Dokuz Eylül Üniversitesi Fen Bilimleri Enstitüsü

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Spatiotemporal Wildfire Spread Prediction Using ConvLSTM

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Introduction

- Climate change has made wildfires more frequent and more intense around the world.
- Current prediction systems often lack accuracy and fail to respond quickly.
- Turkey's Manavgat fire (Jul 2021) burned ≈ 60357 hectares of forest area
- Early next-day forecasts give crews > 12 h head-start.
- The aim is to take pure satellite data and predict a fire mask for next day.

Research Gap and Goal : Physical Models

- FARSITE (Fire Area Simulator):
  - Predicts wildfire spread using terrain, fuel, and weather conditions
  - Effective for planning but limited by static parameterization
- BEHAVE:
  - Uses empirical fire behavior models
  - Predicts point-source fire spread based on fuel, wind, and topography

Related Work: Machine Learning Models

- Support Vector Machines (SVM):
  - Classifies regions at risk based on historical data
  - Good accuracy but lacks temporal modeling capability
- Random Forests:
  - Ensemble method for risk mapping
  - High predictive performance, yet limited in sequential analysis
- Spatial-only CNN models:
  - Effective at spatial pattern recognition
  - Limited temporal dynamics handling
- lack of next-day spread predictors without fire history

Data Sources

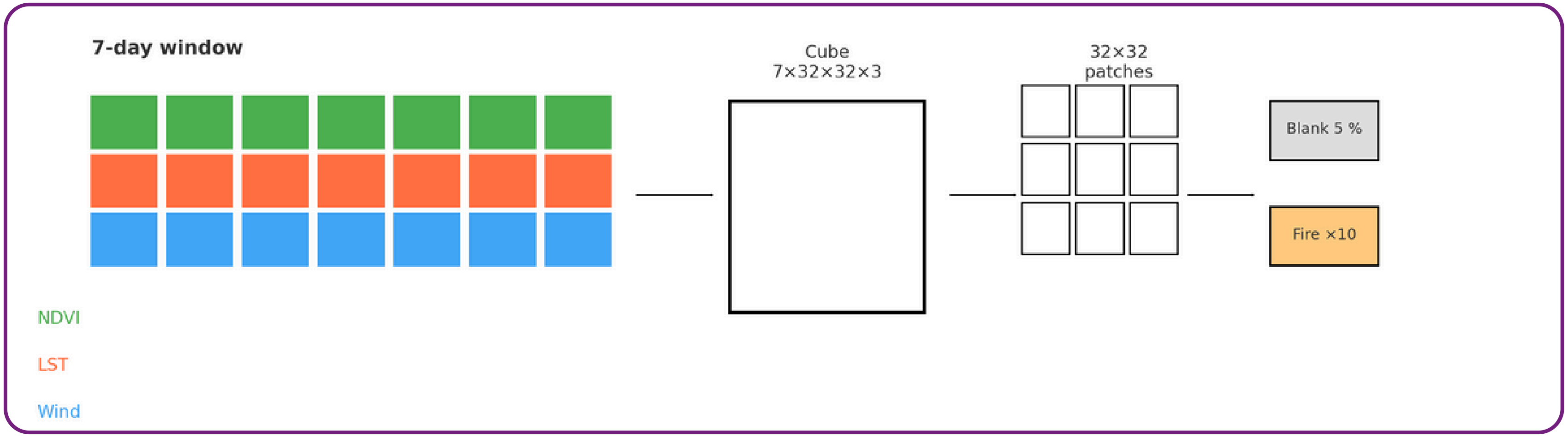
- Burned Area (Ground Truth):
  - MODIS MCD64A1 (Daily burned area, 500m)
- Inputs (Features):
  - NDVI Vegetation (MOD13Q1)
  - Land Surface Temperature (MOD11A1)
  - Wind speed/direction (ERA5 or GEE)
- Spatial Resolution:
  - Original resolution ranges between 250m to 1km
  - Downsampled to uniform 500m resolution for computational efficiency
- Platform: Google Earth Engine
- Location : Turkey, Antalya, Manavgat

Data Sources: (continued)

Layer	Date range	Why
Input features (NDVI, LST, Wind)	21 July 2021 → 14 Aug 2021	We need the seven days before every prediction day, so feature stacks start a week earlier.
Target fire masks	**28 July 2021 → 14 Aug 2021**	These 18 consecutive “burn days” (28 Jul, 29 Jul … 14 Aug) are what we try to predict one day in advance.

Pre-processing

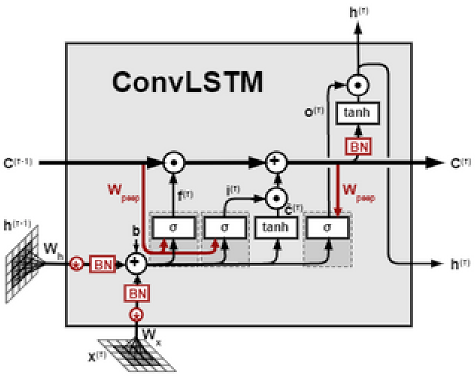
- 7–day window: stack daily NDVI, LST, Wind
- Cube: resize AOI to 32 × 32 px; shape = 7 × 32 × 32 × 3
- Patch extraction: cut cube into non–overlapping 32 × 32 tiles
- Class balance: keep 5 % blank tiles; duplicate each fire tile × 10
- Output: 250 training sequences → Train/Val/Test splits



ConvLSTM Architecture

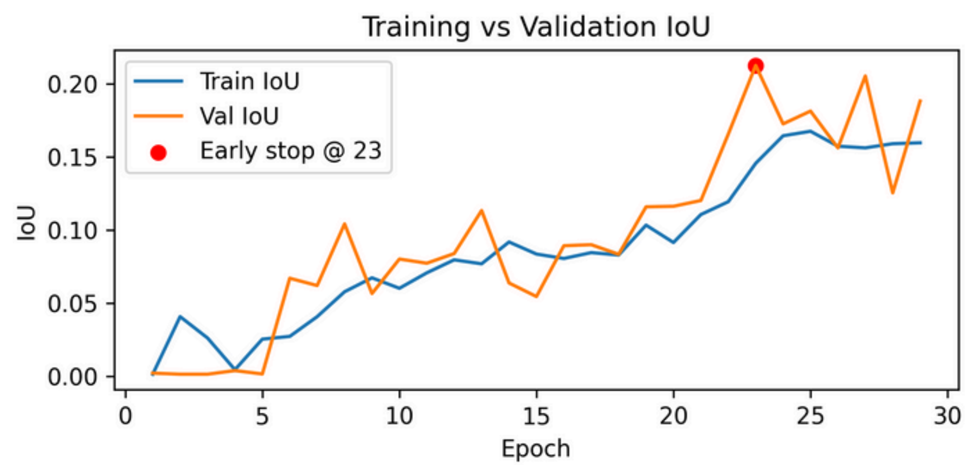
Why ConvLSTM?

- Spatiotemporal memory: hidden-state is a feature map, so the model propagates location-aware context from one day to the next.
- Parameter-efficient: only ≈ 114 k weights (vs > 1 M in a 3-D CNN) → runs on a laptop GPU.
- End-to-end differentiable: loss computed directly on fire-mask pixels (weighted BCE), no post-alignment needed.
- Proven for weather / radar nowcasting → good match for wildfire spread dynamics.



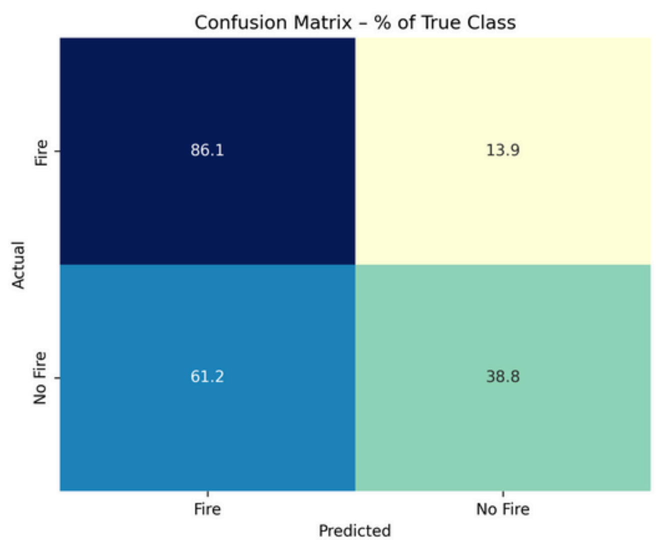
Training Strategy

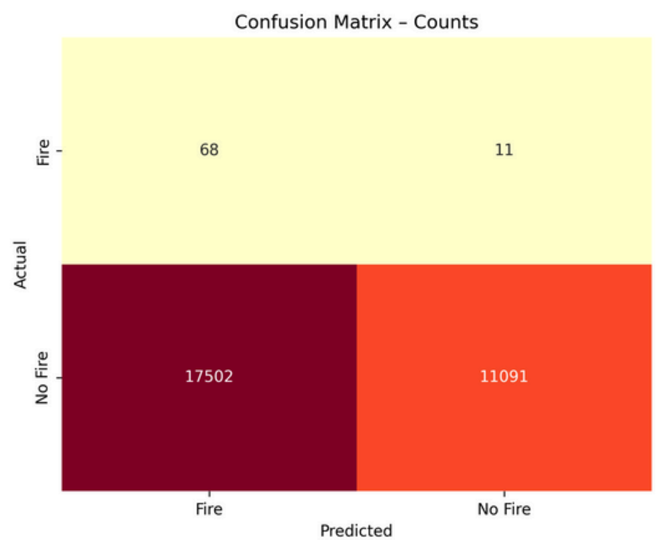
- Weighted BCE loss pos-weight = 120 (derived from 0.28 % fire pixels)
- Adam (LR = 3 × 10^{-4}) + gradient-clip = 1.0
- Batch 8 + on-the-fly aug: random flips & 0–270° rot90
- SpatialDropout3D 0.2 to curb over-fit in ConvLSTM layers
- Early-stop on val IoU best model at epoch 32 / 50
- Train / Val / Test = 174 / 37 / 39 sequences (70 / 15 / 15 %)



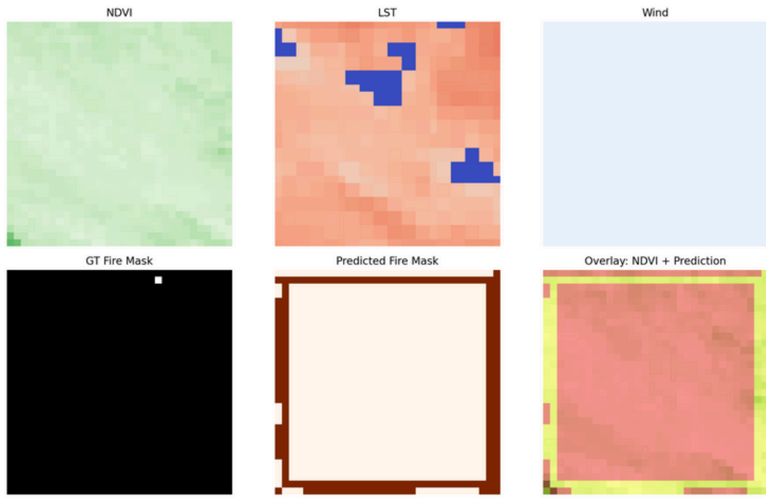
Quantitative Results

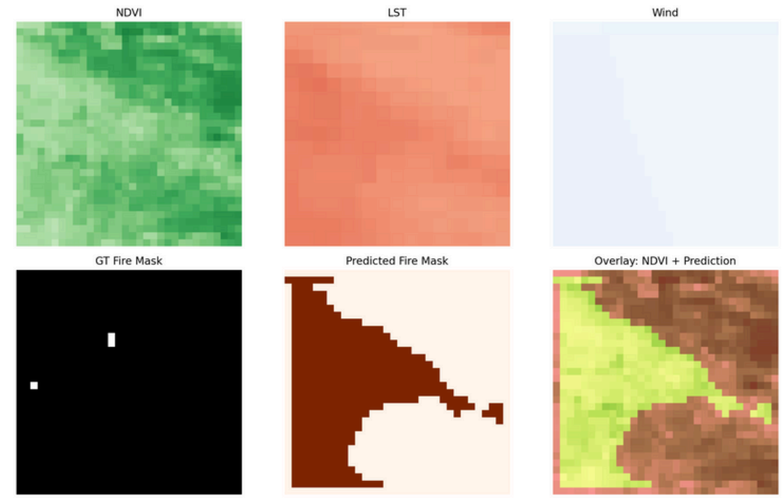
- IoU (Jaccard) = 0.22
- Recall = 0.91 (rarely misses fire)
- Precision = 0.003 (many false alarms)
- F1 score ≈ 0.006
- Best epoch = 32 / 50 (early-stop)
- accuracy = 39%

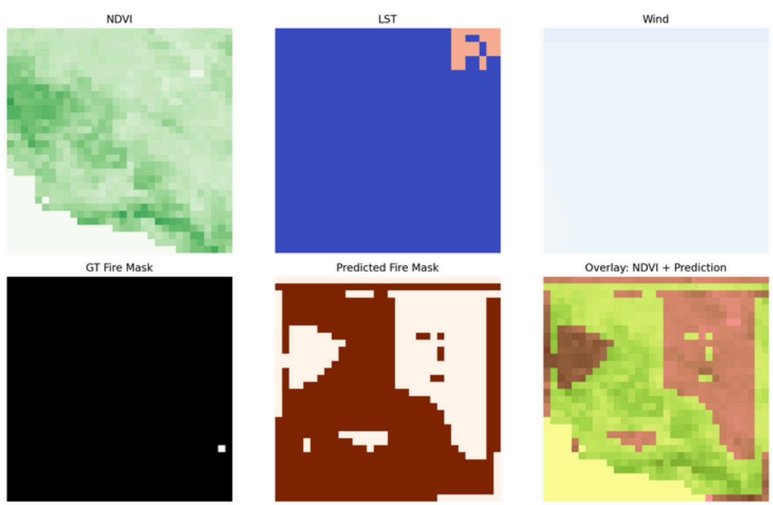


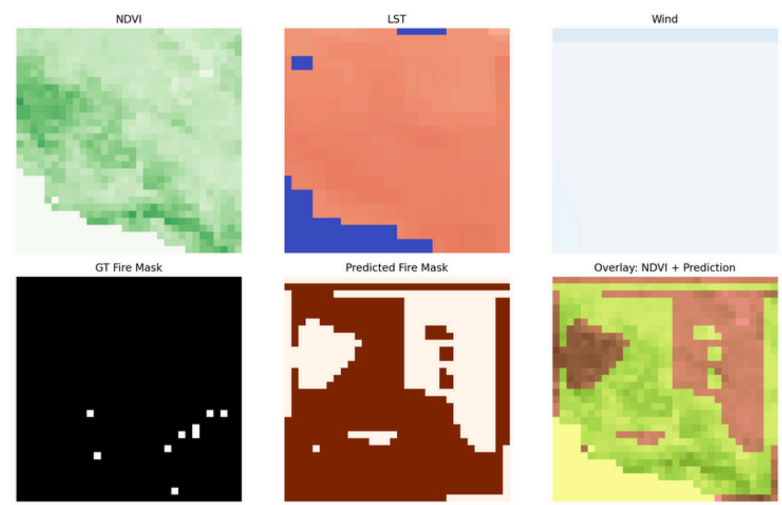


Qualitative Examples









Strengths & Limitations

Strengths	Limitations
High recall (0.91) — rarely misses active fire	**Low precision (0.003)** — many false alarms
Learns **when & where** fire spreads (spatiotemporal)	Restricted to **500 m / 32 px resolution**
Lightweight (~114 k params) — runs on laptop GPU	Trained on **single region & 18 burn days**
Pure **data-driven**, no hand-tuned rules	Ignores topography & humidity so far

Conclusion & Future Works

- ConvLSTM demonstrates strong predictive capabilities for wildfire spread
- The proposed Model will significantly outperforms static and traditional modeling approaches
- There is a Practical applicability in real-time fire management and prevention systems
- Integration of additional meteorological parameters to enhance prediction accuracy
- Development of real-time deployment strategies for emergency response

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Thank you!

Any Questions