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ScienceDirect

Procedia Computer Science 280 (2026) 7–14

Procedia Computer Science

www.elsevier.com/locate/procedia

The 17th International Conference on Ambient Systems, Networks and Technologies (ANT)
April 14-16, 2026, Istanbul, Türkiye

# Forest Lattice-Tree Cellular Automaton for Forest Wildfire Spread Modeling

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**Abstract**

Forest fires pose a significant threat to ecosystems and economies worldwide. This study focuses on the application and evaluation of the Forest Lattice-Tree Cellular Automaton (FL-TCA) model for simulating forest fires in the Curonian Spit, Lithuania. Our approach employed specific states representing various phases of fire spread, including virgin vegetation, ignited, burning, cold burned vegetation, and soil, integrating key factors influencing fire behavior, such as vegetation type and density, humidity, wind direction, and altitude. Spatial accuracy was evaluated using overlap ratio metrics, comparing simulated results with actual fire data. Our approach demonstrated a reasonable level of congruence between the simulated and actual burned areas.



*Keywords:* Forest fire simulation; Cellular Automaton; Wildfire behavior.

## 1. Introduction

The study of forest ecosystems through mathematical and computational models such as twin models [4] well coreelates with the use of cellular automata (CA) in ecological modeling, specifically for forest ecosystems. Operational wildfire models integrate real-time decision-making and strategic planning. Cell2Fire, a cell-based simulator, divides landscapes into fuel, weather, and topography cells, demonstrating high accuracy [16]. PROPAGATOR optimizes prescribed burns by simulating fire spread using high-resolution data [17, 24]. Machine learning enhances predictions, such as LSTM-CA models improving spread rate estimation [12] and FFSBP outperforming traditional methods [23]. ConvLSTM also achieves high precision [11]. Multiscale approaches, like percolation-based CA [18] and ensemble modeling with dynamic fuels [8], address uncertainty in fire behavior.

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1877-0509 

The Forest Lattice Tree Cellular Automaton (FL-TCA) model proposed in this paper extends the traditional CA framework by incorporating specific characteristics and behaviors associated with trees and forest environments. Our model integrates aspects such as tree growth, health status, species diversity, and interactions with environmental factors, all helping to understand the dynamics of forests, particularly in the face of changing environmental conditions and external stressors [3], such as wildfires. We believe, Forest Lattice Tree Cellular Automaton (FL-TCA) models can accurately simulate the spread of wildfires under different conditions, providing valuable information for fire management and prevention strategies. FL-TCA also has the potential to contribute to the field of forest succession and management by simulating different scenarios of tree growth, competition, and environmental changes, as researchers would be able to predict long-term forest dynamics and assess the impact of various forest management practices [20].

Our novel approach incorporates specific characteristics of the forest environment, such as vegetation type, density, humidity, wind direction, and altitude, providing a more precise simulation of fire spread dynamics compared to generic models, and uses data from digital terrain models, land cover maps to better reflect real-world conditions, and enhancing the model's reliability and applicability.

## 2. Related Works

The development and application of cellular automata (CA) in ecological modeling, specifically for forest ecosystems, have been an area of growing interest over the past several decades. Early models of forest dynamics were often deterministic and focused on understanding individual components of forest ecosystems, such as tree growth or species competition [1]. However, these models lacked the spatial and stochastic elements crucial to simulating realistic forest dynamics [21]. The introduction of spatially explicit models marked a significant advancement in this field [19].

One of the critical applications of CA in forest ecology is modeling the spread of wildfires. Early models such as the one proposed by [13] laid the foundation for the use of CA in simulating the spread of fire, with advances seeing more sophisticated models that incorporate factors such as wind, topography, and fuel moisture, providing more accurate predictions of wildfire behavior [22]. Operational models have been developed to support real-time decision-making and strategic planning in wildfire management. Cell2Fire is a cell-based fire growth simulator that integrates landscape management planning models. The simulator divides the landscape into cells characterized by fuel, weather, and topographic characteristics. Cell2Fire has been validated against real fires, showing high accuracy and efficiency [16]. Perello et al. utilized PROPAGATOR to design prescribed fire plans in Liguria, Italy, optimizing wildfire risk mitigation and treatment costs, supporting emergency response and proactive land management strategies [17]. PROPAGATOR simulates fire spread considering high-resolution topographic and vegetation data, calculating the probability of spread of the fire based on the type of vegetation, slope, wind direction and speed, and fuel moisture content [24]. Another study proposed a CA model combined with a long-short-term memory (LSTM) network, enhancing fire spread predictions by accurately estimating the rate of spread (ROS) even with imperfect input parameters [12]. Sun et al. introduced a Forest Fire Spread Behavior Prediction (FFSBP) model, combining CA with machine learning to predict the direction and speed of fire spread, and the extent of burned areas. This model demonstrated superior predictive performance compared to traditional models in small and medium-sized fire scenarios [23]. Similarly, Khalaf et al. evaluated the performance of the CA, FlamMap, and ConvLSTM algorithms, with ConvLSTM showing the highest precision in predicting the spread of wildfires in Golestan National Park, Iran [11]. Multiscale models and ensemble simulations have been applied to capture the complexity of wildfire dynamics. Perestrelo et al. used a 2-scale network combining site percolation and SIR epidemiology rules in a CA model to describe fire spread in the Serra de Ossa region of Portugal, aiming to identify phase transitions in fire regimes and optimize fire-break solutions based on terrain morphology [18]. Gómez-González et al. used national forest data repositories to implement wildfire ensemble modeling, incorporating uncertainty considering variations in meteorological and environmental conditions with dynamic fuel models and the impact of firefighter mitigation efforts [8]. Geoinformation system (GIS)-based models have also been used to simulate the spread of wildfires. Gharakhanlou and Hooshangi developed a GIS-based CA model that considers spatial and temporal drivers such as wind speed, vegetation type, and topography. The model was calibrated using a genetic algorithm and validated with real fire cases, which proved effective in helping fire managers predict and control the spread of wildfires [7].

The application of CA also introduced a new paradigm in ecology for simulating complex spatially dependent processes. CA models, characterized by local interaction rules on a discrete grid, have been effective in capturing the emergent properties of ecosystems [2]. In forest modeling, CA has been used to simulate a range of dynamics, from tree growth and competition to the spread of disturbances [13]. Lattice-based models specifically tailored for forests have gained attention for their ability to integrate various ecological processes within a unified framework [14, 15]. These models incorporate complex interactions between trees, including competition, reproduction, and resilience to environmental changes [10] or the diversity of tree species and spatial patterns [9].

## 3. Methodology

Our forest lattice tree cellular automaton model (FL-TCA) was improved upon the BIO-LGCA [5] used in fluid dynamics, adapting its principles to the context of forest dynamics. In FL-TCA, the forest is represented as a lattice $\mathcal{L}$ where each site can have a tree in different states (healthy, burning, or burnt). The state space $\mathcal{E}$ of each tree includes these states and additional attributes such as moisture content, age, and species. A healthy tree ($s_i$ = healthy) becomes burning ($s_i$ = burning) if at least one of its neighboring trees is burning and certain conditions such as dryness and wind are met:

$$s_i^{(t+1)} = \begin{cases} \text{burning} & \text{if } s_i^{(t)} = \text{healthy and } \exists j \in \mathcal{N}_i : s_j^{(t)} = \text{burning and conditions met,} \\ s_i^{(t)} & \text{otherwise.} \end{cases} \tag{1}$$

A burning tree eventually turns into a burnt state ($s_i$ = burnt) after a certain period of time, representing the consumption of the tree by fire. The transition from a healthy to a burning state depends on factors such as the moisture content of the tree, wind direction, and temperature. This can be represented by a transition probability $P(s_i \to \text{burning}|\mathbf{s}_{\mathcal{N}_i})$ which is higher in dry, windy, and hot conditions.

Random walk is used to model the stochastic spread of fire in the absence of strong environmental cues. The transition probabilities for a random walk are given by:

$$P(s \to s_O) = \frac{1}{Z(s)} \cdot \delta(n(s), n(s_O)), \tag{2}$$

where $Z(s)$ is the normalization constant ensuring mass conservation, i.e., the conservation of fire intensity or spread.

Chemotaxis in wildfire modeling represents the movement of fire influenced by chemical gradients such as the distribution of flammable material. The signal gradient field $G_{\text{sig}}(s_N)$ is defined as:

$$G_{\text{sig}}(s_N) \equiv \sum_{p=1}^{b} c_p c_{p_{\text{sig}}}, \quad s_N = \left((s_1, c_{1_{\text{sig}}}), \ldots, (s_b, c_{b_{\text{sig}}})\right) \in \bar{E}_N, \tag{3}$$

where $\bar{E}_N = E \times \mathbb{R}_+^0$. The transition probabilities for chemotactic response are:

$$P(s \to s_O|s_N;\beta) = \frac{1}{Z(s_N,\beta)} \exp(\beta G_{\text{sig}}(s_N) \cdot J(s_O))\delta(n(s), n(s_O)), \tag{4}$$

with $\beta$ being the sensitivity of the fire to chemical gradients.

Haptotaxis models the influence of the forest structure, such as tree density or type, on the direction of fire spread. The transition probabilities given a vector field $E \in \mathbb{R}^2$ are:

$$P(s \to s_O|E) = \frac{1}{Z(n(s), E, \beta)} \exp(\beta E \cdot J(s_O)) \cdot \delta(n(s), n(s_O)), \tag{5}$$

where fire tends to move preferentially in the direction of the external gradient $E$.

Collective behavior of fire, resembling the alignment of spread due to local interactions, can be modeled through a reorientation operator where the local director field is influenced by the states of adjacent cells:

$$P(s \to s_O|s_N) = \frac{1}{Z(s_N)} \exp(\beta D(s_N) \cdot J(s_O))\delta(n(s), n(s_O)), \tag{6}$$

where $D(s_N) = \sum_{p=1}^{b} J(s_p)$ is the local momentum of fire spread. This operator facilitates the modeling of aligned fire movement.

The dynamic adaptation of time steps is required to accurately simulate the changing intensity of forest fires. As the fire intensity fluctuates, the model time step is adjusted to capture the varying speed of fire spread efficiently. The FL-TCA model employs a variable time step approach, adapting to the current fire conditions.

The speed change rate index ($a_{t_{i,j}}$) reflects the variations in fire spread speed:

$$S_{t+\Delta t_{i,j}} = S_{t_{i,j}} + \left(R_{t_{i-1,j-1}} + \ldots + R_{t_{i+1,j+1}}\right) \frac{\Delta t}{L} \quad (R_{t_{i,j}} = 0), \tag{7}$$

$$a_{t_{i,j}} = \begin{cases} R_{t+\Delta t_{i,j}} - R_{t_{i,j}} & (R_{t+\Delta t_{i,j}} \neq R_{t_{i,j}}), \\ 0 & (R_{t+\Delta t_{i,j}} = R_{t_{i,j}}), \end{cases} \tag{8}$$

$$\Delta t = \Delta t_0 e^{a_{t_{i,j}}}, \tag{9}$$

where $S_{t_{i,j}}$ is the state of the cell, $R_{t_{i,j}}$ is the forest fire spread speed, $L$ is the cell size, and $\Delta t_0$ is the initial time step.

We consider observables such as autocorrelation functions derived from primary forest data. The task then involves maximizing the following functional:

$$\tilde{C}[P_\Gamma] = -\sum_\Gamma P_\Gamma \ln P_\Gamma + \sum_{j=1}^{k} \beta^{(j)} \times \left[\sum_\Gamma P_\Gamma \tilde{U}_j(\{s(r)\}_{r\in L}) - E_j\right] + \lambda\left(\sum_\Gamma P_\Gamma - 1\right), \tag{10}$$

where $P_\Gamma$ is the probability of following a specific spatial trajectory $\Gamma, \beta^{(j)}$ and $\lambda$ are Lagrange multipliers, $\tilde{U}_j(\{s(r)\}_{r\in L})$ represents the value of the optimized observable at time step $j$ based on the lattice configuration, and $E_j$ is the value of the experimental observable at time step $j$. The equation seeks an optimal probability distribution $P_\Gamma$ that maximizes entropy while satisfying constraints related to observed data.

## 4. Experimental setup

The Curonian Spit (Figure 1) is a geographical formation located along the southeastern coast of the Baltic Sea in Lithuania [6]. This area includes varying altitudes with a mix of dense forests, sparse vegetation, and open dunes. The vegetation consists mainly of pine forests and very dry ecosystems, highly susceptible to wildfires. The combination of rugged terrain, dense vegetation cover, and dry sandy soils creates conditions that facilitate the rapid spread of forest fires. Factors such as wind direction from the coast, low humidity levels, and types of dry vegetation play a significant role in influencing the intensity and spread of wildfires in this ecologically sensitive region.

Fig. 1. Map of the Lithuanian part of the Curonian Spit

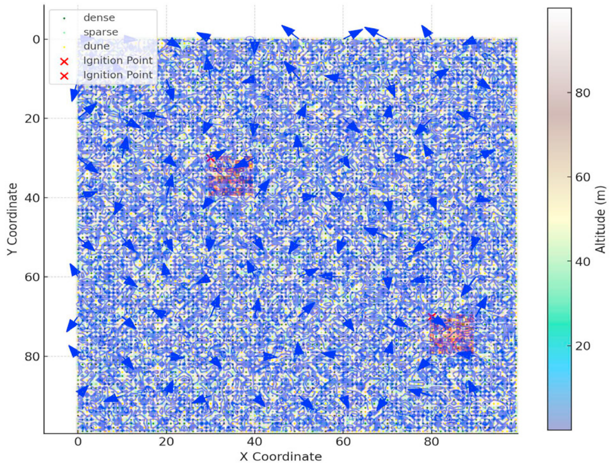


Fig. 2. Simulation of wildfire spread dynamics in the Curonian Spit (fragment).

We included multiple states to represent the different phases of a forest fire's evolution:

- **State 0.** Virgin vegetation, areas not yet affected by the fire.
- **State 1.** Ignited vegetation, where fire has started.
- **State 2.** Actively burning vegetation.
- **State 3.** Cold burned vegetation, representing areas where the fire has passed.
- **State 4.** Soil, indicating areas without vegetation or areas where vegetation cannot burn further.

The von Neumann neighborhood was used to determine the interactions of each cell. The state of a cell at time $t + 1$ depends on its current state and the states of its neighboring cells. The transition rules integrate parameters such as vegetation type and density, humidity, wind direction and power, and altitude to realistically simulate the spread of the fire. The velocity of burning in each cell varied with the type and density of vegetation, denoted by the duration of burning $T_{\text{fire}}$. The model considers different humidity rates ($\alpha_0$, $\alpha_1$, $\alpha_2$) that affect the velocity of spread of the fire ($V_1$, $V_2$). Wind direction and power are also factored into the model. For example, in an eastward wind, the neighborhood set is adjusted to emphasize cells in the wind's path. Wind power levels (low, normal, powerful) modify the spread of fire accordingly. Fire spread predominantly follows increasing slopes, with adjustments made for significant altitude differences. The slope is calculated using the altitudes of neighboring cells.

The spatial accuracy of the forest fire spread model was evaluated using the following metrics.

**Overlap Ratio** ($\mu$) metric quantifies the agreement between the simulated and actual burned areas, defined as the ratio of the overlap area between the simulated and actual fires to the total area of the actual fire ($S_1$ represents the simulated burned area, and $S_2$ denotes the actual fire area): $\mu = \frac{S_1 \cap S_2}{S_2} \times 100\%$.

**Missed Burn Ratio** ($\epsilon_1$) ratio measures the proportion of the actual fire area that was not captured in the simulation and reflects the extent to which the simulation underestimates the actual burned area: $\epsilon_1 = \frac{S_2 - (S_1 \cap S_2)}{S_2} \times 100\%$.

**Excess Burn Ratio** ($\epsilon_2$) metric assesses the part of the simulated burned area that did not correspond to the actual fire and indicates the extent of overestimation by the model in spatial terms: $\epsilon_2 = \frac{S_1 - (S_1 \cap S_2)}{S_2} \times 100\%$.

## 5. Results

Figure 2 illustrates the dynamics of fire spread in the Curonian Spit, showing how various environmental factors influence the behavior of wildfires. The terrain is depicted with altitude gradients. Vegetation types are marked: dark green for dense forests, light green for sparse vegetation, and yellow for dunes. Red dots indicate ignition points where fires begin, and the spread of fire is visualized with red shading, demonstrating its expansion over time. Blue arrows represent wind direction and strength. Blue contour lines show humidity levels, affecting the fire's intensity. Risk zones are indicated with semi-transparent colors: red for high risk, orange for medium risk, and yellow for low risk, pinpointing areas most vulnerable to fire spread.

Figure 3 shows the Overlap Ratio ($\mu$) versus time units for different environmental conditions, which quantifies the agreement between the simulated and actual burned areas. The plot reveals that higher temperatures (30°C and 40°C) combined with lower humidity (0.3) result in a faster increase in the overlap ratio, indicating a more accurate simulation of the actual fire spread. As the temperature increases, the overlap ratio tends to reach higher values faster, reflecting the improved fire spread capacity in hotter conditions. In contrast, scenarios with lower temperatures (20°C) and higher humidity (0.7) show a slower increase in the overlap ratio, suggesting less accurate simulations in such conditions. The results highlight the significant impact of temperature and humidity on fire spread accuracy, with higher temperatures and lower humidity leading to better simulation performance.

Figure 4 displays the missing burn ratio ($\epsilon_1$) versus time units for various environmental conditions, indicating the proportion of the actual fire area not captured in the simulation. The higher temperatures (30°C and 40°C) and lower humidity levels (0.3) result in lower missed burn ratios, signifying better coverage of the actual fire by the simulation. Lower temperatures (20°C) and higher humidity levels (0.7) lead to higher missed burn ratios, especially in the early time units, indicating poorer simulation performance. As time progresses, all conditions show a decrease in the missed burn ratio, converging towards lower values, as simulations became more accurate over time.

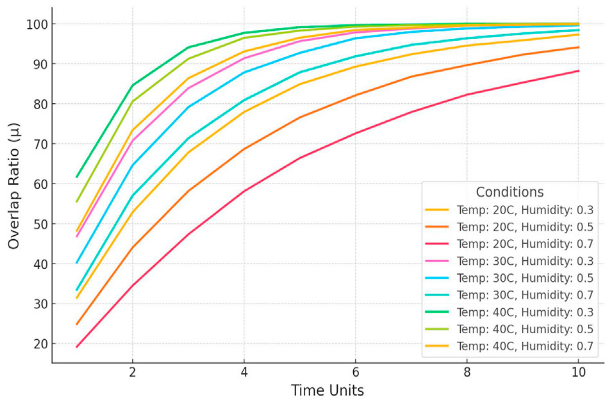


Fig. 3. Overlap ratio for different environmental conditions (temperature and humidity)

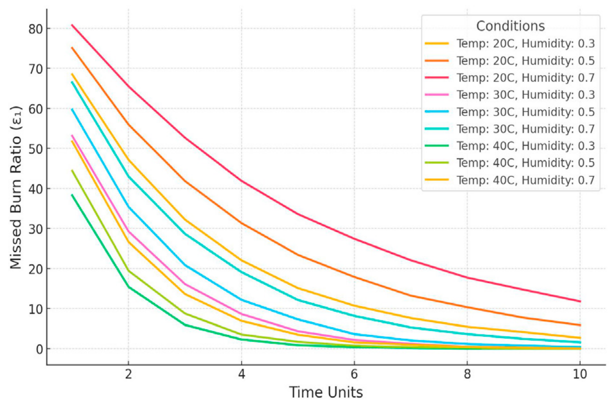


Fig. 4. Missed Burn ratio for different environmental conditions (temperature and humidity)

Figure 5 shows the excess burn ratio ($\epsilon_2$) versus time units for various environmental conditions, illustrating the proportion of the simulated burned area that did not correspond to the actual fire. Higher temperatures and lower humidity levels generally show a slightly more stable excess burn ratio, whereas lower temperatures and higher humidity levels exhibit more fluctuations, especially in the early time units. The results indicate that, while the simulation captures the overall spread of the fire, it tends to overestimate the extent of the burned area, highlighting potential areas for improving the accuracy of the fire spread models under different environmental conditions.

Figure 6 illustrates the relationship between the probability of burns and the average percentage of burned forests in the nonlinear trend: As the probability of burn increases, the average percentage of burned forests initially remains very low and relatively stable until around the 40% probability mark. Beyond this point, there is a marked increase in the percentage of burned forest. In particular, when the probability of burn exceeds 50%, the percentage of burned forest rapidly increases to 100%, which suggests a threshold effect where the probability of burns below 50% have a minimal impact on the extent of the burned area, but the probability above this threshold result in almost complete forest burn, as the spread of the fire is highly sensitive to probability changes beyond a certain critical value, highlighting the importance of controlling factors that influence the probabilities of burns to prevent extensive forest fires.

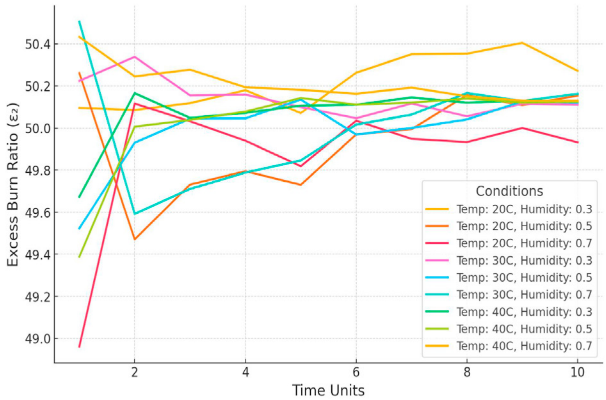


Fig. 5. Excess Burn ratio for different environmental conditions (temperature and humidity)

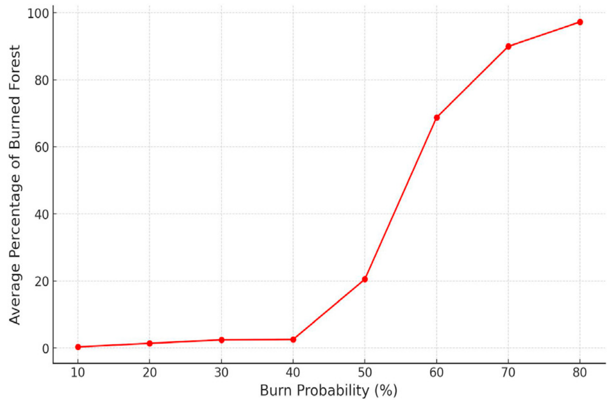


Fig. 6. The impact of burn probability on the percentage of burned forest

Table 1 provides a concise overview of key evaluation metrics and dynamic parameters used in the FL-TCA wildfire model, highlighting its spatial accuracy, stability thresholds, and simulation configuration.

Table 1. Evaluation Summary of the FL-TCA Wildfire Model

| **Metric** | **Value / Range** |
|---|---|
| Best Overlap Ratio $\mu$ | 91.2% (at 40°C, 0.3 humidity) |
| Lowest Missed Burn Ratio $\epsilon_1$ | 6.4% |
| Excess Burn Ratio $\epsilon_2$ | 17–28% |
| Critical Burn Probability Threshold | 50% |
| Dominant Wavelength ($\lambda_{\mathrm{dom}}$) | $\sim \frac{2\pi}{q^*}$, model dependent |
| Dispersion Instability Range | $\beta\bar{\rho} > 0.12$ |
| Grid Resolution | 10 m × 10 m |
| Time Step Adaptation | Variable $\Delta t = \Delta t_0 e^{a_{t_{i,j}}}$ |

## 6. Conclusions

Our FL-TCA model offers a novel approach to understanding and simulating forest fire dynamics, based on the principles of adapted cellular automata for ecological studies. The results illustrated the dynamics of wildfire spread in the Curonian Spit, highlighting the influence of environmental factors like temperature, humidity, wind, and terrain. Higher temperatures and lower humidity significantly improve the accuracy of fire spread simulations, leading to a quicker and more precise overlap between simulated and actual burned areas. Conversely, lower temperatures and higher humidity result in higher missed burn ratios, indicating less accurate simulations, particularly in the early stages. The excess burn ratio shows that simulations often overestimate the burned area, especially under fluctuating conditions. Lastly, the relationship between burn probability and the percentage of burned forests revealed a critical threshold, where probabilities above 50% led to nearly complete forest burn, emphasizing the sensitivity of fire spread to certain environmental conditions.

## Funding

This research has received funding from Horizon Europe Programme, Teaming for Excellence (HORIZON-WIDERA-2022-ACCESS-01-two-stage) - Creation of the centre of excellence in smart forestry "Forest 4.0" No. 101059985.


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