strength of the relationship between the outcome and the explanatory variables and to determine their association. The analysis was critical in the holistic assessment of the PVR analysis and in identifying the key factors contributing to the forest condition, thereby bolstering management efforts.

3 Results

3.1 Burn severity in Mt. Kenya ecosystem from 2012 to 2021

Burnt severity in the Mt. Kenya Forest ecosystem was mapped from 2012 to 2021. The study reveals heterogeneous patterns in space and time (Fig. 3). For instance, moderate to high burnt severity was notable in 2012. This result corroborates the observed fire effects in the study area in 2011 and 2012. However, from 2013 onwards, there was a persistent improvement in areas transitioning from moderate to high burn severity to low severity and unburnt zones. It is worth noting that there was a consistent improvement in vegetation conditions, with enhanced regrowth observed from 2017 onwards.

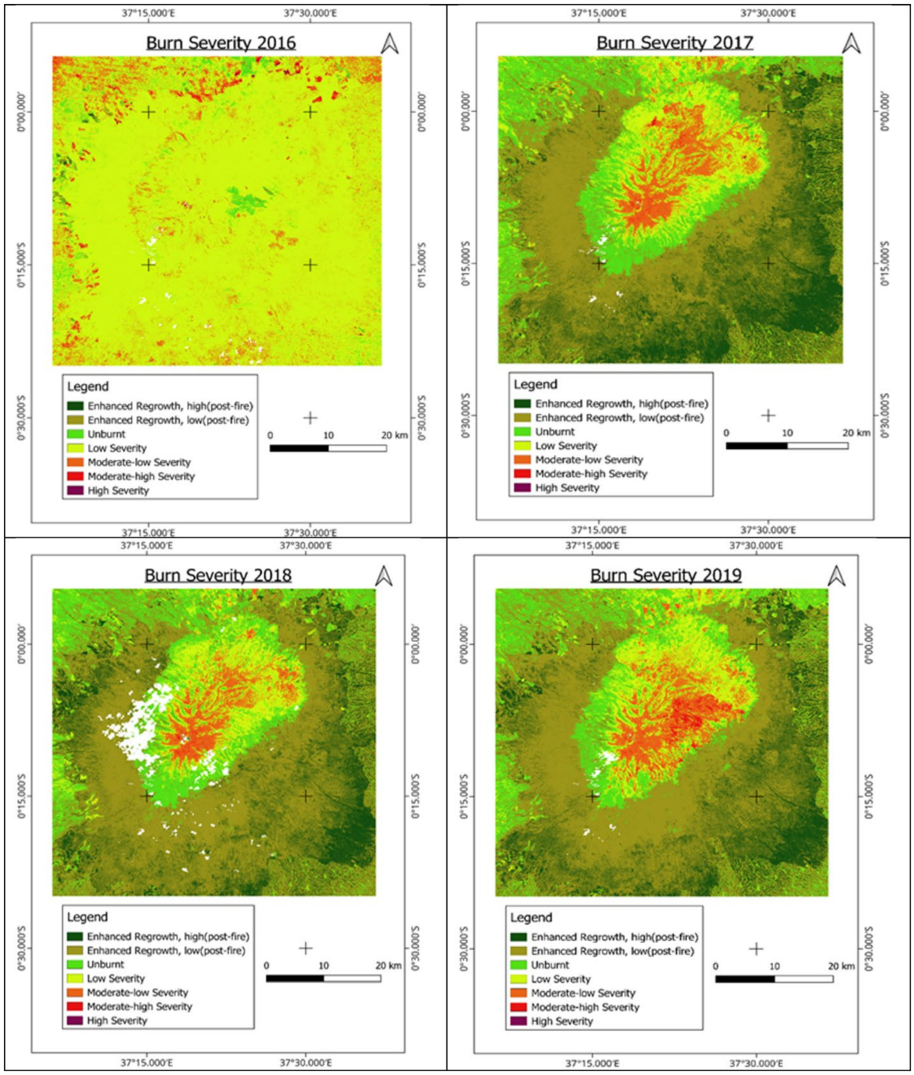
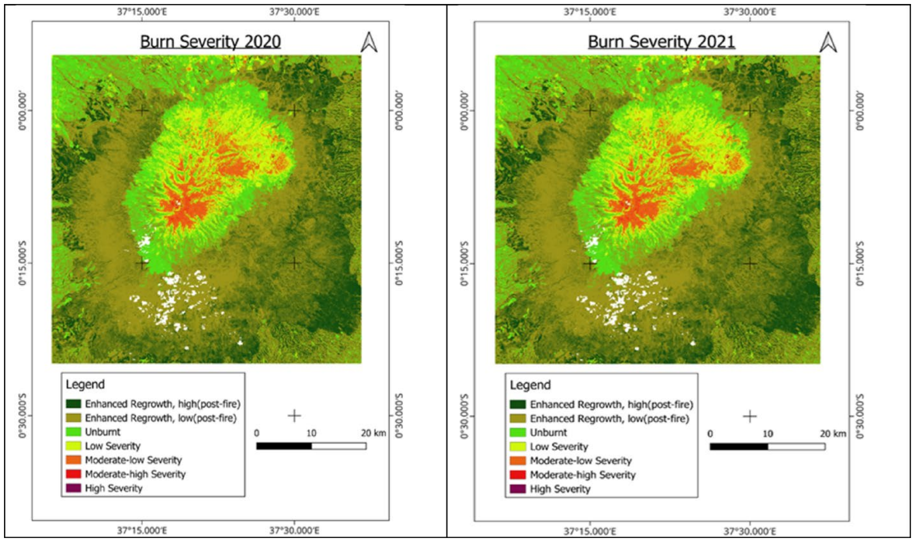


Fig. 3 (continued)

This reveals an improvement in vegetation conditions over time. However, it is noted that the areas to the centre reveal moderate burn severity from 2017 onwards. These areas are dominantly the bare land areas that characterize regions around the peak of Mt. Kenya. It is possible that the low vegetation conditions resulted in the flagging of these areas as moderate severity zones. Similarly, it is expected that as vegetation conditions improve in most zones, areas which tend to record low values due to barren nature are likely to be classified in the moderate to high burn severity zones.

It is notable that from 2011 to 2016, the mean burn severity values were positive for areas with moderate to high severity (Fig. 4). The highest mean values were observed between 2011 and 2012, which coincided with the year of the highest fire incidences in the ecosystem. Notably, recovery began to stabilize from 2013 to 2016, as the NBR values started to level off, suggesting a recovery process, albeit at a slow phase.

The period from 2017 to 2021 shows positive recovery trends, with a notable peak in 2020, reflecting the cumulative effects of successful recovery mechanisms. This trend may also reflect the decreasing frequency of fire events and improved climatic conditions, leading to a more favourable environment for recovery. This positive trend may



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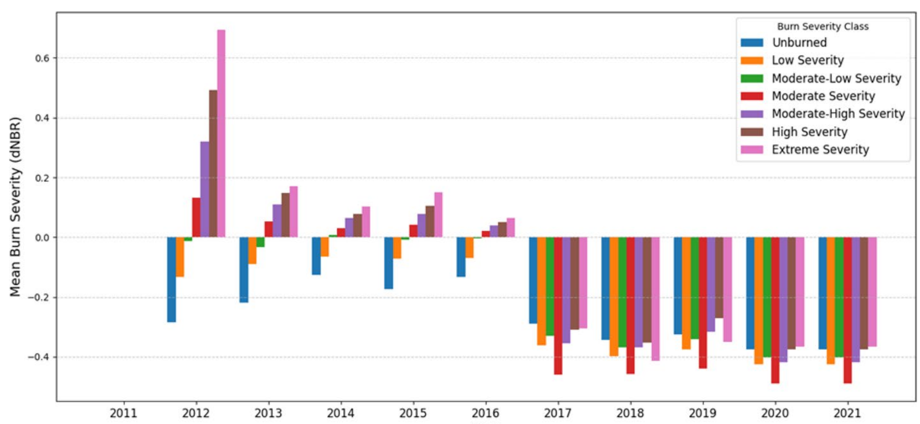

Fig. 4 Bar plot illustrating the temporal trends of burn severity in each class

have also been partly influenced by the implementation of The Mt. Kenya Ecosystem Management Plan (2010–2020) by the KWS, which encouraged community participation in forest management.

3.2 Random forest model results

The RF model demonstrated excellent performance in predicting PVR in the Mt. Kenya ecosystem. This was evident from the low RMSE values and high R-squared (R^2) values in the evaluation phase. A RMSE value of 0.028 was obtained, which indicates a small level of error in the model predictions. This suggests that the model predictions are relatively accurate, a crucial aspect when evaluating vegetation recovery following fire incidences. Similarly, a high R^2 value of 0.901 was obtained, indicating that the model captured 90.1% of the variation in post-fire vegetation recovery, as measured by NBR and explained by the model predictors. This high R^2 value indicates that the model is highly effective in capturing the key factors that influence vegetation recovery. It demonstrates that the relationship between the variables used in the study (such as burn severity, temperature, and soil properties) accounts for most of the observed variance

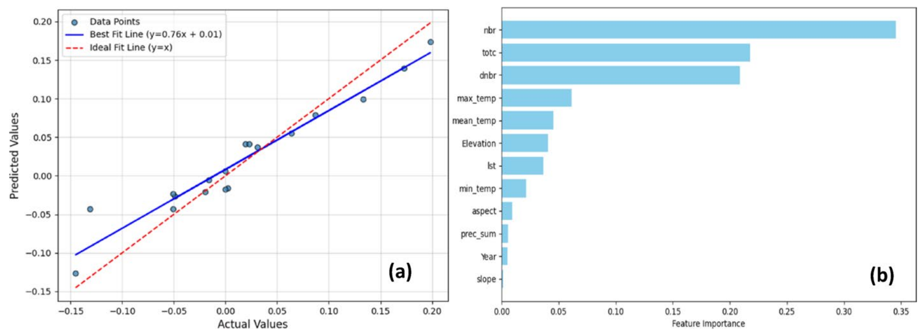

Fig. 5 Scatter plot comparing predicted versus observed NBR values (**a**) and feature importance rankings for variables influencing PVR (**b**)

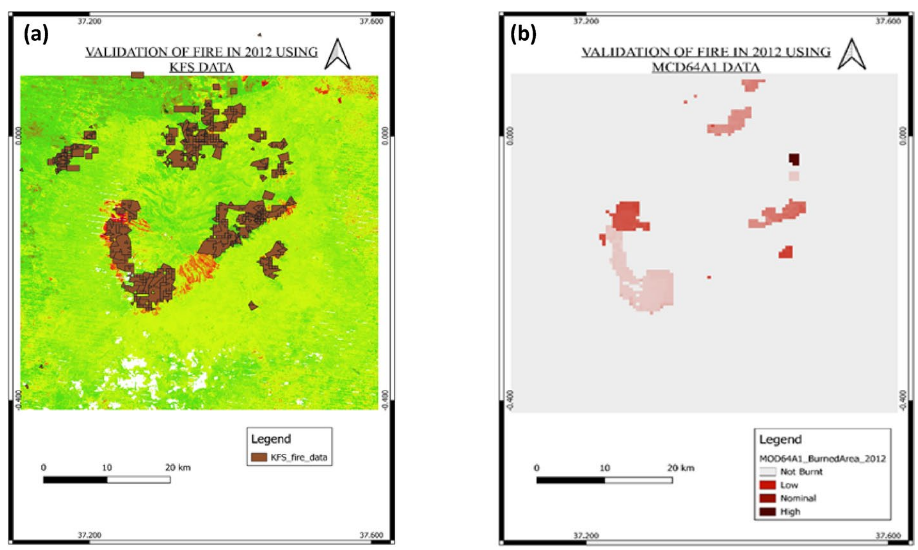

Fig. 6 Burn severity map of 2012 overlaid with KFS burned area data representing the official fire boundaries from the Kenya Forest Service (**a**) and spatial distribution of burned areas in 2012 derived from the MCD64A1 product from MODIS (**b**) that were used for spatial validation

in the recovery process. The scatter plot (Fig. 5a) reveals a good agreement between the predicted outcome and the observations in the ecosystem. The points lie close to the 1:1 line (in red), showing that the model was relatively excellent in predicting PVR recovery in Mt. Kenya and can be used extended to other unstudied periods/epochs and regions.

Furthermore, to reveal the important variables in predicting PVR, a feature importance plot (Fig. 5b) of the 12 input features was generated from the model and the analysed data. NBR, soil organic carbon, maximum temperature, and mean temperature ranked as the most important variables in the model prediction. Variables that ranked the least include slope, precipitation sum, and aspect (Fig. 5b).

Additionally, a spatial validation mechanism was conducted to visualize the agreement between the predicted non-fire and fire zones using KFS data and the MODIS product. It was necessary to visualize regions where a persistent absence of fire was observed, especially after a fire incident that revealed areas of vegetation recovery or stable vegetation conditions. The results for the 2012 fire reveal a good agreement between the predicted burned areas from the RF model and the observed burned zones from the KFS data (Fig. 6a). Similarly, there was a good agreement between the predicted maps and the extracted data from the MCD64A1 product (Fig. 6b). This reveals the potential of the RF model in characterizing burned areas in the study area.

3.3 Contribution of environmental factors to the PVR in MKFE

Furthermore, correlation analysis was performed to analyze the contribution of various environmental and climatic factors to PVR in the study area. This was necessary to establish the factors that have a high correlation and, hence, a strong association with PVR in the region. The results are depicted using a correlation plot (Fig. 7).

The results indicate that the variability of PVR is correlated with various indicators. In general, NBR change is positively correlated with mean temperature, max temperature, and LST, suggesting that warmer conditions are linked with higher recovery in certain burn severity classes. Total soil organic carbon is negatively correlated with recovery, suggesting that soil carbon content may not play a significant role in moderating vegetation regrowth after fire. All the slope variables were negatively correlated with NBR change, revealing their inverse effect on contributing to PVR. Among the variables, elevation depicted the highest correlation, with slope revealing a moderate correlation, while aspect had the lowest correlation. For elevation, the results indicate that lower elevations are associated with higher recovery trends, while high elevations exhibit decreased recovery trends. For the slope variable, lower slopes tend to have higher recovery trends, while higher slopes reveal slow recovery trends. Precipitation, on the other hand, revealed a positive but slight effect of PVR in the region. These correlations highlight the intricate relationships between climate, soil, and topography in shaping post-fire recovery. While temperature and carbon content are critical factors, elevation also plays a significant role in shaping recovery outcomes. Future models could benefit from considering these interactions more explicitly, perhaps through the inclusion of interaction terms or non-linear modelling approaches.

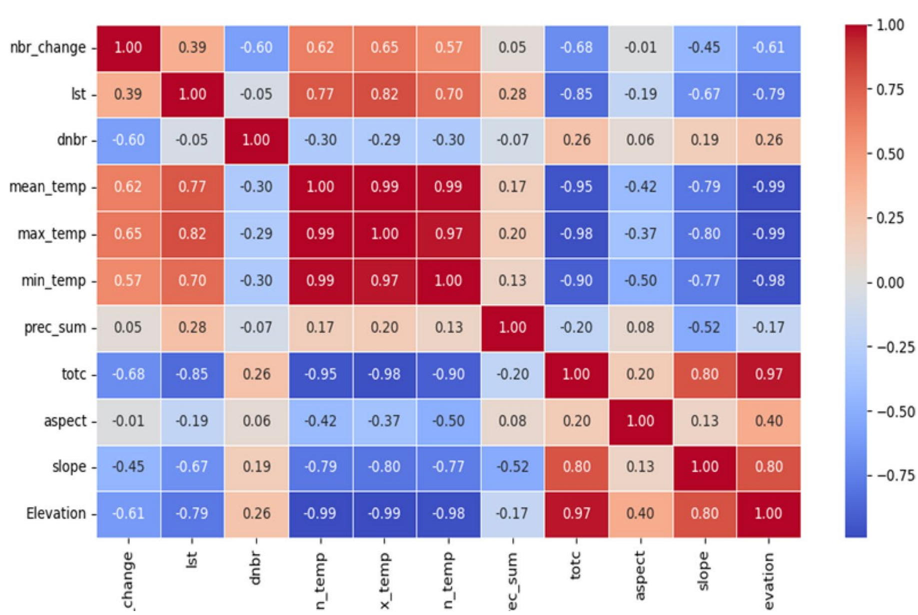

Fig. 7 Correlation analysis with mapped Pearson's correlation coefficient (r) estimated for PVR w NBR change, land surface temperature (LST), Normalized Burnt Ratio (dNBR), mean temperature, maximum temperature, minimum temperature, precipitation, soil organic carbon, aspect, slope and elevation

3.4 Trends in vegetation recovery and significant variables

The temporal analysis of vegetation recovery from 2012 to 2021 indicates a slow and steady recovery from the catastrophic fire in 2012. The NBR change over time shows a sharp decline in 2012 (Fig. 8a), with an average drop of −0.15, indicative of the significant damage caused by the fire. This dramatic decrease is expected, as fires often result in extensive vegetation loss, which would be captured by a negative change in NBR. Recovery began to stabilize from 2013 to 2016, as the NBR values started to level off near zero, indicating that initial recovery processes were underway, albeit slowly. The period from 2017 to 2021 shows positive recovery trends, with a notable peak in 2020, reflecting the cumulative effects of successful recovery mechanisms. This trend may also reflect the decreasing frequency of fire events and improved climatic conditions, leading to a more favourable environment for recovery (Fig. 8b).

3.5 Statistical analysis

The ANOVA results showed a significant F-statistic of 12.16 with a p-value of < 0.05, which results in rejecting the null hypothesis and accepting the alternative hypothesis of statistically significant differences in vegetation recovery across the different burn severity classes. Burn severity, therefore, plays a critical role in determining the extent and rate of post-fire vegetation recovery. The significance of this finding aligns with previous studies that have shown a clear relationship between fire intensity and the recovery process, where more severe fires typically result in slower recovery rates.

Further proceeding and performing the Tukey HSD tests, the results revealed pronounced between severity groups 1 (Unburned) and Groups 3, 4, 5, 6, and 7 (representing Moderate-Low to Very High Severity), highlighting that as burn severity increases, the recovery trajectory becomes more distinct, with severe burns leading to longer and more unpredictable recovery times (Fig. 9). These findings emphasize the importance of incorporating burn severity as a primary factor in recovery models, as different severities require tailored post-fire management strategies. Areas with very high burn severity may need more intensive restoration efforts to facilitate faster recovery.

4 Discussion

The present study highlights the potential of machine learning models and remote sensing in monitoring PVR in montane ecosystems. The study clearly demonstrates that vegetation recovery is not a uniform process but rather varies across space and time. This is engineered by underlying environmental and climatic factors that vary across the study region. The burn severities across the MKFE depicted varying trends across the regions

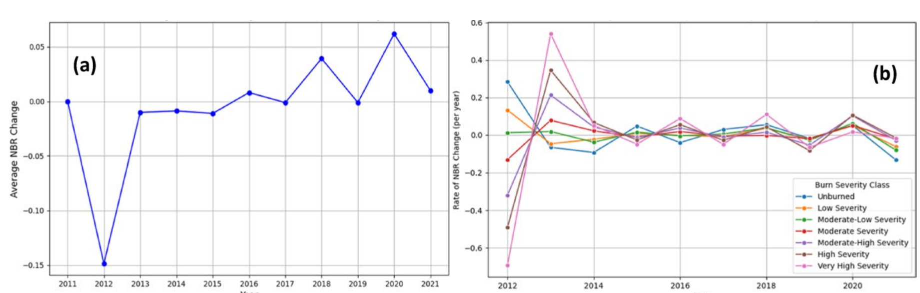

Fig. 8 Temporal trends of PVR in the Mt. Kenya ecosystem showing the mean annual NBR change (**a**) and the annual NBR change rates classified by burn severity class (**b**)

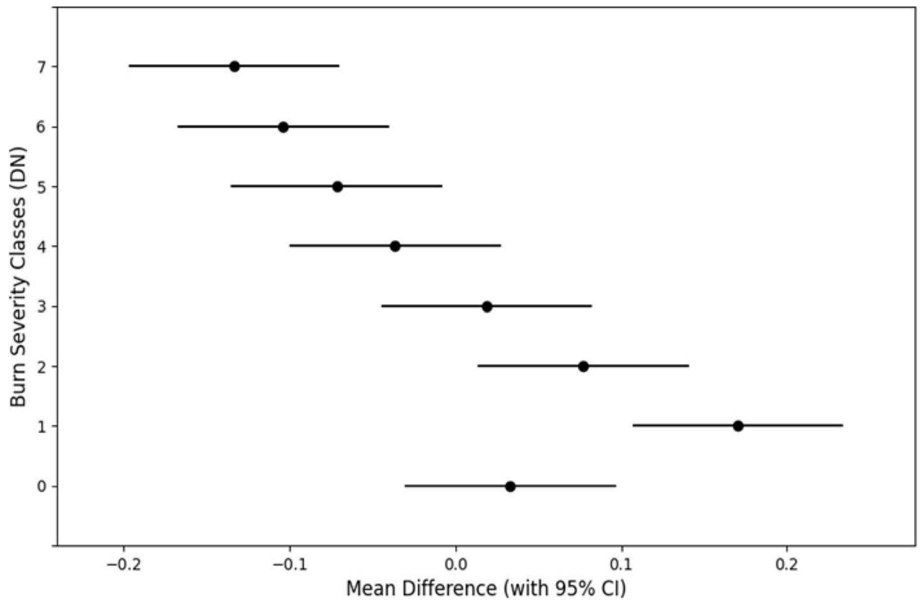

Fig. 9 Tukey HSD test results illustrate pairwise comparisons of mean NBR change among burn severity classes, indicating statistically significant differences in post-fire vegetation response across varying fire intensities

and the years under the study. Therefore, post-fire recovery strategies should consider both burn severity and temporal and spatial variations in environmental factors, making the application of integrated models for better monitoring and management crucial. Burn severity data, therefore, provide crucial evidence for assessing the effectiveness of land management decisions globally.

Besides determining the burn severity classes, it is also crucial to establish factors that play a crucial role in contributing to PVR in forest ecosystems [29]. Both human disturbances and environmental factors are key drivers of long-term post-fire vegetation recovery [30]. Statistical and machine learning models are indispensable in modelling various environmental factors and facilitating key management decisions. In the present study, the RF model was used to model burn severities established from pre-season and post-season fires in the Mt. Kenya ecosystem. The model achieved excellent results in predicting the PVR rates in the study area. Effectively, the predictors used in building the model accounted for approximately 90% of the variation in PVR across the study area. The excellent performance of the model is also corroborated by other studies which assessed PVR in other regions [31, 32].

Variable importance analysis was further conducted to analyse how variables contribute to the model prediction. The present study found that NBR, soil organic carbon, and temperature variables contribute significantly to the model prediction. In contrast, topographical variables such as slope, aspect, and elevation were recorded to have low importance scores in the present study. The findings align with other studies, which have established high importance scores for temperature variables and low scores for topographical variables [31]. The strong predictive power of temperature variables, soil organic carbon, and NBR in the model is expected, as these factors directly regulate vegetation regrowth through their influence on microbial activity, nutrient cycling, and moisture retention (Onwuka & Mang, 2018). In contrast, topographical factors such as slope, aspect, and elevation have an indirect impact (He et al. 2022), resulting in their lower importance in model prediction.

Regarding the rates of recovery, the present study found that stable vegetation conditions were achieved 5 years after a severe fire incident. This finding corroborates other studies, which also established that burn areas regain high normalized difference vegetation index values in five to six years from a pre-fire year [33]. Other studies have found a slightly longer period, spanning 7–10 years, which could be attributed to the differences in landscape and vegetation conditions between our study location and that of the study [34].

The relative influences of various environmental, climatic and topographic covariates were analysed to evaluate PVR in the study area. The present study found a high influence of temperature and LST variables, whereas precipitation and topographic variables recorded a low influence. Our findings align with the study of [33], who found that precipitation has a low influence on PVR in Australia. Similarly, other studies in the Amazon and the Congo Basin reveal a high influence of temperature and LST variables on PVR [35]. Furthermore, other studies in the Congo Basin highlight the role of environmental factors in post-fire recovery [36].

Our study identified that environmental factors such as temperature and LST likely played a role in the observed recovery patterns. Temperature, LST and precipitation are the variables that revealed positive effects on PVR, albeit at different magnitudes. Temperature variables (minimum, mean, and maximum) temperatures had the strongest influence on PVR. The possible reason for the strong correlation between temperature variables and PVR is that increased temperature provided more favourable conditions for vegetation to thrive in the years following the fire. This is especially so in the Mt. Kenya region, which at times can record very relatively low minimum and maximum temperatures of up to − 3.2 °C and 2.4 °C, respectively [37].

Additionally, areas with higher elevations, where temperatures are generally lower, appeared to recover more rapidly compared to lower-elevation regions. The precipitation variable was found to have a very low effect on PVR. This is expected as the entire Mt. Kenya forest ecosystem receives high precipitation of up to 2500 mm [38], with minimal variation across the ecosystem, thus influencing PVR at a uniform rate across the region. Topographic variables were found to have an inverse relationship with PVR. This result is attributed to the interplay between climatic factors, edaphic factors and plant communities in the ecosystem. For instance, slow vegetation recovery at higher elevations and slopes is attributed to the lower temperatures that occur as the elevation rises. Trees require optimum temperatures for faster growth, and therefore, low regions in the ecosystem with relatively warm temperatures tend to experience faster PVR trends [39]. For slope, higher slopes demonstrated slow PVR, which is attributed to, among other factors, the underlying soil and vegetation conditions. Higher slopes are prone to erosion and landslides and, therefore have poor soil conditions for optimal root and vegetation growth [40]. Vegetation on lower slopes benefits from dense soils, which can facilitate adequate root establishment and optimal vegetation growth. The study supports decisions, including effective monitoring and adaptive management, which are essential for supporting recovery efforts in fire-prone ecosystems.

5 Conclusion

The present study analyzed PVR in the Mt. Kenya Forest Ecosystem. The random forest machine learning model was used to model PVR and establish factors that influence the rate of vegetation recovery in the study area. The developed model demonstrated high predictive accuracy (R^2 = 0.901, RMSE = 0.028) in capturing vegetation recovery patterns, successfully integrating multiple environmental variables to explain recovery trajectories. Temporal analysis of PVR during the 2012–2021 period revealed the long-term nature of vegetation recovery, characterized by initial sharp declines followed by gradual improvement and stabilization after five years. The recovery trajectory exhibited distinct phases, ranging from an immediate post-fire decline to stabilization and ultimately positive recovery trends, offering valuable insights into the temporal dynamics of ecosystem regeneration.

Burn severity emerged as a fundamental determinant of vegetation recovery patterns, among other variables such as temperature and land surface temperature. Further statistical analysis revealed significant differences in recovery rates across burn severity classes ($p < 0.05$), with more severely burned areas requiring longer recovery periods and showing more unpredictable recovery patterns. This informs the need for policymakers and conservation managers to prioritize post-fire burn severity assessments. Establishing rapid response protocols for severity mapping immediately after fire events can inform more effective allocation of restoration resources. Given the disproportionate recovery challenges in high-severity burn zones, our findings suggest implementing intensive ecological interventions, including active reforestation, erosion control, and enhanced protection against secondary disturbances such as illegal logging. Policymakers should incorporate burn severity data into forest management plans and post-fire rehabilitation programs to ensure targeted recovery actions are implemented.

The study also revealed a positive relationship between temperature, LST, and precipitation, albeit the magnitude of precipitation was low. However, topographical variables played the least role in predicting PVR in the ecosystem. The study concludes that management strategies should incorporate measures to moderate surface temperatures in recovering areas, particularly through techniques such as strategic shading and the selection of suitable species for replanting efforts.

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Author contributions
LAO: Conceptualization; methodology; formal analysis; original draft; review; and editing; TO: Formal analysis; methodology; review and editing; BR: Methodology; review; and editing; KL: Methodology; review; and editing; HKK: Supervision; formal analysis; review; and editing.

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Data availability
Data and materials used to present the study findings are available upon a reasonable request.

Declarations

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