

**Research Article**

Weekly Spatiotemporal Dynamics of Forest Fire Hotspots in Tak Province, Thailand: A GIS-Based Directional Analysis

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Forest fires are recurrent dry-season hazards in northern and western Thailand, yet their short-term spatial dynamics remain insufficiently understood. In this study, weekly spatiotemporal dynamics of forest fire hotspots in Tak Province, Thailand, were examined using Visible Infrared Imaging Radiometer Suite (VIIRS) active-fire data and GIS-based directional analysis. Hotspots from five fire seasons (2021–2025) were grouped into 24 weekly intervals beginning on 1 December. The analysis integrated weekly hotspot counts, forest-type compositions, mean-center trajectories, standard deviational ellipses, temporal changes in topographic characteristics, and fishnet-based hotspot persistence mapping. The results revealed that fire activity was highly concentrated during the middle of the fire season, with 20,957 hotspots or 89.45% of all detections occurring during weeks 8–16. Dry dipterocarp forest and mixed deciduous forest together accounted for more than 96% of all the hotspots. Directional analysis indicated that hotspot activity was not distributed randomly but became most spatially organized during the middle phase, when centroid movement was more consistent and hotspot distributions showed a stable northwest–southeast directional alignment. Weekly hotspot occurrence also shifted toward higher elevations, deeper forest interiors, steeper slopes, and more rugged terrain as the fire season progressed. Persistence analysis further revealed that high- and very high-persistence cells represented only 5.81% of the grid system but formed recurrent fire-prone cores concentrated in deciduous mountain forests. These findings demonstrate that forest fire activity in Tak Province is characterized by seasonal concentration, directional organization, temporal changes in topographic characteristics, and spatial persistence. The GIS-based directional framework provides an operational basis for identifying priority periods and locations for targeted fire monitoring and prevention.

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Introduction

Forest fires are among the most recurrent environmental disturbances in Thailand, particularly during the dry season, when biomass burning contributes to ecosystem degradation, carbon emissions, and severe haze pollution. In Thailand, burning from forestland and agricultural areas is a major source of particulate matter, especially PM_{2.5}, and its impacts are most

pronounced in the northern and western regions during dry months (Junpen et al., 2020; Suriyawong et al., 2023). Previous studies have also shown that the occurrence of forest fires in Thailand is strongly seasonal and spatially structured rather than randomly distributed across landscapes (Talukdar et al., 2024).

The occurrence of forest fires in Thailand is influenced by aridity, vegetation moisture, temperature,

precipitation, and topographic setting (Talukdar et al., 2024). Deciduous forest formations, especially those on upland terrain and moderate slopes, are widely recognized as highly fire-prone environments (Junpen et al., 2013; Talukdar et al., 2024). Repeated burning can further alter fuel characteristics, forest structure, and regeneration dynamics in mixed deciduous forest systems (Chernkhunthod and Hioki, 2020a; b). These conditions are especially relevant to Tak Province, where extensive deciduous forests, mountainous terrain, and recurrent dry-season burning create favorable conditions for repeated hotspot occurrence.

Satellite remote sensing has substantially improved the capacity to monitor active fires across large areas and short time intervals. Active-fire products are widely used for near-real-time detection, seasonal monitoring, and wildfire assessment from local to global scales (Cunningham et al., 2024; Jones et al., 2024; Schroeder et al., 2014; Wooster et al., 2021). Among these, the Visible Infrared Imaging Radiometer Suite (VIIRS) 375 m active-fire product is particularly suitable for short-term spatiotemporal fire analysis because it improves the detection of smaller and lower-intensity fires relative to earlier coarse-resolution sensors (Dong et al., 2023; Giglio et al., 2016; He et al., 2024; Schroeder et al., 2014). However, hotspot data are most informative when integrated with geographic analysis, which is capable of revealing how fire activity shifts, becomes concentrated, and reorganizes over time (Wooster et al., 2021; Zhang et al., 2024).

Despite these advances, most fire studies in Thailand continue to emphasize annual, monthly, or seasonal hotspot totals and broad fire-risk relationships (Talukdar et al., 2024). Recent wildfire studies increasingly highlight the importance of examining short-term and seasonal spatiotemporal dynamics because fire activity can change rapidly in response to vegetation moisture, weather conditions, topography, and land-scape configuration (Deng et al., 2025; Fu et al., 2023; Xu et al., 2024; Zhang et al., 2024). Less attention has been given to weekly fire dynamics in Thailand, particularly in ways that capture how hotspot activity changes through time, becomes directionally organized, expands across mountainous forest terrain, and repeatedly reoccupies specific locations. This limitation is important because wildfire dynamics are defined not only by hotspot frequency but also by spatial displacement, directional spread, temporal changes in topographic characteristics, and recurrence structure.

Beyond conventional hotspot counts and fire risk mapping, spatial direction statistics provide a complementary approach for examining how fire activity is relocated and reorganized across a landscape over time. The mean center summarizes the average geographic position of a point distribution and can be used to track the temporal displacement or migration of

hotspot activity between consecutive periods. The standard deviational ellipse (SDE) extends this interpretation by describing the dominant orientation, dispersion, and elongation of the spatial distribution, thereby revealing whether hotspot occurrence is broadly dispersed, directionally concentrated, or changes in its principal axis over time (Yuill, 1971). Recent forest fire research has also demonstrated that hotspot analysis, centroid displacement, and standard deviational ellipses can reveal temporal changes in fire concentration, spatial dispersion, and directional organization across landscapes (Kim et al., 2025; Shao et al., 2023).

Unlike fire risk modeling, which estimates the relative influence of environmental or human-related predictors on fire occurrence, the present study uses weekly mean-center trajectories and SDEs to characterize the observed movement, orientation, and seasonal reorganization of hotspot activity. This GIS-based directional perspective therefore provides the central analytical framework for interpreting how forest fire hotspots evolve across space and time in Tak Province.

GIS-based directional analysis provides a useful framework for addressing this gap. Spatial statistical techniques such as the mean center and standard deviational ellipse can quantify shifts in spatial concentration, directional orientation, and centroid movement through time (Yuill, 1971). However, their integration with weekly hotspot concentration, temporal changes in topographic characteristics, and persistent recurrence remains limited in the Thai context.

Therefore, in this study, the weekly spatiotemporal spread dynamics of forest fire hotspots in Tak Province, Thailand, were investigated using VIIRS hotspot data and GIS-based directional analysis. The analysis focuses on four interrelated dimensions: (1) weekly hotspot distribution, (2) directional spread, (3) temporal changes in the topographic characteristics of hotspot occurrence, and (4) persistent hotspot clusters. By integrating temporal concentration, spatial directionality, topographic characteristics of hotspot occurrence through time, and persistence mapping, this study aims to provide a more operational understanding of wildfire dynamics in northern and western Thailand and to support more spatially targeted fire monitoring, prevention, and management in mountainous forest landscapes.

Materials and methods

1) Study area and temporal framework

The study was conducted in forested areas of five districts in Tak Province, western Thailand: Ban Tak, Mae Ramat, Mae Sot, Mueang Tak, and Sam Ngao. The study area extends from 427,875.07 to 549,924.08 m E and from 1,828,001.85 to 1,971,812.93 m N in the WGS 1984 UTM Zone 47 N coordinate system. It

covers 8,825.45 km², of which forests account for 68.89% of the total area. The elevation ranges from 91 to 1,922 m above mean sea level, reflecting substantial topographic heterogeneity across the landscape. Such mountainous forest settings are important for fire analysis because elevation, slope, terrain roughness, and vegetation type can influence the spatial organization of fire occurrence (Deng et al., 2025; Talukdar et al., 2024; Xu et al., 2024). The forest matrix is dominated by deciduous formations, particularly dry dipterocarp forest and mixed deciduous forest, which are commonly associated with dry-season fire activity in mainland Southeast Asian forest landscapes

(Chernkhunthod and Hioki, 2020a; b; Junpen et al., 2013; Talukdar et al., 2024) (Figure 1).

The analysis covered five fire seasons from 2021 to 2025. For temporal consistency, each fire season was defined from 1 December of the preceding year to the late dry season of the target year; accordingly, the 2021 fire season began on 1 December 2020. Each season was divided into 24 consecutive weekly periods, with week 1 corresponding to 1–7 December. This weekly framework was applied consistently throughout the analyses of hotspot distribution, directional spread, temporal changes in the topographic characteristics of hotspot occurrence, and persistent hotspot clusters.

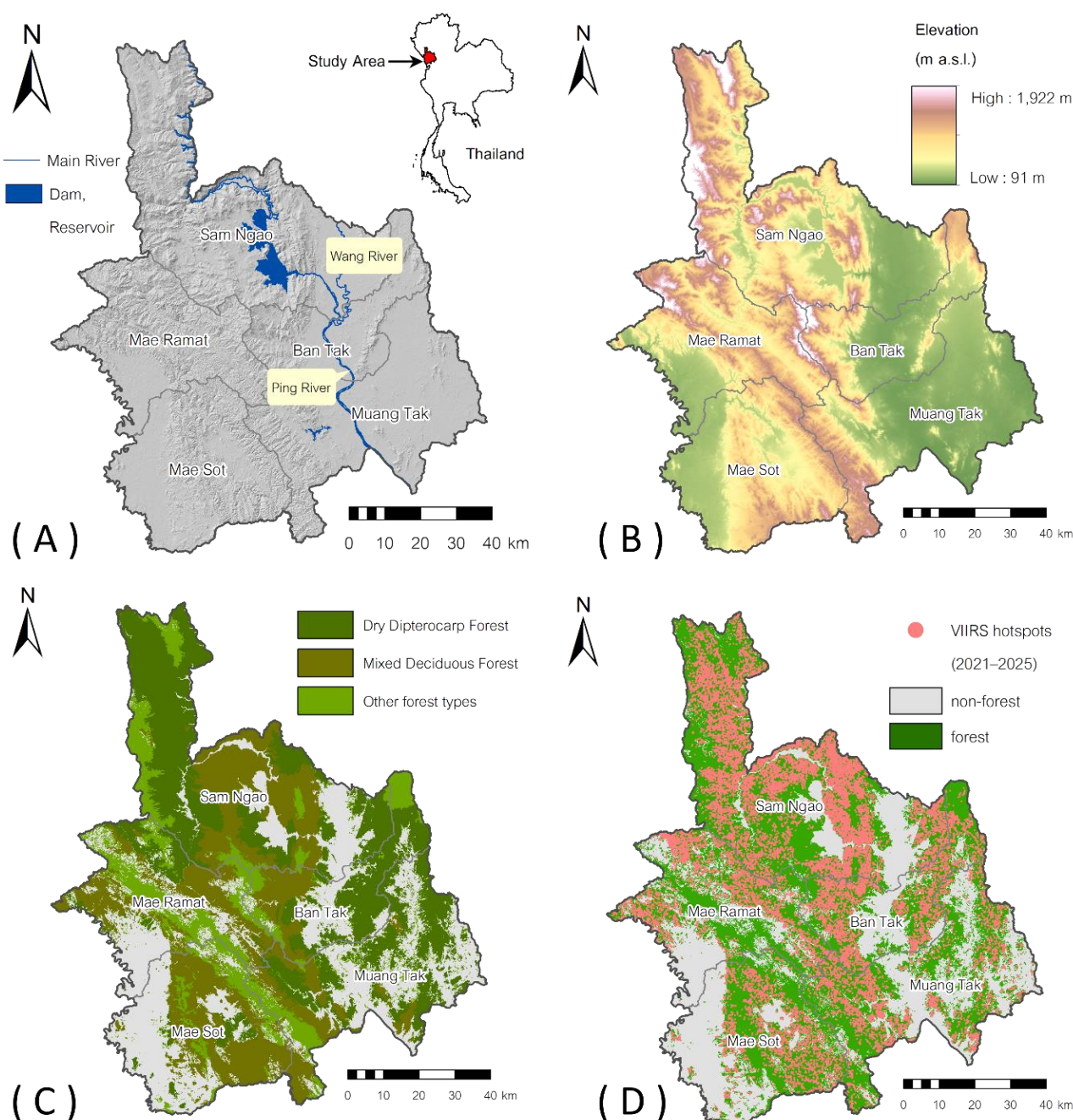


Figure 1 Study area and environmental context of the analysis in Tak Province, Thailand: (A) study area location and district boundaries, (B) elevation, (C) dominant forest types, and (D) forestland and nonforest areas with VIIRS hotspots (2021–2025).

2) Data sources

In this study, VIIRS active-fire hotspot records, Sentinel-2 multispectral imagery, Shuttle Radar Topography Mission (SRTM) elevation data, and GIS-derived forest and distance-based layers were integrated. VIIRS active-fire hotspots were used as the primary fire dataset (NASA, 2026). The Sentinel-2 imagery was processed in the Google Earth Engine to derive the normalized difference moisture index (NDMI) for weekly moisture profiling at hotspot locations (Copernicus Programme, n.d.; Gorelick et al., 2017). Elevation data were obtained from the SRTM 1 arc-second global digital elevation model (DEM) (U.S. Geological Survey, 2018), from which the slope and terrain roughness index (TRI) were derived in GIS.

The 2025 forest boundary was obtained from the Royal Forest Department forest-area mapping dataset

(Royal Forest Department, 2025), whereas the forest-type data were obtained from the 2019 Royal Forest Department forest-type mapping dataset (Royal Forest Department, 2019). Forest polygons were used to delineate the forest study area and generate the forest interior distance (FID), whereas forest-type classes were overlaid with hotspot locations to determine the hotspot composition by forest type. Administrative boundaries and drainage networks were obtained from the Tak Province spatial database provided by the Land Development Department and were used as contextual layers for map preparation and spatial interpretation (Land Development Department, 2021). A hillshade was derived from the Shuttle Radar Topography Mission digital elevation model and used to represent the terrain context. A summary of the spatial data layers and their preparation procedures is presented in Table 1.

Table 1 Spatial data layers used in this research

Deriving factors (theme)	Year/period	Sources and data preparation
VIIRS active-fire hotspots	2021–2025 fire seasons	Retrieved from the NASA Fire Information for Resource Management System (FIRMS). Hotspot records were clipped to the forest study area, checked for acquisition date and location, and assigned to 24 consecutive weekly periods beginning on 1 December for each fire season.
Forest type	2019	Derived from the Royal Forest Department forest-type mapping dataset. Forest-type classes were spatially overlaid with hotspot locations to determine hotspot composition by forest type.
Forest boundary	2025	Derived from the Royal Forest Department forest-area mapping dataset. The 2025 forest boundary was used to delineate the forest study area, clip hotspot records, generate Forest Interior Distance (FID), and create the fishnet persistence grid.
Normalized difference moisture index (NDMI)	2021–2025	Derived from Sentinel-2 multispectral imagery processed in Google Earth Engine. Cloud-affected pixels were masked before calculating NDMI, and weekly mean NDMI values were extracted at hotspot locations.
Elevation (Digital elevation model; DEM)	2020	Obtained from the Shuttle Radar Topography Mission (SRTM) 1 arc-second global DEM. Elevation values were extracted to hotspot locations for weekly and phase-based analysis.
Slope	2020	Generated from the SRTM DEM using the slope function in GIS. Slope values, expressed in degrees, were extracted to hotspot locations.
Terrain ruggedness index (TRI)	2020	Generated from the SRTM DEM using a neighborhood-based terrain ruggedness calculation in GIS. TRI values were extracted to hotspot locations to characterize terrain complexity.
Forest interior distance (FID)	2025	Generated from the forest boundary using Euclidean distance analysis in GIS. The resulting raster represented distance from forest edges toward interior forest areas and was extracted to hotspot locations.
Fishnet persistence grid	Generated in this study	A 1,000 × 1,000 m fishnet grid was generated and clipped to the 2025 forest boundary. Cumulative VIIRS hotspot detections from the five fire seasons (2021–2025) were aggregated to each grid cell and classified using predefined frequency intervals: Very Low, Low, Moderate, High, and Very High.
Administrative boundaries and drainage network	2021	Obtained from the Tak Province spatial database provided by the Land Development Department (2021). Administrative boundaries and drainage networks were used as contextual layers for map preparation and spatial interpretation.
Hillshade	2020	Derived from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model using GIS-based hillshade analysis to represent terrain context.

Note: VIIRS = Visible Infrared Imaging Radiometer Suite; NDMI = normalized difference moisture index; DEM = digital elevation model; TRI = terrain roughness index; FID = forest interior distance.

For temporal consistency, the hotspot records covered five fire seasons from 2021 to 2025. The environmental variables used for weekly profiling included the NDMI, elevation, slope, TRI, and FID. These layers were integrated into a unified geospatial database to support weekly hotspot distribution, directional spread, temporal changes in the topographic characteristics of hotspot occurrence, and persistent hotspot cluster analyses.

3) Hotspot data and preprocessing

Forest fire hotspot data were derived from VIIRS active-fire detections for five fire seasons (2021–2025) (NASA, 2026). Each record contained the geographic coordinates, acquisition date and time, and temporal attributes required for weekly classification. To standardize the intraseasonal analysis, all hotspot records were assigned to a 24-week fire-season framework, with Week 1 defined as 1–7 December. This weekly classification provided the temporal basis for all subsequent analyses.

The hotspot dataset was integrated with the forest type, NDMI, elevation, slope, TRI, and FID. The forest type was assigned to each hotspot through spatial overlay. NDMI values were extracted from Sentinel-2-derived weekly imagery, whereas elevation, slope, and TRI values were extracted from SRTM-derived raster layers. The FID was calculated as the Euclidean distance from the forestland boundary to the interior forestland areas. These variables were summarized by week, seasonal phase, or persistence class according to the objective of each analysis.

4) Analytical framework

The analytical workflow comprised four sequential components: (1) weekly hotspot distribution analysis, (2) directional analysis of hotspot spread, (3) temporal changes in the topographic characteristics of hotspot occurrence, and (4) persistent hotspot cluster analysis (Figure 2).

5) Weekly hotspot distribution analysis

Weekly hotspot distribution analysis was conducted to characterize the temporal concentration and environmental context across the 24-week fire season. All hotspot records were grouped by week to calculate weekly hotspot counts and their proportional contributions to the seasonal total. Hotspot composition by forest type was then summarized to identify the dominant vegetation settings associated with fire occurrence. In addition, selected environmental indicators, including elevation, forest interior distance, and NDMI, were summarized weekly to examine changes in topographic position, forest interior penetration, and vegetation moisture conditions over time (Fu et al., 2023; Gao, 1996; He et al., 2026; Marino et al., 2024; Yebra et al., 2013).

For each weekly period, the mean value of an environmental variable was calculated as the arithmetic mean of the values extracted at all hotspot locations during that week. To facilitate interpretation, weekly hotspot counts and environmental summaries were further aggregated into three seasonal phases: early (Weeks 1–7), middle (Weeks 8–16), and late (Weeks 17–24).

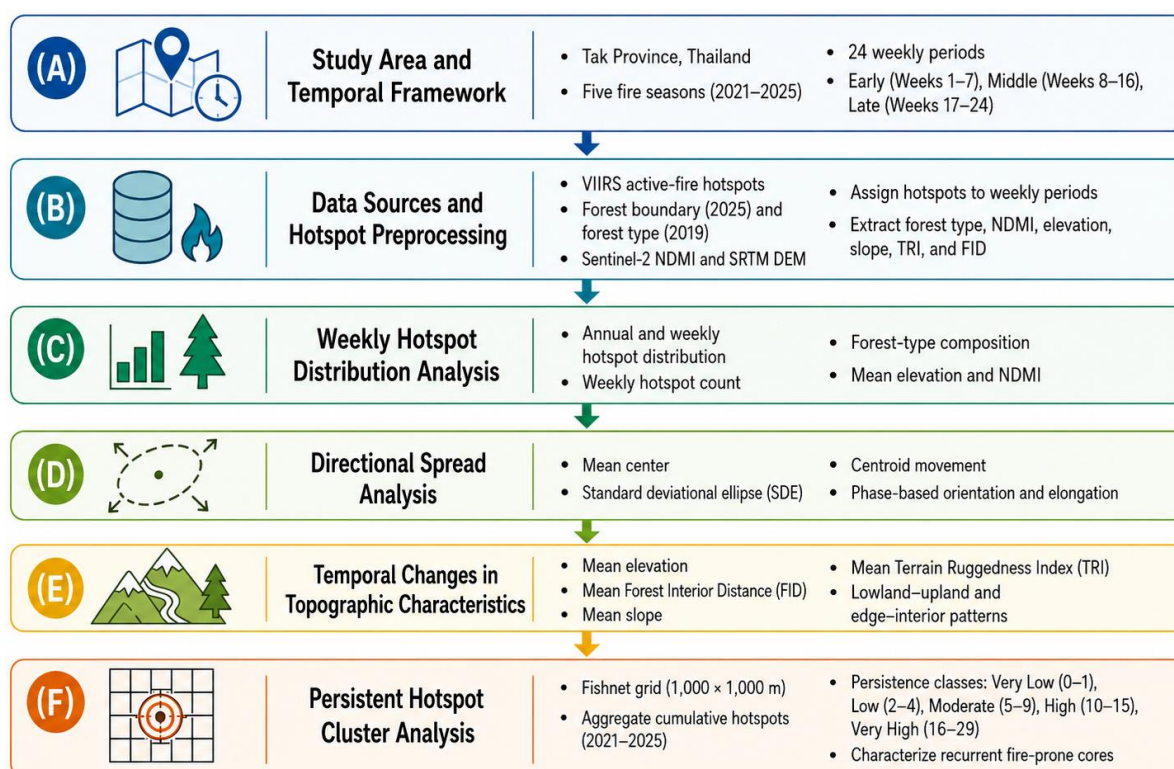


Figure 2 Methodological framework of the study.

6) Directional analysis of hotspot spread

Directional analysis was conducted to evaluate weekly changes in the spatial center, orientation, and extent of hotspot occurrence. For each of the 24 weekly periods, a mean center was calculated to represent the average geographic position of hotspot activity. Consecutive weekly mean centers were then compared to assess centroid displacement over time. Standard deviational ellipse statistics were used to characterize the directional geometry, including the dominant orientation and degree of elongation of hotspot distributions. These indicators were subsequently summarized into early, middle, and late fire-season phases (Shao et al., 2023; Yuill, 1971).

7) Temporal changes in the topographic characteristics of hotspots

This analysis examined whether hotspot occurrence shifted toward higher, more interior, and more rugged forest environments as the fire season developed. Weekly mean values of elevation, forest interior distance, slope, and terrain ruggedness were calculated for hotspot records in each weekly period and then compared across the early, middle, and late phases. Hotspot records were also grouped into elevation and forest interior distance classes to evaluate changes in concentration across lowland-upland and edge-interior forest environments (Deng et al., 2025; Guo et al., 2024; Liu et al., 2024a; b; Talukdar et al., 2024; Xu et al., 2024).

8) Persistent hotspot cluster analysis

Persistent hotspot cluster analysis was conducted to identify areas of repeated forest fire occurrence across the full study period and to distinguish recurrent fire-prone cores from the broader background of low-frequency hotspot activity. Grid-based hotspot aggregation and recurrence mapping are typically used to identify spatially stable fire-prone zones and support targeted fire monitoring (Bastarrika et al., 2024; Chartasa, 2021; Peris-Llopis et al., 2024; Talukdar et al., 2024). A regular fishnet grid with a cell size of 1,000 × 1,000 m was generated to cover the forest study area. The grid was clipped to the forest boundary to ensure that the analysis represented only forest fire hotspots.

All VIIRS forest fire hotspot records from the five fire seasons (2021–2025) were spatially joined to the fishnet grid. The cumulative number of hotspot detections within each grid cell was then calculated. Each cell was assigned a persistence value equal to the total number of recorded hotspots during the study period. Grid cells located outside the 2025 forest boundary were excluded from the analysis. Forest grid cells with zero or one hotspot detection were retained and classified as the very low persistence class.

The resulting hotspot frequency values ranged from 0 to 29 detections per grid cell and were classified into five persistence levels using frequency-based intervals: very low (0–1 hotspots), low (2–4 hotspots), moderate (5–9 hotspots), high (10–15 hotspots), and very high (16–29 hotspots). The high- and very high-persistence classes were interpreted as recurrent fire-prone cores because they represented grid cells with repeated hotspot occurrence over multiple fire seasons. These cells were further characterized using the forest type, elevation, forest interior distance, slope, and TRI to identify the environmental setting of the recurrent fire-prone zones.

Results

1) Annual spatial distribution of forest fire hotspots

The annual hotspot distribution varied markedly across the five fire seasons. The 2023 fire season recorded the greatest number of forest fire hotspots ($n = 6,282$), followed by 2025 ($n = 6,070$), 2021 ($n = 5,178$), and 2024 ($n = 4,959$), whereas 2022 showed substantially lower activity ($n = 941$). Despite this interannual variation in hotspot abundance, recurrent hotspot concentrations were generally observed within the broader deciduous mountain-forest landscape of the study area. These annual patterns provide the spatial context for the subsequent weekly directional analysis (Figure 3).

2) Weekly forest fire distribution

Forest fire hotspots in Tak Province exhibited a strongly concentrated weekly pattern across the 24-week fire season. A total of 23,430 hotspots were recorded, but their temporal distribution was highly uneven. The activity remained very low during the first weeks before increasing sharply after week 7. The main fire period occurred during Weeks 8–16, which together accounted for 20,957 hotspots (89.45%), whereas Weeks 1–7 and Weeks 17–24 contributed only 2.13% and 8.43%, respectively. The seasonal peak was reached in week 16, with 3,734 hotspots (15.94% of the seasonal total). Overall, the weekly fire regime was characterized by a short but intense middle-season pulse rather than a gradual seasonal progression.

The weekly fire regime was dominated by deciduous forest landscapes throughout the season. Dry dipterocarp forest and mixed deciduous forest together accounted for more than 96% of all hotspots, confirming that the seasonal hotspot pulse in Tak Province was fundamentally associated with the deciduous forest mosaic. The increase in hotspot occurrence was also accompanied by a clear environmental shift toward higher and more interior

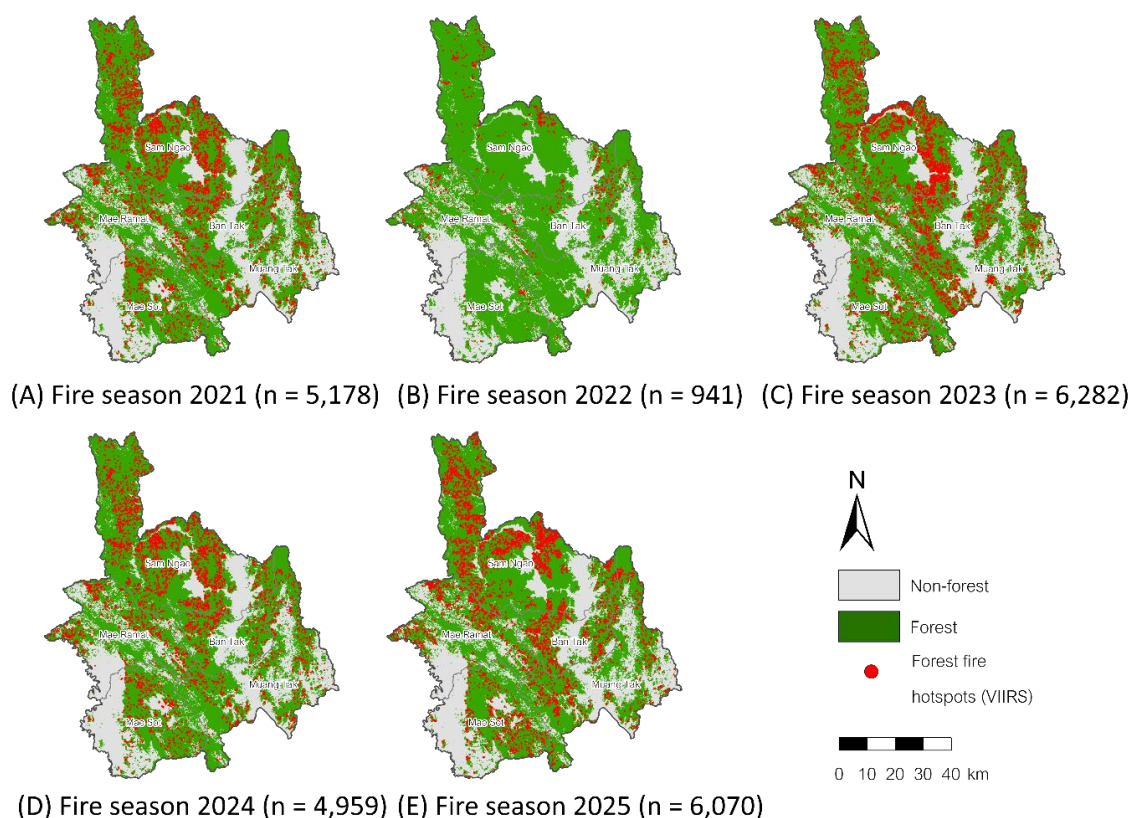


Figure 3 Annual spatial distribution of forest fire hotspots in Tak Province, Thailand, across the 2021–2025 fire seasons. Panels show the spatial distribution of VIIRS forest fire hotspots for each fire season. Each fire season was defined from 1 December of the preceding year to the late dry season of the target year.

forest environments. The mean hotspot elevation increased from 414.43 m in Week 1 to 576.62 m in Week 16, while the forest interior distance increased markedly during the rising and middle phases, indicating that the main fire period was associated with expansion into broader upland and interior forest environments.

NDMI showed substantial weekly variability but still provided a meaningful seasonal context. Lower NDMI values occurred during the early-to-rising stage, corresponding to the period immediately before and during the first major increase in hotspot activity, whereas higher values appeared during the late phase after hotspot counts had declined. Taken together, these results indicate that the weekly forest fire distribution in Tak Province was shaped by strong seasonal concentrations, deciduous forest dominance, upslope movement, and deep forest penetration during the middle of the fire season (Figure 4).

3) Directional spread of forest fire hotspots

Directional analysis revealed that forest fire hotspots in Tak Province did not expand as simple one-way fronts. Instead, the spatial center of hotspot occurrence shifted repeatedly through time, indicating an oscillating but seasonally organized spread pattern within a persistent mountain–forest corridor. During the

24-week fire season, the cumulative movement of the weekly mean center reached approximately 212.62 km, with the greatest weekly displacement occurring between Week 1 and Week 2 (40.30 km). These results indicate substantial spatial reorganization of hotspot activity over time but suggest that hotspot spread remained constrained within the same broader fire-prone system.

A clear seasonal contrast was evident in centroid movement and ellipse geometry. During the early phase (Weeks 1–7), the mean weekly centroid movement was 15.26 km, and the hotspot orientation was relatively unstable, with a mean rotation of 96.71° and an elongation ratio of 1.72. During the middle phase (Weeks 8–16), the mean weekly centroid movement decreased to 6.33 km, whereas the mean orientation became more consistently northwest–southeast (153.31°). This phase retained a relatively elongated spatial pattern, with a mean elongation ratio of 1.64, indicating that the most organized directional hotspot configuration occurred during the fire season. During the late phase (Weeks 17–24), the mean weekly centroid movement increased slightly to 8.01 km, whereas the elongation ratio decreased to 1.50, indicating spatial contraction despite continued directional organization.

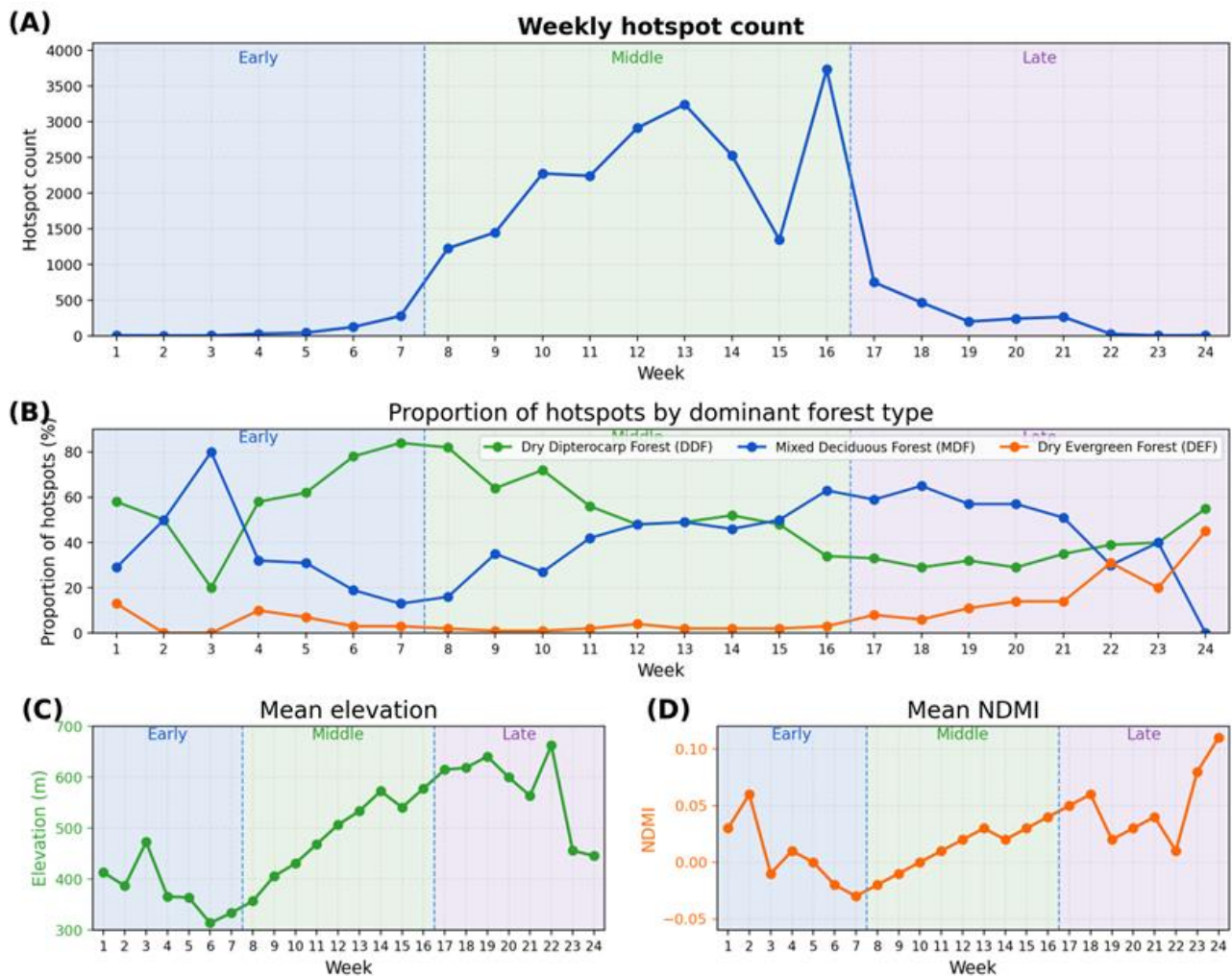


Figure 4 Weekly hotspot dynamics in Tak Province, Thailand: (A) weekly hotspot count, (B) proportional hotspot composition by dominant forest type, (C) weekly mean elevation, and (D) weekly mean NDMI.

Taken together, the mean-center trajectory and standard deviational ellipse analyses indicate that the spread of directional hotspots became most spatially coherent during the middle of the fire season (Figure 5).

4) Temporal changes in topographic characteristics of forest fire hotspots

The weekly hotspot records revealed clear temporal changes in the topographic characteristics of forest fire activity in Tak Province. Hotspot occurrence progressively shifted toward higher elevations, deeper forest interiors, steeper slopes, and more rugged terrain as the fire season developed. This pattern indicates that the seasonal fire regime was not only concentrated in time but also increasingly associated with interior upland forest environments.

A pronounced upslope shift was observed across the three fire-season phases. The mean hotspot elevation increased from 335.15 m during the early phase (Weeks 1–7) to 503.30 m during the middle phase (Weeks 8–16) and further to 609.62 m during the

late phase (Weeks 17–24). The middle phase accounted for 20,957 hotspots, or 89.45% of all recorded hotspots, indicating that it represented the principal period of hotspot concentration across upland forestland landscapes. At the weekly scale, the elevation increased throughout the core fire period and remained relatively high during the late season.

The forest interior distance showed a similar seasonal transition. The mean forest interior distance increased from 644.97 m during the early phase to 903.32 m during the middle phase before declining to 759.52 m during the late phase. This finding indicates that the middle fire season represented the period of strongest penetration into interior forest environments. Early-season hotspots were more frequently located near forest boundaries, whereas the main fire period was associated with substantially deeper forest locations.

Topographic complexity also increased as the season progressed. The mean slope increased from 10.76° during the early phase to 17.05° during the middle phase and 18.81° during the late phase.

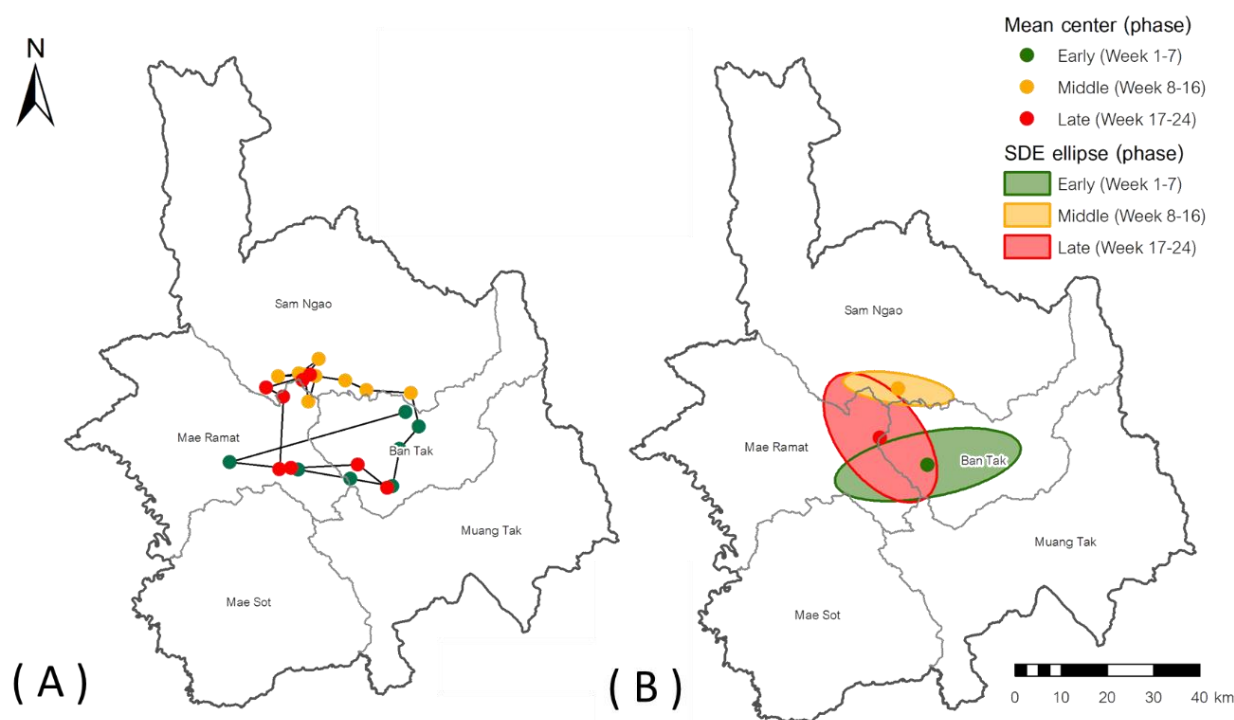


Figure 5 Directional spread of forest fire hotspots in Tak Province, Thailand: (A) weekly mean-center trajectories showing centroid shifts across the early (Weeks 1–7), middle (Weeks 8–16), and late (Weeks 17–24) fire-season phases; and (B) seasonal standard deviational ellipses showing changes in orientation, directional concentration, and spatial extent. The mean weekly centroid movement was 15.26 km, 6.33 km, and 8.01 km during the early, middle, and late phases, respectively.

The mean TRI increased in parallel from 12.40 to 19.75 and 21.91. These results indicate that hotspot occurrence became increasingly associated with steeper and more dissected mountain terrain throughout the fire season. Overall, the middle phase represented the principal period of hotspot concentration in interior upland forests, whereas the late phase presented the highest average elevation, slope, and terrain ruggedness (Figure 6).

5) Persistent forest fire clusters

The fishnet-based analysis revealed a markedly uneven pattern of recurrent fire occurrence across the study area. When a 1,000 × 1,000 m grid was used, most cells fell within the very low (0–1 hotspot) and low (2–4 hotspot) persistence classes, accounting for 4,566 cells or 75.10% of the total grid system. In contrast, the high (10–15 hotspots) and very high (16–29 hotspots) classes together represented only 353 cells, or 5.81% of the total grid system. These results indicate that repeated fire occurrence in Tak Province was highly spatially selective and concentrated in a limited number of stable fire-prone cores rather than distributed broadly across the landscape.

High- and very high-persistence cells were overwhelmingly concentrated in deciduous forest landscapes, particularly mixed deciduous forest (50.41%) and dry dipterocarp forest (48.96%). Their environmental cha-

racteristics strongly correlated with interior mountain forests, with a mean elevation of 535.46 m, mean forest interior distance of 1,092.85 m, mean slope of 18.36°, and mean TRI of 21.04. Overall, the persistence results indicate that repeated fire occurrence in Tak Province was concentrated in a limited number of spatially stable fire-prone cores, which should be treated as priority zones for targeted monitoring and management (Table 2; Figure 7).

Discussion

The results show that forest fire activity in Tak Province was not only strongly seasonal but also spatially structured across the mountain-forest landscape. The marked concentration of hotspots in Weeks 8–16, together with the dominance of dry dipterocarp forest and mixed deciduous forest, is consistent with previous studies showing that dry-season fire occurrence in Thailand is concentrated in deciduous forest systems and is closely associated with aridity, vegetation conditions, and topographic setting (Chernkhunthod and Hioki, 2020a; b; Junpen et al., 2013; 2020; Suriyawong et al., 2023; Talukdar et al., 2024). Similar seasonal and spatial concentration patterns have also been reported in recent active-fire and hotspot-based studies in Asia, where VIIRS and MODIS fire records have been used to characterize fire seasonality, interannual variability,

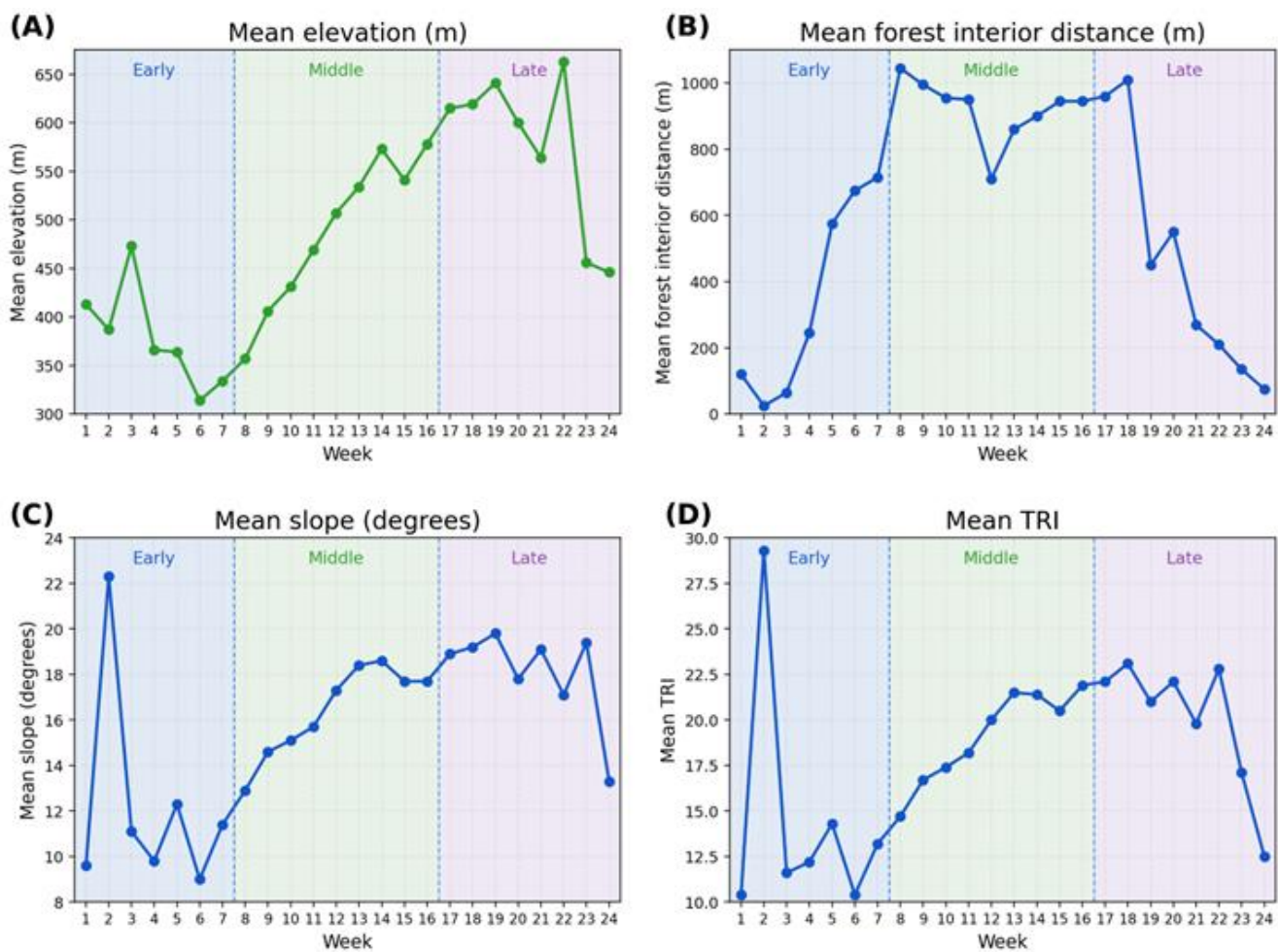


Figure 6 Temporal changes in the topographic characteristics of forest fire hotspots in Tak Province, Thailand: (A) weekly mean elevation, (B) weekly mean forest interior distance, (C) weekly mean slope, and (D) weekly mean terrain ruggedness index (TRI). Across the early, middle, and late phases, the mean elevation increased from 335.15 m to 503.30 m and 609.62 m, respectively, whereas the mean slope increased from 10.76° to 17.05° and 18.81°, respectively.

and regional fire-prone zones (Chart-asa, 2021; Deng et al., 2025; Dong et al., 2023; He et al., 2024; Xu et al., 2024). This study extends that literature by demonstrating that the seasonal fire regime can be resolved more clearly at the weekly scale, revealing a short but intense middle-season pulse rather than a gradual seasonal progression.

A key contribution of the study is that the middle fire season was not only the period with the highest hotspot abundance but also the period with the strongest spatial organization. The mean center trajectory and standard deviation ellipse analyses indicate that hotspot spread became more directionally coherent during the middle phase. This finding is consistent with recent forest fire research showing that hotspot analysis, centroid displacement, and standard deviational ellipses can reveal temporal changes in fire concentration, spatial dispersion, and directional organization that are not apparent from fire counts alone (Kim et al., 2025; Shao et al., 2023; Yuill, 1971). The Tak results further suggest that hotspot activity

remained organized within a broader mountain-forest corridor rather than dispersing randomly across the landscape.

The northwest–southeast alignment of the seasonal hotspot corridor broadly corresponds to the prevailing mountain–forest configuration of the study area shown in Figure 1. This correspondence suggests that the observed directional organization was spatially constrained within the broader configuration of continuous forest and mountainous terrain. Recent studies have also shown that topography, vegetation structure, and landscape configuration can influence the spatial pattern of forest fire occurrence and burn severity in mountainous forest regions (Guo et al., 2024; Liu et al., 2024a; b; Xu et al., 2024; Zhang et al., 2025). However, the present analysis was designed to characterize hotspot movement and directional concentration rather than to quantify the causal effects of terrain structure, wind fields, fuel continuity, accessibility, or human ignition sources.

Table 2 Persistence structure and environmental characteristics of recurrent forest fire hotspot cells in Tak Province, Thailand

Class (Frequency range)	Cells	%	Dominant forest type(s)	Mean DEM (m)	Mean FID (m)	Mean slope (°)	Mean TRI
Very Low (0–1)	3,043	50.05	–	–	–	–	–
Low (2–4)	1,523	25.05	–	–	–	–	–
Moderate (5–9)	1,161	19.10	–	–	–	–	–
High (10–15)	314	5.16	MDF, DDF	533.02	1,103.33	18.33	21.03
Very High (16–29)	39	0.64	MDF, DDF	555.28	1,007.98	18.58	21.11

Note: MDF = mixed deciduous forest; DDF = dry dipterocarp forest; FID = forest interior distance; DEM = digital elevation model; TRI = terrain ruggedness index.

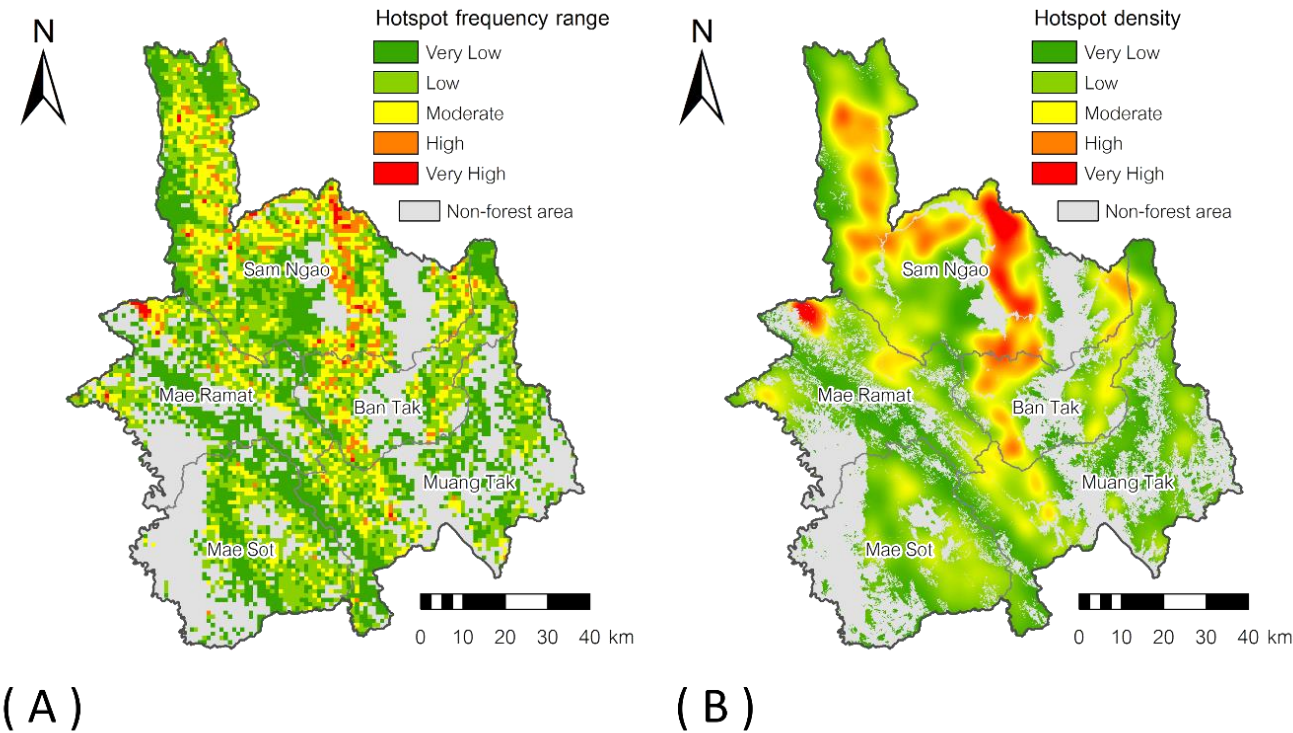


Figure 7 Persistent forest fire hotspot patterns in Tak Province, Thailand: (A) fishnet hotspot counts and (B) hotspot density derived from cumulative VIIRS hotspot records, 2021–2025.

The temporal changes in the topographic characteristics of hotspot occurrence further reinforce this interpretation. From the early to late fire season, hotspot occurrence shifted toward higher elevations, greater forest interior distance, steeper slopes, and higher terrain ruggedness. This finding indicates that the seasonal fire regime not only intensified numerically but also progressively expanded upward and inland into more rugged interior forest environments. This pattern is consistent with studies showing that elevation, slope, rugged terrain, and forest type can shape fire occurrence, fire spread, and burn-severity patterns in subtropical and mountainous forests (Deng et al., 2025; Guo et al., 2024; Liu et al., 2024a; b; Xu et al., 2024). The NDMI results also support this seasonal transition. Although the NDMI did not function as a strict week-by-week predictor, its lower values during the early-to-rising stage and higher values during the declining stage are consistent with broader fire literature identifying vegetation water content and live

fuel moisture as important controls on ignitability and fire activity (Fu et al., 2023; Gao, 1996; He et al., 2026; Marino et al., 2024; Yebra et al., 2013).

Another important finding is that fire recurrence was highly spatially selective. Most of the landscape fell within the very low and low persistence classes, whereas only a small proportion of cells formed high and very high persistence clusters. This finding indicates that repeated fire occurrence in Tak Province was concentrated within a limited number of stable fire-prone cores rather than distributed diffusely across the forest matrix. Similar grid-based and hotspot-based approaches have been used to identify clustered or recurrent fire-prone areas for monitoring and management in other fire-prone regions (Bastarrika et al., 2024; Chart-asa, 2021; Peris-Llopis et al., 2024; Talukdar et al., 2024). The environmental profile of these cells, characterized by deciduous forest dominance, relatively high elevation, substantial forest interior distance, and rugged terrain, suggests that persistent fire activity was

concentrated in interior upland forests rather than in lowland edge environments.

Taken together, the results suggest that forest fire dynamics in Tak Province are best understood as a seasonally concentrated, directionally organized, mountain-forest fire system with persistent recurrent cores. This interpretation has direct management implications. The middle fire season should be treated as the principal intervention window, while monitoring and prevention efforts should prioritize upland deciduous forest corridors, interior forest zones, and recurrent persistence hotspots. Recent work on operational fire monitoring, burned-area mapping, and multisource remote sensing also supports the value of integrating active-fire records with higher-resolution burned-area and environmental datasets for more targeted fire management (Bastarrika et al., 2024; Gao et al., 2025; Padilla et al., 2026).

Limitations and future work

This study should be interpreted within the scope of hotspot-based spatiotemporal analysis. First, VIIRS hotspot data represent active-fire detections rather than the total burned area, fire intensity, or burn severity. The results therefore reflect the spatial and temporal patterns of detected fire activity but do not fully capture the complete ecological impact of each fire event. Second, some early and late fire season weeks contain relatively few hotspot observations, which may reduce the stability of weekly direction statistics and phase-based comparisons. Third, the study emphasized descriptive-spatial interpretation and did not explicitly model causal relationships among hotspot occurrence, climate variability, fuel conditions, and human activities.

Future research should integrate hotspot analysis with burned-area products, fire severity indicators, and higher-temporal-resolution environmental data to improve the interpretation of weekly fire dynamics (Bastarrika et al., 2024; Gao et al., 2025; Padilla et al., 2026). Greater attention should also be given to anthropogenic drivers, such as land use practices, accessibility, and settlement proximity, which may help explain why recurrent fire-prone cores persist in specific mountain-forest corridors. In addition, a comparative analysis across provinces or fire seasons with different climatic conditions would help test the broader applicability of the weekly GIS-based framework developed in this study.

Future research should integrate time-matched wind fields, fuel-moisture conditions, forest fuel continuity, accessibility, land-use practices, and ignition-source information within spatially explicit modeling frameworks to quantify the mechanisms underlying the observed northwest-southeast directional pattern (He et al., 2026; Liu et al., 2024a; b; Zhang et al., 2025).

Conclusion

This study demonstrated that forest fire hotspot activity in Tak Province followed a strongly structured weekly spatiotemporal pattern rather than a random sequence of isolated fire events. Fire occurrence was highly concentrated in the middle of the fire season, with 89.45% of all hotspots recorded during Weeks 8–16, and was dominated by dry dipterocarp forest and mixed deciduous forest. Directional analysis revealed that hotspot spread was seasonally reorganized, with the middle phase exhibiting the clearest directional concentration and the strongest spatial coherence. Analysis of temporal changes in topographic characteristics further revealed a shift in hotspot occurrence toward higher elevations, deeper forest interiors, steeper slopes, and more rugged terrain. In addition, a persistence analysis revealed that repeated fires were concentrated in a limited number of stable fire-prone cells rather than distributed broadly across the landscape. Taken together, these findings indicate that wildfire activity in Tak Province can be understood through four interrelated dimensions: seasonal concentration, directional spread, temporal changes in topographic characteristics, and spatial persistence. This weekly GIS-based framework provides a more operational basis for targeted fire monitoring, prevention, and management in mountainous forest landscapes. Future work should integrate burned-area and fire-severity products with time-matched meteorological, fuel-moisture, and ignition-source data to further examine the mechanisms underlying the observed weekly directional patterns.

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Data availability statement

Information and data used in the study will be disclosed upon request.

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Author contributions

Suphatphong Ruthamnong: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – Original draft, Writing – Review & editing, Visualization, Project administration, Funding acquisition

Conflicts of interest

The authors declare that there are no conflicts of interest in competing financial or personal relationships that could have appeared to influence the work reported in this work.

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