Integrating Human Domain Knowledge into Artificial Intelligence for Hybrid Forest Fire Prediction: Case Studies from South Korea and Italy

15 April | 2024

Hyun-Woo Jo
Postdoctoral Fellowship

1) OJEong Resilience Institute (OJERI), Korea University
2) Agriculture, Forestry, and Ecosystem Services (AFE) Research Group, Biodiversity and Natural Resources (BNR) Program, IIASA
Forest Fire Dynamics
Interplay of Biophysical and Anthropogenic Factors


Burned Area

Population Density

Forest Fires in South Korea (2016.01-2022.03)
Comparison of Modelling Methods
Process-Based Model & Machine Learning

<table>
<thead>
<tr>
<th></th>
<th>Process-Based Model</th>
<th>&gt;&gt;&gt;&gt; Hybrid &lt;&lt;&lt;</th>
<th>Machine Learning</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Pros</strong></td>
<td>• Already structured and guided by human knowledge.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Predictable for unseen dataset</td>
<td>• Powerful tool for solving complex problems</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Decreasing performance when the problem is too complex for modeling</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Setting appropriate parameters is time-consuming</td>
<td>• Efficient at optimization by its nature of end-to-end learning</td>
<td></td>
</tr>
<tr>
<td><strong>Cons</strong></td>
<td></td>
<td>• Need large amount of data for training</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Unpredictable for unseen dataset</td>
<td></td>
</tr>
</tbody>
</table>

Transferring Human Knowledge into Artificial Intelligence

- Model generalization
- Training efficiency
- Interpretability

Integrating Human Domain Knowledge into Artificial Intelligence for Hybrid Forest Fire Prediction
Transferring IIASA’s Forest Fire Model (FLAM) into the Neural Networks (FLAM-Net)
Transferring IIASA’s Forest Fire Model (FLAM) into the Neural Networks (FLAM-Net)

Preserving Gradients

Log-Transformation on Probabilities

Log-transformation allows for expressing very small number, which has advantage on modeling disaster probability.
Transferring IIASA’s Forest Fire Model (FLAM) into the Neural Networks (FLAM-Net)

**Dataset**
- **Label**
  - Historical forest fires

**Process-Guided Inputs**
- Population
- Road density
- Lightning frequency
- Agricultural land
- Fuel availability
- Fuel moisture

**Process-Unguided Inputs**
- Topography
- Forest type

**Future Scenario**
- Population change
- SSP 1-2.6 and SSP 5-8.5
- Fuel moisture
- Forest Management: Current, Over-Protection, and Ideal
  - Fuel availability

**Section 3.1**
- FLAM-Net
  - Shallow
  - Interpretable

**Section 3.2**
- Multi-Scale Application
  - (1, 4, 16, 64, 256, 1024 km²)
- FLAM-Net
  - Deep
  - Complex

**Section 3.3**
- Spatio-Temporal Validation

**Reproduction on Historical Forest fire frequency (Probability/Day/km²)**

**Projection on Future Forest fire frequency (Probability/Day/km²)**

**Parameters**

<table>
<thead>
<tr>
<th>No</th>
<th>k</th>
<th>n</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3</td>
<td>8</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>16</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>32</td>
</tr>
<tr>
<td>4</td>
<td>2</td>
<td>64</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>128</td>
</tr>
<tr>
<td>6</td>
<td>1</td>
<td>256</td>
</tr>
</tbody>
</table>

**Parameters**

<table>
<thead>
<tr>
<th>No</th>
<th>k</th>
<th>n</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>3</td>
<td>8</td>
</tr>
<tr>
<td>4</td>
<td>3</td>
<td>16</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>32</td>
</tr>
<tr>
<td>2</td>
<td>2</td>
<td>64</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>128</td>
</tr>
</tbody>
</table>

**Future Scenarios**
- (1 Population × 2 SSP × 3 Forest Management)

**U-Net**
- Label (1 km²)
- Feature (1 km²)
- Feature (4 km²)
- Feature (16 km²)
- Feature (64 km²)
- Feature (256 km²)
- Feature (1024 km²)

**Spatio-Temporal Validation**
- Encoder
- Decoder
- Conv2D
- Custom Activation
- Max Pooling
- Up Sampling

**Output**
- (1 km²)
- (4 km²)
- (16 km²)
- (64 km²)
- (256 km²)
- (1024 km²)
Parameter Optimization Results
Interpreting Biophysical & Anthropogenic Factors

Seasonal impact

Agricultural area within 100m from forest

Ignition probability

Jan.

Apr.

Jul.

Oct.
Parameter Optimization Results
Interpreting Biophysical & Anthropogenic Factors

• Population dispersed from city center to the outskirts
  → Creating **forest fire hotspots** near metropolitan cities
• Dispersion rapidly decreases by distance
  → Needs further algorithm advancement by incorporating **networks analysis**

Before Dispersion

After Dispersion

Population flow

- Before Dispersion
  - Zoom Window
  - People/km²
    - High: 10,217
    - Low: 0

- After Dispersion
  - Zoom Window
  - People/km²
    - 1,024 km²
      - People/km²
        - Gain: 769.44
        - Loss: -1641.22
    - 256 km²
      - People/km²
        - Gain: 595.40
        - Loss: -1018.15
    - 64 km²
      - People/km²
        - Gain: 355.40
        - Loss: -629.07
    - 16 km²
      - People/km²
        - Gain: 3004.87
        - Loss: -3412.18
    - 4 km²
      - People/km²
        - Gain: 3501.30
        - Loss: -5219.50
    - 1 km²
      - People/km²
        - Gain: 2559.62
        - Loss: -3374.70
Month-Wise Validation

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.789</td>
<td>0.986</td>
<td>0.854</td>
<td>0.694</td>
<td>0.959</td>
<td>0.871</td>
<td>0.726</td>
<td>0.785</td>
<td>0.431</td>
<td>0.987</td>
<td>0.757</td>
<td>0.698</td>
</tr>
</tbody>
</table>

Overall high month-wise Pearson's $r$
Only 17 fire events observed over 6-year in September (smallest among the months)

There is a strong seasonal pattern of frequent forest fire in spring.
Does it merely reproduce this pattern?
Or able to differentiate among the same seasonality

Pearson’s $r$
Future Projection
Impact of Population Density

Rapidly decreasing population after 2050, while hotspots keep formed near metropolitan cities.
Future Projection
Impact of Fuel Moisture (Climate Change)

Peak ignition probability between 2030 and 2050
Future Projection
Impact of Fuel Load (Forest Management)

Current Management
- Clear-cut of 15,000 ha per year (legal final cutting age)
- Thinning practices at a rate of 30% of AGB across 165,000 ha per year

No Management
- No clear-cut
- No thinning practices

National Management Plan (6th) in the Future
- Clear-cut of 35,000 ha per year
- Thinning practices at a rate of 30% of AGB across 165,000 ha per year
Future Projection on Fire Frequency

Peak fire frequency between 2030 and 2050

Historical

Current Management

No Management

National Management Plan (6th)
The Case of Sardinia, Italy
Conclusion

IIASA's FLAM incorporates process-based algorithms for interpreting biophysical and anthropogenic factors affecting forest fires.

FLAM-Net effectively integrates FLAM processes into a machine-learning framework, augmented with additional algorithms tailored to national contexts. i.e. agricultural burning and its seasonal patterns, as well as a diverse range of fire hotspots near metropolitan cities in South Korea.

The optimization of FLAM-Net yields interpretable insights into future fire frequency*, while enhancing its applicability through end-to-end optimization capabilities.

* FLAM includes algorithms for estimating burned area, while FLAM-Net was examined only for frequency.
Thank you.

International Institute for Applied Systems Analysis (IIASA)
Schlossplatz 1, A-2361 Laxenburg, Austria

Hyun-Woo Jo
Postdoctoral Fellowship
1) OJEong Resilience Institute (OJERI), Korea University
2) Agriculture, Forestry, and Ecosystem Services (AFE) Research Group Biodiversity and Natural Resources (BNR) Program, IIASA
endeavor4a1@gmail.com
johyunwoo@iiasa.ac.at