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Assessing the suppression difficulty of wildland fires for initial attack response

Adrián Cardil[A,B,C,*], Adrián Jiménez-Ruano[A], Santiago Monedero[A], Phillip SeLegue[D], Macarena Ortega[A,E], Raúl Quilez[A], Jeff Fuentes[D], Geoff Marshall[D], Robert Clark[D], Tim Chavez[D], Sergio de-Miguel[B,C], Tomás Quiñones[A], Fernando Bezares[A], Scott Purdy[A], Kristen Allison[F], Tim Metzger[A], Chris Waters[A], Midhun Mohan[G] and Joaquín Ramirez[A,H,*]

For full list of author affiliations and declarations see end of paper

***Correspondence to:**
Adrián Cardil
Technosylva Inc, La Jolla, CA, USA
Email: acardil@technosylva.com

Joaquín Ramirez
Technosylva Inc, La Jolla, CA, USA
Email: jramirez@technosylva.com

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ABSTRACT

Background. Fire simulation frameworks and decision support systems (DSSs) are critical tools in fire response dispatching that need to consider factors influencing fire spread and suppression difficulty while provide easily interpreted indexes. **Aims.** We present a new user-friendly Initial Attack Assessment (IAA) index, ranging from 1 to 5, designed to quickly and efficiently evaluate wildfires from their onset. **Methods.** We used 26,907 California's wildfire ignitions to run automatic simulations. The Fire Behavior Index (FBI), Terrain Difficulty Index (TDI) and IAA were determined using size-based and fire behavior outputs from each simulation. Initial attack success was evaluated by comparing simulations with real fire sizes. Binary models were calibrated and validated to predict success based on IAA, FBI and TDI, and suppression response time. **Key results.** The IAA effectively identified fires exceeding suppression capacity. Higher levels of IAA, FBI and TDI were associated with reduced success odds, IAA=5 giving a 90% decrease in the odds of initial attack success. Response time and its interaction with terrain difficulty were also influential. **Conclusions.** The IAA is a powerful index to feed DSSs, prioritizing fire response and predicting the probability of control at a small size. **Implications.** This ensures practicality for end-users, allowing agencies and utilities to better respond to wildfires.

Keywords: decision-making, dynamic wildfire risk modeling, FBI, Fire Behavior Index, fire simulators, fire suppression, IAA, Initial Attack Assessment, suppression difficulty, TDI, Terrain Difficulty Index, wildland fire.

Introduction

Wildfires are a global phenomenon with remarkable impacts on both the environment and economic realms (Molina-Terrén *et al.* 2019). In the context of changing fire regimes and more intense fires due to climate change (Duane *et al.* 2021), the importance of decision support systems (DSSs) aiming to aid fire suppression is increasing worldwide, particularly in the United States (Fillmore and Paveglio 2023). The California Department of Forestry and Fire Protection (CAL FIRE) has developed advanced DSSs since 2014. These include the Resource Deployment Index (RDI), a forecasting system that helps to optimize resource allocation before fires escalate, the Resource Deployment Strategy 2 (RDS 2), a real-time tool used during active incidents to improve deployment decisions, and the Incident Support Analysis (ISA), which provides incident-specific analysis to guide decision-making, ensuring that operations are aligned with the situation needs. These systems incorporate geospatial data, graphics coupled with operational fire behavior indicators such as fire ignition probability, behavior (intensity, rate of spread), fire simulations and weather forecasts (all these elements are integrated in Technosylva's Wildfire Analyst (WFA)). This allows CAL FIRE and other agencies to assess wildfire dynamic risks effectively.

DSSs operate across several phases of fire management including prevention, preparedness, detection, response and suppression, and recovery. Operational fire risk assessments enable forecasting of areas at risk, facilitating early warning and pre-organization of firefighting units on the territory (Calkin *et al.* 2011; Brown *et al.* 2021; Taylor and Nadeem 2022), and informing decision-making in the utility sector to mitigate ignition potential from electrical infrastructure (Technosylva 2025). Estimation of potential fire behavior is critical to assess fire risk and evaluate the probability of fires becoming large at the beginning of any fire events. In this sense, Initial Attack (IA) refers to fires that can be contained by the first resources dispatched, without a substantial augmentation and within the first several hours of the reported time (Merrill and Alexander 1987; Rashidi *et al.* 2018). Generally, early actions may be sizing up, patrolling, monitoring, holding action, or aggressive IA (National Wildfire Coordinating Group 2014). Efforts involved in the IA are coordinated by an incident commander, who sets fire spread containment objectives. In Mediterranean regions, fires that escape IA are those that result in the largest burned areas (Rodrigues *et al.* 2019). These fires have the potential to cause severe impacts on the environment, infrastructure and human lives, and they frequently incur the highest economic costs (Rideout *et al.* 2011; Rodrigues *et al.* 2020; Sakellariou *et al.* 2023). Recently, the rise of megafires has highlighted the need for better understanding and management of incipient wildfires (Varga *et al.* 2022). In this context, it has become essential to build more explicit indexes that group together the most significant factors in incipient fires aiming to explain the potential for a fire to exceed initial suppression attack.

IA success can be measured using different metrics such as final fire size and time to control fire spread, among others (Cardil *et al.* 2019). In the United States, CAL FIRE established a fire containment threshold objective of approximately 4 ha (10 acres) for all unplanned fires until under control during the first burning period (State of California, unpubl. data). Indeed, their target for a successful IA is high (95% of incidents). However, the substantial impact of only 3% or fewer of fires – which cause most of the impact – underlines the importance of this metric. Factors influencing fire suppression success in the IA are diverse and several studies have addressed this topic. Cardil *et al.* (2019) pointed out that fuel types, ignition cause and fire intensity significantly influenced IA success in eastern Canada. Rodrigues *et al.* (2019) stated that early detection, ground accessibility and aerial support governed the broad spatial pattern of fire containment probability. Other authors found that situational information about a fire obtained during IA provides better estimates of its initial containment success likelihood compared with models relying only on initial report data (Wheatley *et al.* 2022). In general terms, it seems that weather conditions, travel delay, slope and distance from roads are factors that allow acceptable discrimination of those wildfires contained to ∼4.9 hectares(Plucinski *et al.* 2023).

Here, we proposed an Initial Attack Assessment index (IAA) as a dynamic risk indicator easily comprehensible by operational end-users. It synthesizes the wildfire risk modeling implemented in Technosylva's WFA. Since its inception in 2019, fire agencies, electrical utilities and the insurance sector have employed the IAA index in both America and Europe. Its main advantage is that it brings together multiple factors in a single numerical and chromatic category, so that firefighting brigades already have an estimation of what to expect before they even see the fire. The IAA is the result of collaboration between CAL FIRE and Technosylva aiming to address California's challenging wildfires, with over 4 years of implementation demonstrating its value through extensive operational use. It was built based on expert criteria to summarize terrain difficulty and fire behavior metrics into a single index valuable for preparedness, dispatching, response and incident prioritization. Specifically, it aims to evaluate the difficulties anticipated by the response teams during the first 1–2 h after ignition time, being used by CAL FIRE to prepare the most appropriate emergency resources for dispatching and responding in the early phases of wildfires.

In this work, we sought to evaluate IAA index performance in terms of likelihood of IA success. Therefore, we explored how different fire behavior metrics and difficulty indices relate to IA outcomes. We collected and simulated a total of 26,907 wildfires retrieved from the Integrated Reporting of Wildfire Information (IRWIN) and examined the response time of fire suppression resources deployed by CAL FIRE for 9886 incidents. Our main objectives were: (a) assess the odds of IA success employing the proposed IAA index; (b) estimate wildfire potential when the IA failed; (c) explore the strength and sign of the associations between IA and the IAA levels and fire-terrain related sub-indices; (d) evaluate the contribution of response time of suppression resources in the prediction of IA success or fail; and (e) demonstrate the performance of the IAA index with recent incidents in other areas.

Materials and methods

Study area

The study area encompasses the entire territory of the state of California, USA. Over the last decades, wildfires significantly impacted both forested lands and wildland–urban interface areas within this region (Fig. 1). The main vegetation types are shrublands, forests and herbaceous according to the United States National Land Cover Database (NLCD), representing 39.0, 18.6 and 13.5% of the territory, respectively (Jin *et al.* 2019). The region is characterized by Mediterranean climate, with two main variations (California Department of Fish and Wildlife 2021): (a) a temperate climate along the Pacific coast and the western face of the Sierra

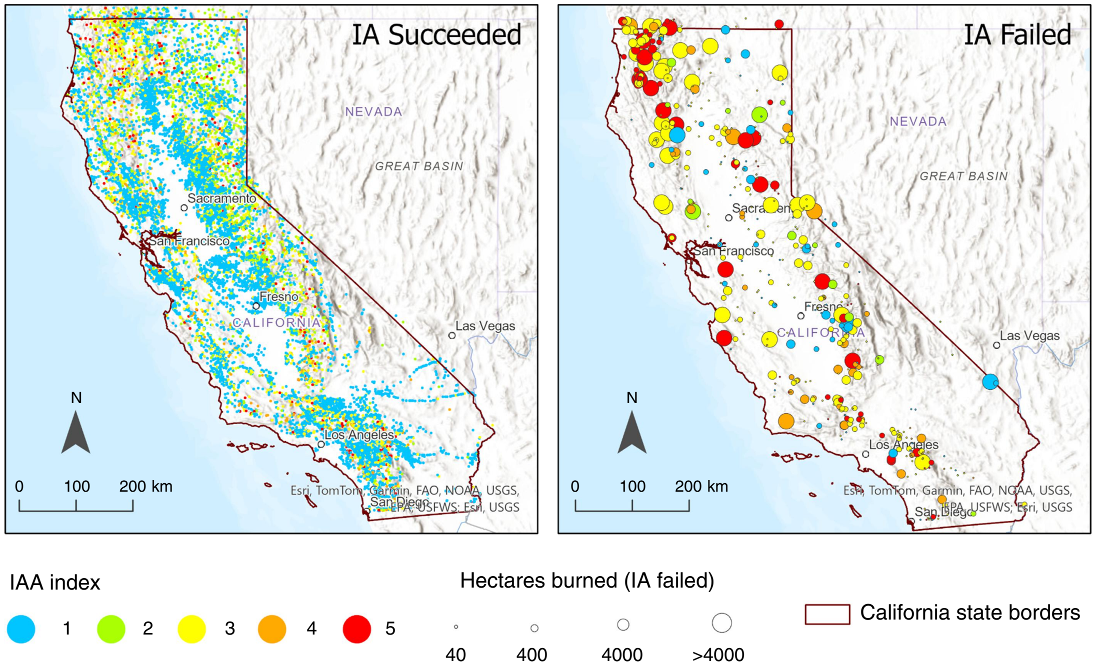


Fig. 1. Initial Attack Assessment index (IAA) for Californian fires retrieved by IRWIN from 2020 to 2023 (n = 26,907) considering the initial attack success (left: success (fire size <4 ha); right: fail (fire size >4 ha). Wildfires were independently simulated using WFA to obtain their corresponding IAA. The actual reported fire size is represented by graduated circles.

Nevada Ranges, and (b) more continental conditions in the hinterlands characterized by hotter summers and colder winters. In both areas, precipitation is concentrated during winter. In addition, there are north-to-south increasing and decreasing gradients in annual temperature and precipitation, respectively. From September to May, the dry and strong Diablo and Santa Ana winds typically come from the Great Basin towards the west, having a very marked desiccating effect, especially in early fall (autumn), when they produce great temperatures, noticeable drops in relative humidity and high wind gusts (Raphael 2003; Mass and Ovens 2019). As a result, wildfire risk and fire behavior increase considerably.

Data

Fire data

Wildfire data in the period 2020–2023 were retrieved from a total of 26,907 fire records in the IRWIN interagency database, which collects and reports fire events with a unique identification code for both federal and non-federal fires (Picotte *et al.* 2020). Its main advantage is that it facilitates the exchange of data between many wildland fire applications, reducing redundant data, and improving data consistency, accuracy and availability (National Interagency Fire Center 2023). Fire incidents reported across the US provide detailed information (Sanchez *et al.* 2021) and we selected the variables shown in Table 1.

CAL FIRE suppression data

We included an exploratory analysis of the response time of fire suppression resources deployed by the CAL FIRE agency for 9886 incidents in the period 2020–2023. The fields included were: Incident Number (i.e. same ID as from IRWIN), incident date, name, final burned area, coordinates, and two date–time fields (alarm date/time and first resource on scene). From these last two fields, we computed a new time variable: response time (RT) as the number of minutes between the 'AlarmDateTime' and 'FirstResourceOnScene' fields, representing the time between a fire alert being received and the arrival of the first resources at the ignition site (Arienti *et al.* 2006). It should be noted that a fire may have started before the alarm was issued, which could affect our results. Prior to inclusion in the models, RT required a logarithmic transformation because its distribution was left-skewed.

WFA automated simulations and Initial Attack Assessment index computation

We automatically simulated fire incidents with weather forecasts and diverse semi-empirical fire spread models implemented in WFA. We employed Rothermel's (1972) surface fire spread model, Van Wagner's (1977) crown initiation fire model, Rothermel's (1991) crown spread model, Albini's (1976) spotting model, Andrews' (2012) conversion factor of wind profile and Finney's (2002) Minimum Travel

Time algorithm. Regarding the surface fuel types and canopy characteristics, Technoslyva Inc. generated several layers (one per year at the start of the fire season) at 30-m spatial resolution using the Scott and Burgan (2005) fuel family improved with custom fuel types for timber areas (see Cardil *et al.* (2023) for more details). We retrieved hourly gridded weather data at 2 km employing an improved version of the Weather Research and Forecasting (WRF) model. These high-resolution mesoscale weather predictions have been applied in California's daily fire risk, rainfall and prevailing wind events (Brewer and Clements 2020). The WRF forecast serves to drive fire spread models and its configuration has been validated specifically for high-impact fire weather scenarios (Carpenter *et al.* 2024). It is initialized daily using the Global Forecast System, minimizing model uncertainty or drift that can be introduced by inaccurate boundary conditions. Mean wind speed and direction at 10 m height above the terrain were employed. For dead Fuel Moisture Content (FMC) calculation, we followed Nelson's (2000) method using weather data, which included a soil moisture correction. In turn, live FMC was computed using machine learning models trained with the US National Fuel Moisture Database (WFAS 2022; Cardil *et al.* 2023).

Table 1. Description of the variables selected from the IRWIN dataset and fire-related variables from fire simulations using WFA.

Code	Data element description
IncidentCode	**Unique fire identifier in string format**
IncidentName	**Name of the fire incident**
ReportedTimestamp	**Fire discovery date/time with the format Y-M-D HH:MM:SS**
IncidentLocationX	**Ignition location – latitude in UTM Mercator (m)**
IncidentLocationY	**Ignition location – longitude in UTM Mercator (m)**
DailyAcres	**A measure of area burned reported for a fire**
DiscoveryAcres	**An estimation of area burning on the discovery of the fire**
IAA	Initial Attack Assessment index (from 1 to 5)
FBI	Fire Behavior Index (from 1 to 5)
TDI_2h	Average Terrain Difficulty Index at 2 h within the simulated fire perimeter (from 1 to 5)
SIZE_1H	Fire size at 1 h of the simulated fire (ha)
PERIMETER_1h	Length (m) of the simulated fire perimeter 1 h after the ignition time
FLAME_LENGTH	Average length of the flame (m) within the simulated fire perimeter in the first hour
ROS	Average rate of spread (km/h) within the simulated fire perimeter in the first hour
AVG_SLOPE	Averaged slope (%) at the location of the fire

Bold rows indicate variables selected from the IRWIN dataset.

The IAA was computed using two different sub-indices: Fire Behavior Index (FBI) and Terrain Difficulty Index (TDI); see Supplementary Materials S2 and S3 for details. The IAA, FBI and TDI are represented by five categories, from 1 to 5 (Tables 2 and 3). The higher the value, the more active the fire behavior, the more complex the terrain, and thus the more likely the IA is to fail, posing a potential threat.

Modeling process

The different statistical modeling approaches employed in this study to assess the relationships between IA success and the proposed indexes are shown in Fig. 2. Firstly, we fitted a logistic Generalized Linear Model (GLM) using the binomial family and setting the binary dependent variable, using the threshold of 4 ha burned as a wildfire successfully contained. We included the five IAA classes as predictors (i.e. IA Success–Failure ~ IAA levels) and employed 26,907 real fire incidents reported in California from 2020 to 2023. We also compared the IAA index between wildfires reported by CAL FIRE and other agencies to evaluate differences in IA success for the different IAA categories. In addition, another binomial univariate GLM was adjusted by incorporating the simulated sub-indices employed to compute IAA index (FBI and TDI) to evaluate the strength and sign of their association with the response variable (i.e. IA Success–Failure ~ TDI + FBI). Finally, we conducted an additional GLM to analyze the effect

Table 2. Fire Behavior Index (FBI) construction matrix that relates rate of spread (ROS, km/h) and flame length (FL, m) to be categorized into five classes following the criteria of Rothermel (1983).

FBI		ROS (km/h)					
		0–0.04	0.04–0.1	0.1–0.4	0.4–1	1–3	>3
FL (m)	0–0.3	1	1	1	1	2	3
	0.3–1.2	1	1	2	2	3	4
	1.2–2.4	1	2	2	3	4	5
	2.4–3.6	1	2	3	3	4	5
	3.6–7.6	2	3	3	4	5	5
	>7.6	3	3	4	4	5	5

of RT on IA success (i.e. IA Success–Failure ~ TDI × RT + FBI) with 9886 fire incidents from the CAL FIRE agency from 2020 to 2023. In this case, we included an interaction term for the sub-indices TDI × RT together with the FBI.

In order to assess the association between the different levels of IAA and its sub-components and the odds of IA success, we evaluated odds ratio (OR) coefficient estimates. OR is commonly employed in the context of logistic regression models, and represents the ratio of the probability of an event occurring relative to the odds of it not occurring, given one or more predictors (Hauck 1987).

Additionally, we conducted a correlation analysis with all the main fire behavior metrics from simulation and an ANOVA test to compare them based on IA failure and success (Chambers *et al.* 1992). Models training and calibration were carried out using the R environment (R Core Team 2021) and the R package *stats* was employed for ANOVA testing correlation analyses and for odds ratio coefficients estimation.

Finally, we conducted individual WFA simulations for six incidents outside California to demonstrate the performance of IAA in other environments and fire conditions. Three wildfires were recorded on USA Labor Day of 2020 (in Oregon), one was recorded in Colorado (July 2020), one in Montana (August 2023) and a wildfire in Spain (July 2022). The Spanish case was well monitored by firefighters and affected a wildland–urban interface (WUI). Further, the model's performance was assessed during the 2025 Los Angeles fires to examine a scenario characterized by fire simultaneity.

Table 3. Initial Attack Assessment (IAA) index construction matrix that relates Terrain Difficulty Index (TDI) and Fire Behavior Index (FBI) to be categorized into five classes.

IAA index		TDI				
		1	2	3	4	5
FBI	1	1	1	1	2	3
	2	1	2	2	3	3
	3	3	3	3	4	5
	4	4	4	5	5	5
	5	5	5	5	5	5

Results

IAA index performance

Table 4 shows the number of fires, their average and total burned area in California for each IAA category. The total burned area statewide was almost 3 million ha, with a maximum burned area per incident of 389,837 ha (Dixie fire, July 2021). The actual mean burned area for all fires was 111.5 ha. Regarding the official total surface burned area by IAA classes, IAA-3 accounted for the highest (946,742 ha) and IAA-1 for the lowest (354,829 ha).

Terrain conditions (TDI, Accessibility Index, Penetrability Index, Construction Index and AVG_SLOPE), fire behavior (rate of spread (ROS) and FBI), fire spread metrics (such as PERIMETER_1h) and the IAA index were significantly higher

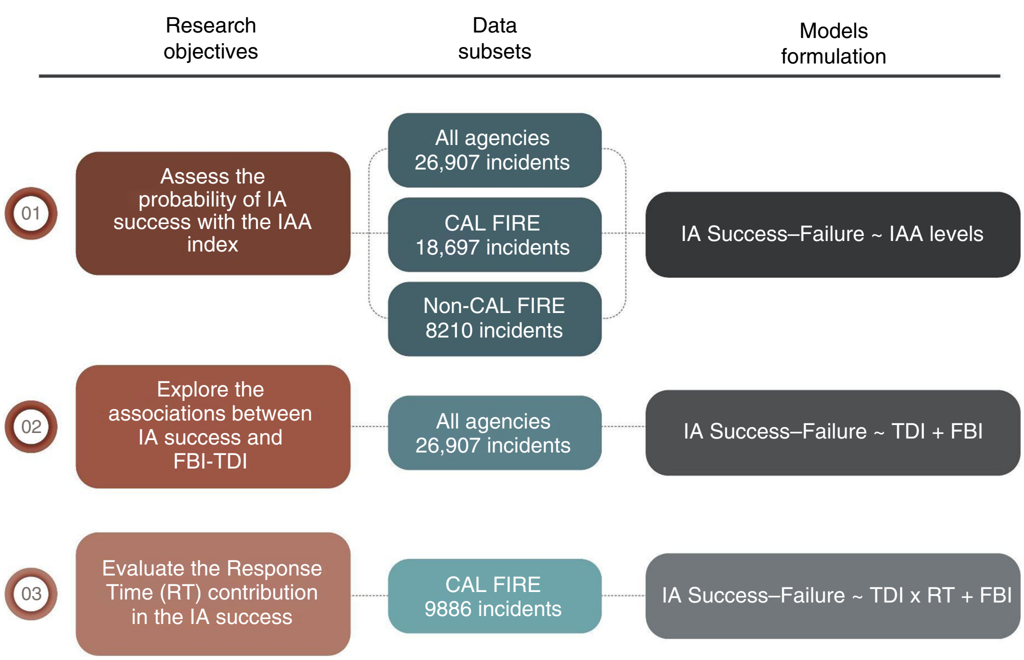


Fig. 2. Schematic modeling process that includes the three main research objectives related with the wildfire data subsets employed and their corresponding univariate logistic regression models.

Table 4. Summary of the number of fire incidents (*N*), mean and total burned area (BA) in hectares for each IAA level and their corresponding initial attack success rate (in parentheses).

Metric	IAA-1	IAA-2	IAA-3	IAA-4	IAA-5
N	19,220 (98.3%)	2175 (95.5%)	4246 (94.5%)	809 (92.8%)	457 (84.2%)
Mean BA (ha)	18.45	204	223	574	1731
Total BA (ha)	354,829	443,362	946,472	464,711	790,991

Table 5. Fire behavior metrics from fire simulations based on the initial attack failure and success.

Variable (unit)	Initial attack failure	Initial attack success
IAA	2.29 ± 1.32***	1.53 ± 0.95***
FBI	2.25 ± 0.941***	1.79 ± 0.788***
TDI_2h	2.09 ± 1.39***	1.40 ± 0.905***
Accessibility Index	6.14 ± 4.17***	4.03 ± 3.9***
Penetrability Index	4.79 ± 1.96***	3.58 ± 1.85***
Construction Index	2.14 ± 2.14***	1.55 ± 1.36***
SIZE_1H (ha)	21.8 ± 95	17.21 ± 1161
PERIMETER_1h (m)	1612 ± 5318***	444.43 ± 2,202.68***
FLAME_LENGTH (m)	1.65 ± 2.06	1.15 ± 10.4
ROS (km/h)	0.364 ± 0.411**	0.225 ± 1.36**
AVG_SLOPE (%)	10.7 ± 9.68***	6.54 ± 7.53***

The table shows the mean and s.d. values. Significant differences between IA failure and IA success are indicated based on ANOVA *P*-values (****P* < 0.001; ***P* < 0.01).

in fires where the IA failed compared with those where it was successful (Table 5), highlighting the potential of using fire simulations and suppression difficulty indices to assess IA success. For instance, in cases where the IA was successful, the total simulated fire perimeter at Hour 1 (PERIMETER_1h), without considering fire suppression, was 444.43 m (1.23 ha), far below the CAL FIRE success threshold size. When the IA failed, PERIMETER_1h was significantly larger, with an average value of 1612 m. The only variables with a non-significant difference were SIZE_1H and flame length.

The GLM fitted with the five categories of IAA index as predictors (i.e. IA Success–Failure ∼ IAA levels) illustrated its contribution to IA success. In that sense, all the classes were significant in the model (Table 6). Moreover, there was an increase in negative estimated coefficients, showintg that as the IAA index increases, IA success decreases.

When comparing the GLMs trained with different wildfire agencies, moderate differences appear (Table 7). For the GLM fitted with CAL FIRE incidents, the probability of IA success increases above 89%, including the highest values of

Table 6. Model coefficients obtained for the generalized logistic regression model using the five categories of IAA as predictors.

IAA category	Coefficient	s.e.	*Z* value	*P* value
IAA-2	−0.990	0.117	−8.444	<0.001
IAA-3	−1.189	0.087	−13.591	<0.001
IAA-4	−1.483	0.147	−10.082	<0.001
IAA-5	−2.367	0.139	−16.929	<0.001

Note that IAA-1 was considered by the model as the reference category.

Table 7. Comparison between probability of initial attack success for CAL FIRE incidents and those from other agencies.

Success threshold (4 ha)	*N*	IAA				
		1 (%)	2 (%)	3 (%)	4 (%)	5 (%)
All agencies	26,907	98.3	95.5	94.5	92.8	84.2
CAL FIRE	**18,697**	**97.9**	**96**	**94.4**	**94.8**	**89.5**
No CAL FIRE	8210	97.2	93.2	92.8	89	81.1

Modeled logistic probability based on the IAA index classes for a fire incident threshold greater than 4 ha. Bold values indicate successful initial attack probabilities for CAL FIRE incidents.

IAA (4 and 5, with a 94.8 and 89.5%, respectively). In contrast, excluding these wildfires from the database, the probability of being successful in the IA slightly decreased to 89 and 81.1% for the IAA-4 and IAA-5 categories, respectively.

The probability of IA success based on the different IAA values for different fire size thresholds is shown in Figs 3 and 4. The limit established by 4 ha follows the same parallel decreasing line as the rest (i.e. 2, 20 and 40 ha), while the level of the IAA index increases (Fig. 3, panel *a*). However, when fires escape IA, the index explains that the average final fire size (in hectares) is larger as the index grows (Fig. 3, panel *b*), especially for the highest IAA values (4 and 5).

IAA levels, fire behavior–terrain metrics and initial attack success: odds ratios

Fig. 4 shows the strength and sign of the relationship between the IAA levels (panel *a*), fire behavior–terrain metrics (panel *b*) and IA success employing the GLMs adjusted with the IAA classes (i.e. IA Success–Failure ∼ IAA levels) and its subcomponent categories (i.e. IA Success–Failure ∼ TDI + FBI). Note that a value greater than 1 indicates an increase in the odds (positive association), less than 1 indicates a decrease (negative association) and close to 1 means no significant effect. Generally, the highest levels of the predictor (i.e. IAA-5, FBI-5 and TDI-5) showed the strongest relationships with IA success, all showing a negative association. Using IAA-1 as the reference category, results indicated a significant and progressive decrease in the odds of IA success across higher IAA levels. Compared with IAA-1, the odds of success were 64% lower in

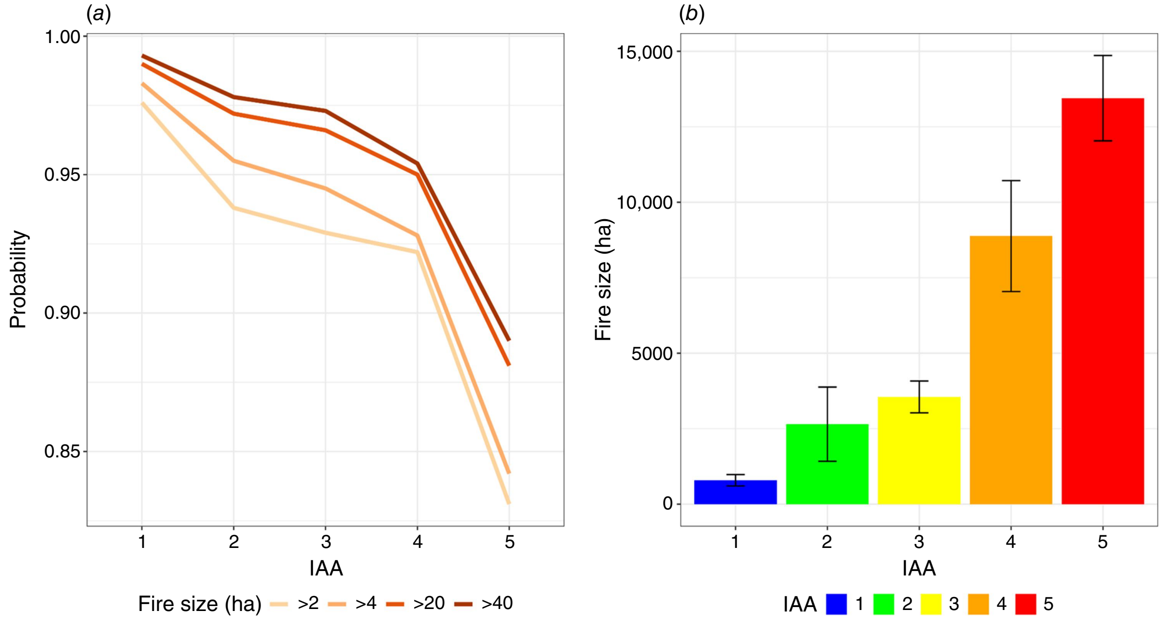


Fig. 3. (*a*) Comparison of the modeled probability of initial attack success based on the IAA classes for different fire size objectives in ha. (*b*) Comparison of average fire size (ha) when the initial attack fails (i.e. those escaped fires > 4 ha) for each IAA class.

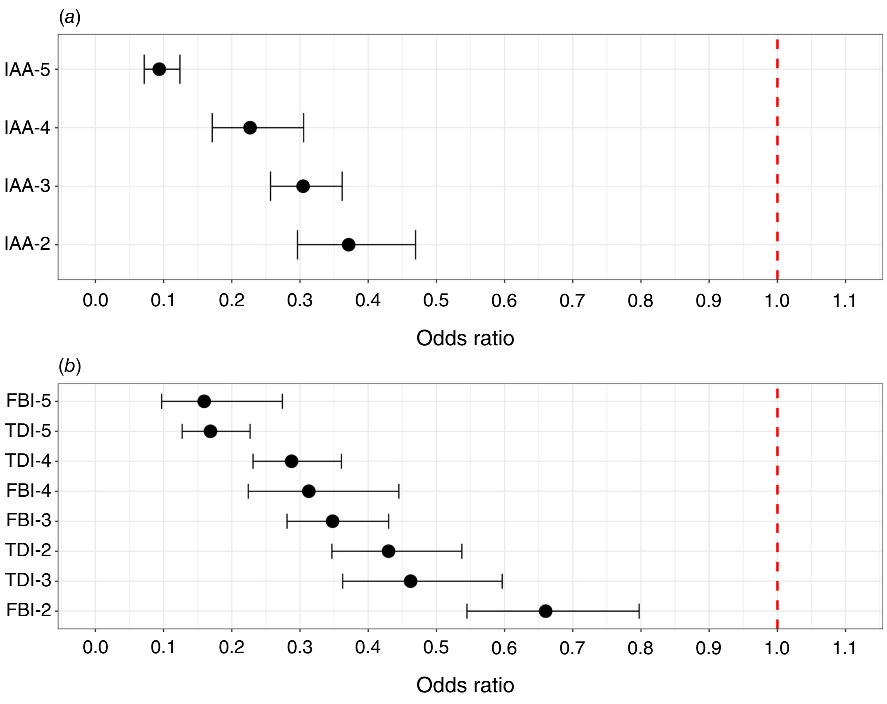


Fig. 4. Odds ratios (*x*-axis) of the association between IAA levels (*y*-axis on panel *a*), Fire Behavior Index (FBI) and Terrain Difficulty Index (TDI) categories (*y*-axis on panel *b*) and initial attack according to the binomial GLMs: IA Success–Failure ~ IAA levels and IA Success–Failure ~ TDI + FBI, respectively. Black points show the estimated odds ratio (OR) and horizontal lines represent the 95% confidence level. The dashed red vertical line (OR = 1) indicates that there is no effect or association between the explanatory variables and the response variable. Note that IAA-1, TDI-1 and FBI-1 are the reference groups (OR = 1).

IAA-2 (OR = 0.37), 70% lower in IAA-3 (OR = 0.30), 78% lower in IAA-4 (OR = 0.23) and 90% lower in IAA-5 (OR = 0.10).

A similar pattern was observed for FBI and TDI coefficient ORs (Fig. 4, panel *b*). As values increased across both indices, the odds for successful IA declined markedly. For instance, the ORs for FBI-5 and TDI-5 were 0.15 and 0.17, respectively, indicating an approximately 85% reduction in the odds of IA success relative to their respective reference groups (i.e. FBI-1 and TDI-1). Intermediate categories, such as FBI-3 (OR = 0.35) and TDI-3 (OR = 0.46), also showed substantial decreases. In addition, FBI and TDI indices are not strongly correlated (see Supplementary Fig. S1 in the Supplementary Material S1).

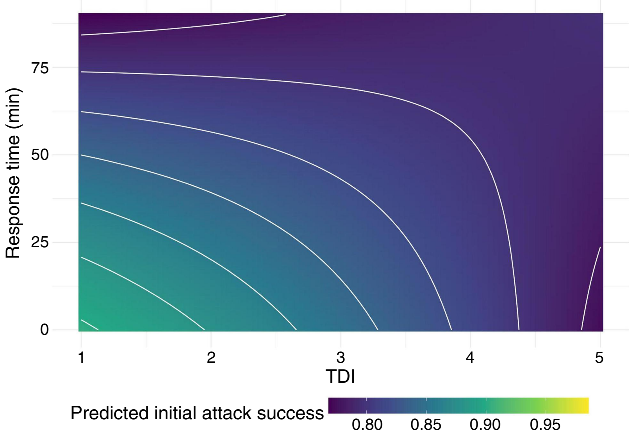


Fig. 5. Interaction plot between response time (RT; in minutes) and TDI for predicted Initial Attack success employing the GLM: IA Success–Failure ~ TDI × RT + FBI. Note that the closer the value to 1, the more probable that the IA is successful, and vice versa.

Response time effect on initial attack success

Fire simulation metrics had a significant effect on the IA success (Tables 5 and 6). However, fire suppression resources also played a key role in explaining the IA success. Here, we analyze the RT and TDI from fire incidents involving CAL FIRE's suppression resources during IA (employing the GLM: IA Success–Failure ∼ TDI × RT + FBI). We found a significant interaction between TDI and RT (Fig. 5), which had a substantial influence on IA success. Overall, the probability of successfully containing the fire within the first 2 h decreases as both TDI and response times increase. In other words, longer response times and higher TDI values are associated with lower chances of successful initial containment, with probability values ∼0.80. Although the probability of IA success was higher (over than 0.95) at lower TDI values (Fig. 5), it decreased as RT grew. Conversely, when TDI values were high, the RT had a little effect, resulting in the lowest IA success rates.

IAA use cases

2025 January Californian fires

On 6–9 January 2025, two significant and damaging wildfires – the Palisades and Eaton fires – occurred in the Los Angeles area. Even though there was a high fire simultaneity scenario with 360 ignitions across California during this period, most fires remained small and were successfully contained during the IA phase. However, the Palisades Fire destroyed 6837 structures and caused 12 civilian fatalities (CAL FIRE 2025*a*), making it the most damaging wildfire recorded in Los Angeles and the third-most destructive in California. The Eaton fire caused even greater losses, with 9414 structures destroyed and at least 19 fatalities (CAL FIRE 2025*b*), ranking it as the second-most destructive wildfire in the state's history.

From all IRWIN's incidents reported from 6 to 9 January 2025, we selected those that were automatically simulated by CAL FIRE's WFA (n = 360, see Fig. 6, panel *a*). The Palisades and Eaton fires (Fig. 6, panel *b*) affected the largest areas (9489 and 5674 ha, respectively) and represented the greatest challenges to containment (i.e. both incidents with an IAA-5). Most of the remaining incidents reported those days were successfully contained during the IA phase (312 incidents were assigned IAA-1, 1 was classified as IAA-2, 30 as IAA-3, 4 as IAA-4 and 7 as IAA-5). Importantly, all these fires remained small (with burned areas under 4 ha), indicating no significant propagation. Only two wildfires (Tayler and Scout) slightly exceeded the 4-ha threshold, but their limited size does not warrant classification as escaped fires. In contrast, the Kenneth and Hurst fires grew to 425.7 and 323.0 ha respectively, with an IAA value of 3. These larger extents may be partially attributed to the simultaneity of incidents across California during those days, which could have constrained suppression resources.

WFA simulations outside California

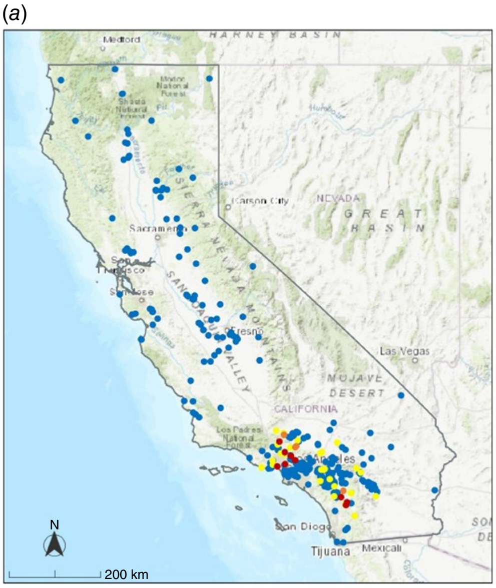
We conducted six simulations through WFA outside California to demonstrate IAA performance in other regions (Table 8). The selected fires became large through their duration, with different fire spread patterns. Note that the IAA index was designed for the IA phase (first 2 h after reported ignition) and thus, the results must be interpreted with that consideration. In those events when fire agencies are not capable of containing incipient fires in that time, it is probable that any incident will become a large and very destructive one (e.g. Archie Greek in Oregon or Pine Gulch in Colorado). For instance, the Archie Creek Fire showed fast growth (∼60 km/h winds) reaching almost 4900 ha during the first 2 h (Borsum and Plouffe 2022), exceeding fire suppression capabilities, with an IAA value of 5. In the Pine Gulch Fire, uncontrollable propagation in the early stages of the attack forced large evacuations (NOAA 2020). In other cases, although the FBI was less intense but the TDI was high, the latter factor could really complicate fire accessibility and lead to an escaped fire (e.g. Lionshead fire Oregon). In this particular case, this natural-caused fire ignited with initial slow propagation in the first days (FBI = 2), until on 8 September, it grew large, driven by a historic strong-wind event (USDA Forest Service 2020). In contrast, other fire incidents registered a moderate TDI but a high or extreme FBI, such as Holiday Farm in Oregon (Urness and Rein 2021), Pine Gulch in Colorado and Pont de Vilomara in Spain, generally leading to more relevant impacts in terms of area burned and buildings threatened or destroyed as well as significant population evacuations. In the case of the Spanish wildfire, rapid convective propagation with adverse fire behavior (FBI = 5) impacted 29 residences in a nearby WUI during the first hour after ignition. Finally, wildfires with both indices high (e.g. Archie Greek Fire in Oregon and River Road East in Montana) represent the worst scenario in terms of fire containment.

Discussion

In this study, we propose a dynamic index, the IAA, to evaluate the difficulty of IA, validated extensively with data from 26,907 real wildfires in California from 2020 to 2023, simulated using Technosylva's WFA. The index was initially developed based on expert criteria and preliminarily tested against fires during the latest fire seasons by Technosylva and CAL FIRE. Building on this foundation, this paper provides further insights into the performance of the IAA by utilizing more fire data and analyzing how other fire-related metrics may improve estimation of IA success.

The IAA index behaves with a negative relationship with the odds of IA success. The GLM-IAA model's OR analysis showed that a fire with an IAA-5 rating has 90% higher odds of escaping control than one with an IAA-1 (Fig. 4, panel *a*). Even more importantly, in those cases when IA failed, the index was able to capture the fire's potential to become large (Fig. 3, panel *b*). Also, logistic regression employing fire behavior and terrain metrics (i.e. IA Success–Failure ~ TDI + FBI) showed that FBI and TDI also have strong and negative relationships with IA success (Fig. 4, panel *b*), highlighting that both IAA sub-components are strongly associated with

(*a*)



(*b*)

IAA	Number of fires	IA success rate	Escaped and large wildfires
1	313	99.68%	Tayler (5.8 ha)
2	1	100%	–
3	33	90.9%	Scout (4.7 ha) Kenneth (425.7 ha) Hurst (323 ha)
4	4	100%	–
5	9	77.8%	Eaton (5674 ha) Palisades (9489 ha)

Fig. 6. (*a*) Fire simulations (n = 360) were automatically conducted for the period of 6–9 January 2025. The colored dots represent the IAA category assigned to each simulation. (*b*) The number of incidents per IAA level, along with the IA success rate (%), and the names of escaped (>4 ha) and large wildfires are shown across IAA classes (1–5). Fire names are followed by their respective burned area in hectares.

Table 8. Description of the fire incidents studied outside California employed for demonstration of the performance of the IAA generated in the WFA simulations.

Name (State)	Date/time (h)	Size (ha)	IAA	FBI	TDI	Impacts observed
Holiday Farm (Oregon)	07 Sep 2020 20:20	70,169	5	5	2	Most structures of Blue River were destroyed (400 homes).
Archie Creek (Oregon)	08 Sep 2020 7:37	53,254	5	5	4	Fire grew rapidly (64 km/h gusts); in the first 2 h, burned nearly 3035 ha.
Lionshead (Oregon)	16 Aug 2020 10:45	80,267	2	1	4	Lightning fire spread slowly until 8 Sep, ending with 264 homes lost.
River Road East (Montana)	18 Aug 2023 13:18	7006	5	4	4	More than 55 buildings destroyed (including 15 residences).
Pine Gulch (Colorado)	31 Jul 2020 17:15	56,171	5	5	3	Lightning fire that initial attack was unable to contain, as it spread rapidly, ending in evacuation of residences.
Pont de Vilomara (Spain)	17 Jul 2022 13:04	1696	5	5	3	Rapid convective propagation in the first hour (29 residences affected).

Date/time is in local time; size: official reported burned area in hectares. IAA, FBI and TDI indices values in the simulation output, and main impacts observed distinguishing that particular wildfire event.

decreased containment odds. These relationships support the use of the IAA index to justify the deployment of additional resources and the prioritization of specific fires during periods of fire simultaneity, especially considering the substantial costs and damages associated with IA failures in California (Fried *et al.* 2008; Legislative Analyst's Office 2020).

Following the 4 ha threshold adopted for fires by CAL FIRE (Li and Banerjee 2021), the IA success rates were very high in line with the predictions of the IAA model. This likely reflects CAL FIRE's overall more aggressive response strategy than intrinsic differences in fire behavior. However, we identified some fire events that exceeded the IA for the highest IAA classes (i.e. 4 and 5). Our findings highlighted that most of these fires were associated with difficult terrain, adverse accessibility conditions and high fuel continuity – factors largely captured by the TDI – as well as challenging fire behavior, captured by the FBI. Some of these fires started and propagated in very remote areas, thus with higher chances to escape control (Kucuk *et al.* 2017). Steep slopes were among the most critical factors affecting the effectiveness of IA, primarily owing to the difficulties for ground suppression brigades in carrying out fire control tasks (Rodrigues *et al.* 2019), increasing the need for aerial operations in the majority of cases (Plucinski *et al.* 2012). Furthermore, high density and continuity of mature fuel types could aggravate actual access through the terrain, representing a major obstacle to opening effective suppression lines (Reimer *et al.* 2019), while, at the same time, being one of the main triggers for fire spread (O'Connor *et al.* 2017). Moreover, accessibility or time spent by containment efforts along a road network determines the success of the IA. All of these aspects were integrated into and represented by our TDI, inspired by the Suppression Difficulty Index proposed by Rodríguez y Silva *et al.* (2020), and in the developed IAA index. Our analysis also highlights distinct differences in fire behavior metrics derived from simulation outputs when comparing cases of IA success versus failure. For instance, PERIMETER_1h, ROS and FBI largely determined the probability of fire potential early containment, in line with previous research (Arienti *et al.* 2006). These aspects are really relevant, because fire behavior influences suppression method choices (Daniels *et al.* 2024) and fast-growing fires are the most destructive and deadly (Balch *et al.* 2024). Also, this factor may become even more important considering that severe and extreme fire-weather conditions could be exacerbated as a consequence of anthropogenic climate change (Dong *et al.* 2022; Jones *et al.* 2022).

When a fire starts, fire responders conduct a size-up to determine strategy and tactics. This process considers factors like fire location, fuel type, fire behavior and short-term fire weather forecast, which are considered by our IAA model. However, beyond FBI and TDI, there are more factors that may influence IA failure, such as travel delays caused by low site accessibility, as well as the availability, type, amount and response speed of suppression resources (Arienti *et al.* 2006; Rodrigues *et al.* 2019; Sakellariou *et al.* 2023). Our analysis revealed a significant interaction between suppression RT and TDI. This suggests that RT could be incorporated into a future Initial Response Assessment index (IRA) as a third dimension (i.e. TDI × RT × FBI). The likelihood of IA success is greater in more accessible terrain, whereas this probability decreases as RT increases. In that sense, some studies have pointed out the crucial importance of minimizing delays within the first hours after fire discovery to reduce the likelihood of an escaped fire (Marshall *et al.* 2022).

Use of the IAA index can support the appropriate dispatch of suppression resources (Wollstein *et al.* 2022). Situation reports for a particular incident support decision-making under conditions of fire simultaneity – such as the 2025 LA fire event – by enabling fire agencies and utilities to identify areas at risk and prioritize fire response to more effectively reduce overall impacts (Plucinski 2013). These findings point to seeking a balance between the initial fire size and behavior, the available resources and their location, and the potential threat to high-value assets at risk. Collectively, all of these factors will condition the response to fire in the first attack. This underscores the value of the Technosylva's Response Complexity (RCX) metric that integrates IAA with fire simultaneity and assets threatened (e.g. buildings impacted). Such a composite metric could also support more consistent prioritization by quantifying not just the likelihood of containment success, but the relative consequence of each incident, enabling more data-driven, equitable suppression decisions across multiple simultaneous events.

The IAA can be effectively extrapolated to regions outside California, as shown in this study. In all cases, both our index, IAA, and its two sub-indices, FBI and TDI, produced results consistent with the diversity of containment probability, fire behavior and terrain difficulty. However, we recognize some limitations of our study. Notably, we are aware of the inherent imbalance in the fire data, because the majority of fires (97.02% of the cases) had a successful IA. Our analysis does not account for other critical factors influencing IA success, such as the amount and type of resources deployed within the first 2 h after a fire begins, owing to data limitations. Lastly, the initial fire coordinates recorded by fire departments are sometimes inaccurate, occasionally located outside the officially reported perimeter or near roads, which can lead to erroneous IAA values. This represents a potential source of error that should be considered.

Since 2020, CAL FIRE has leveraged advanced GIS (Geographic Information System)-based technologies, including the IAA index to manage the complexity of wildfires more efficiently. In that sense, the IAA index is valuable, as it simplifies complex fire dynamics into a scalable metric, evaluated daily across units, providing real-time data to field teams. At the same time, each reported fire is automatically simulated and assigned an IAA score, along with its sub-indices FBI and TDI. These assessments are integrated into the Computer Aided Dispatch (CAD) system, delivering one-page reports and interactive maps to incident commanders, supervisors and responders. In 2023, CAL FIRE collaborated with Technosylva to validate fire spread modeling, confirming that current fire spread models are accurate for real-time assessment of IA fires, supporting CAL FIRE's operational decisions (Cardil *et al.* 2023). In addition, CAL FIRE integrates WFA's platform with complementary technologies and data sources, enhancing accuracy through ongoing simulation calibration and predictive verification. Currently, WFA provides daily forecasting and real-time spread predictions, allowing the CAL FIRE dispatch system to preposition resources based on predictive fire analysis, which enhances their ability to respond effectively to incipient wildfires. Finally, the IAA is being adopted beyond California, including North American utilities, the British Columbia wildfire service (Canada), several agencies in Europe and the European FIRE-RES project aimed at dealing with extreme wildfire events, underscoring its importance in improving wildfire response and management strategies.

Conclusions

In this study, we introduced the IAA index for assessing initial attack success, validated through 26,907 California wildfires from 2020 to 2023. Our analysis, which employed logistic regression models incorporating the IAA index and its key sub-components – the Terrain Difficulty Index (TDI) and Fire Behavior Index (FBI) from Technosylva's Wildfire Analyst (WFA) – along with suppression response time, revealed strong and statistically significant relationships with IA outcomes. The analysis showed a clear negative correlation between IAA values and IA success rates: fires rated at IAA-5 were found to have 90% higher odds of escaping initial control compared with those rated IAA-1, highlighting the index's critical role for operational decision support and strategic planning. Both the FBI and TDI showed strong negative correlations with IA success, and response time significantly influenced the probability of IA success in interaction with terrain difficulty. To conclude, the IAA index remains a valuable tool owing to its simplicity and robustness. It continues to support utilities, CAL FIRE and other fire agencies in key stages of daily and real-time decision-making, including the preparation and allocation of appropriate resources for fire risk analysis, as well as dispatch and response during the early detection of wildfires.

Supplementary material

Supplementary material is available online.

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Data availability. The data that support the findings of this study are classified. Restrictions apply to the availability of these data, which were used under license for this study.

Conflicts of interest. The authors declare that they have no conflicts of interest.

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Author affiliations

[A]Technosylva Inc, La Jolla, CA, USA. Email: ajimenez@technosylva.com, smonedero@technosylva.com, mortega@technosylva.com, rquilez@technosylva.com, tquinones@technosylva, fbezares@technosylva.com, spurdy@technosylva.com, tmetzger@technosylva.com, cwaters.c@technosylva.com

[B]Department of Agricultural and Forest Sciences and Engineering, University of Lleida, Lleida, Spain. Email: sergio.demiguel@udl.cat

[C]Forest Science and Technology Centre of Catalonia (CTFC), Solsona, Spain.

[D]CAL FIRE Sacramento Headquarters Intel, Sacramento, CA, USA. Email: phillip.selegue@fire.ca.gov, jeff.fuentes@fire.ca.gov, robert.clark@fire.ca.gov, tim.chavez@fire.ca.gov

[E]Forest Fire Laboratory, Department of Forest Engineering, University of Córdoba, Campus de Rabanales, 14071, Córdoba, Spain.

[F]USDA Forest Service, Pacific Southwest Region, Operations Southern California, Riverside, CA 92518, USA. Email: kristen.allison@usda.gov

[G]Department of Geography, University of California-Berkeley, Berkeley, CA 94709, USA. Email: mid_mohan@berkeley.edu

[H]Department of Agricultural and Forest Sciences, University of León, 24009, León, Spain.