

Spatiotemporal Data Analytics on Large Event Data

Atsushi Nara

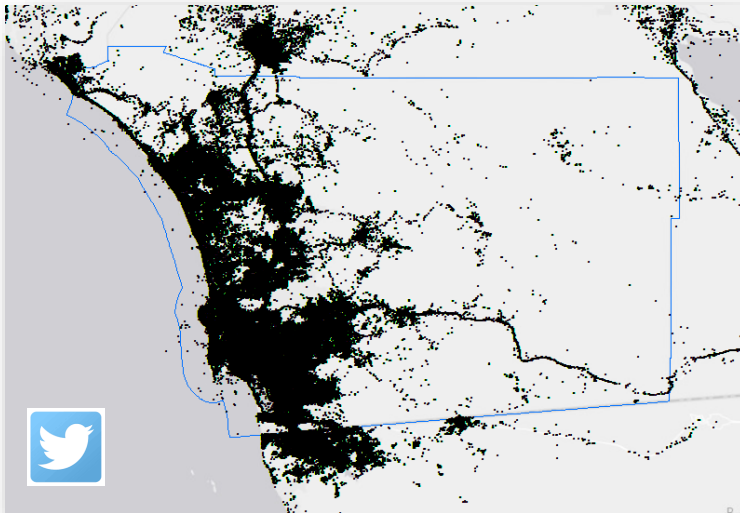
Assistant Professor, Department of Geography

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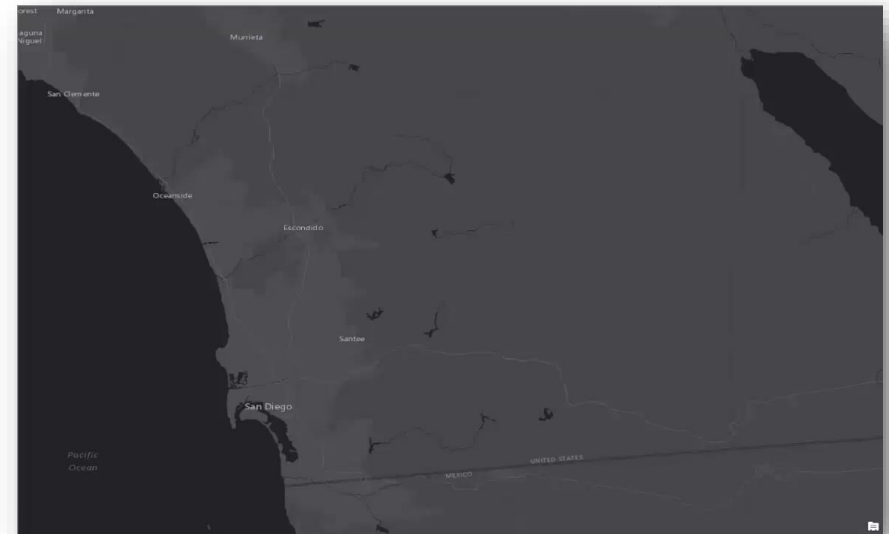
San Diego State University

The Age of Big Spatiotemporal Data

SPACE × TIME



Geo-referenced tweets



Extracting movements from tweets

The Age of Big Spatiotemporal Data

SPACE × TIME

Example: Tracking Movements by GPS devices

1 person per hour for a year:	$1 \times 24 \times 365 = 8,760$
1 person per minute for a year:	$1 \times 60 \times 24 \times 365 = 525,600$
1 person per second for a year:	$1 \times 60 \times 60 \times 24 \times 365 = 31,536,000$

The Age of Big Spatiotemporal Data

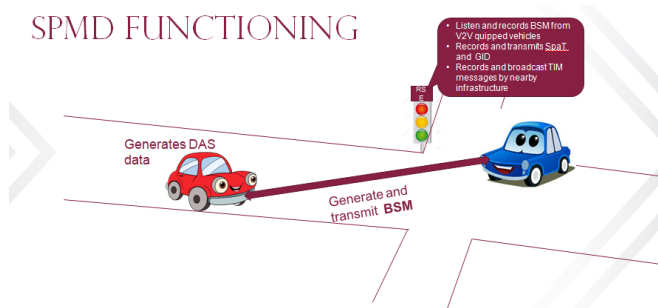
SPACE × **TIME**



Chen, Y., Tsou, M-H., Nara, A. (2019)

Example: Safety Pilot Model Deployment (SPMD) Data

SPMD FUNCTIONING



Subject:

2,836 Vehicles

Duration:

1 month

Frequency:

≈ **10 Hz**

Data points:

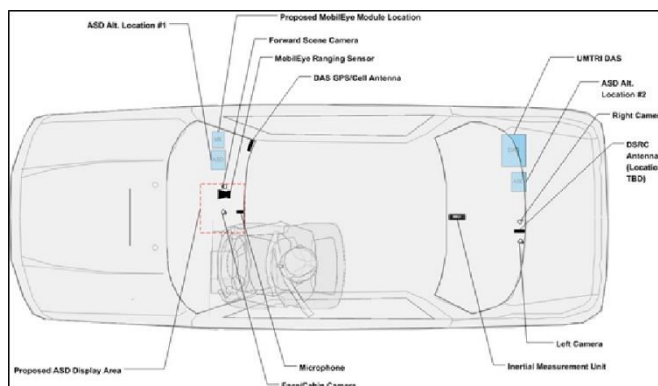
> **1.5 billion GPS points**

File size:

205 GB in CSV

Attributes:

speed, location, direction, yaw rate, heading, etc.



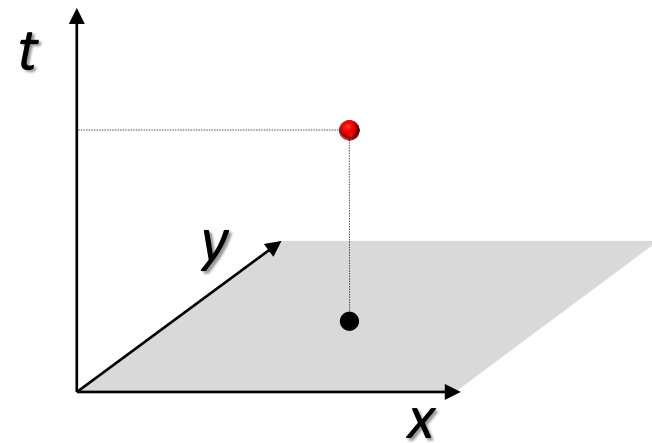
$$\textit{Event} = (S, T, A)$$

S: Spatial Attributes (point, line, polygon, pixel, ...)

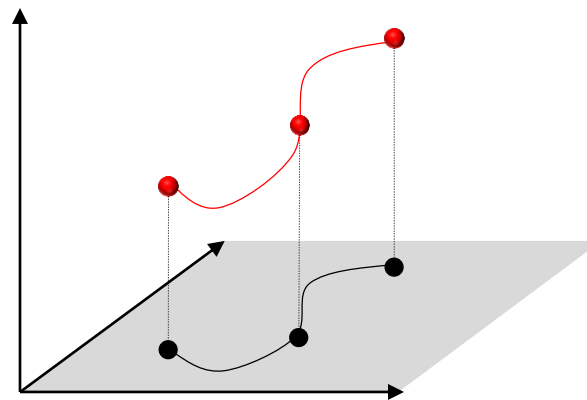
T: Temporal Attributes (start-end time, duration)

A: Event Attributes (id, name, ...)

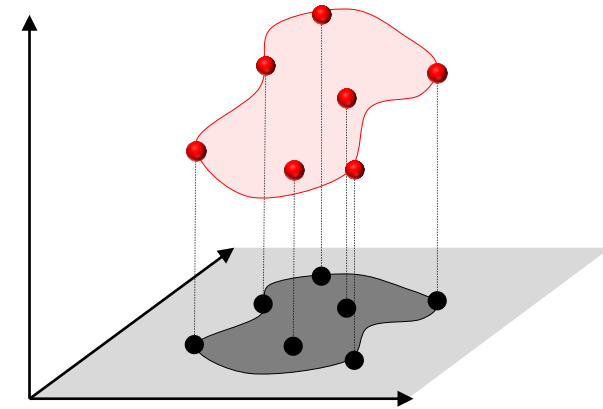
Time Geography Representation (Vector)



$$e = (x_1, y_1, t_1, A)$$

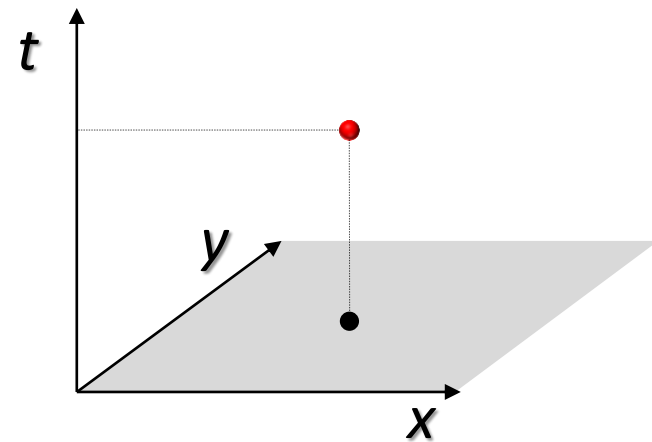


$$e = \{ (x_1, y_1, t_1), \\ (x_2, y_2, t_2), \\ (x_3, y_3, t_3), \\ A \}$$

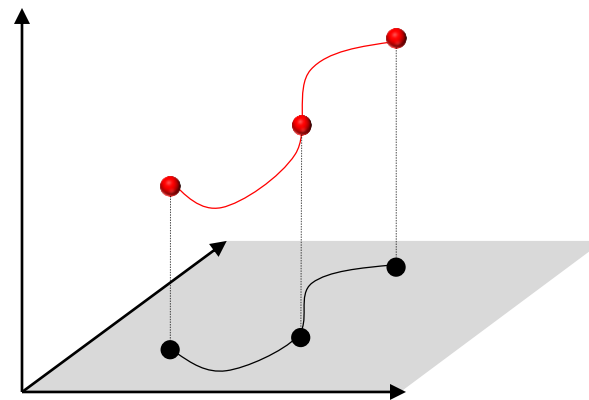


$$e = \{ (x_1, y_1, t_1, a_1), \\ (x_2, y_2, t_2, a_2), \\ \dots \\ (x_n, y_n, t_n, a_n) \}$$

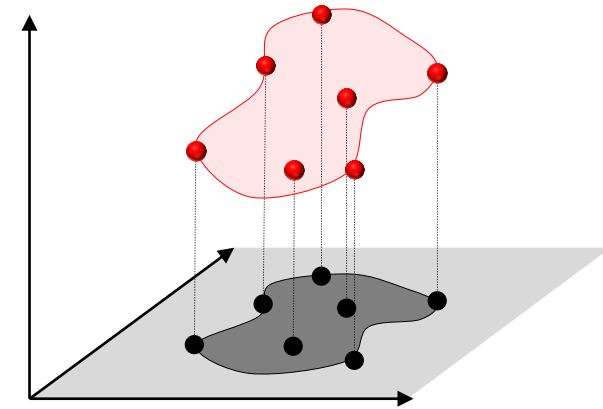
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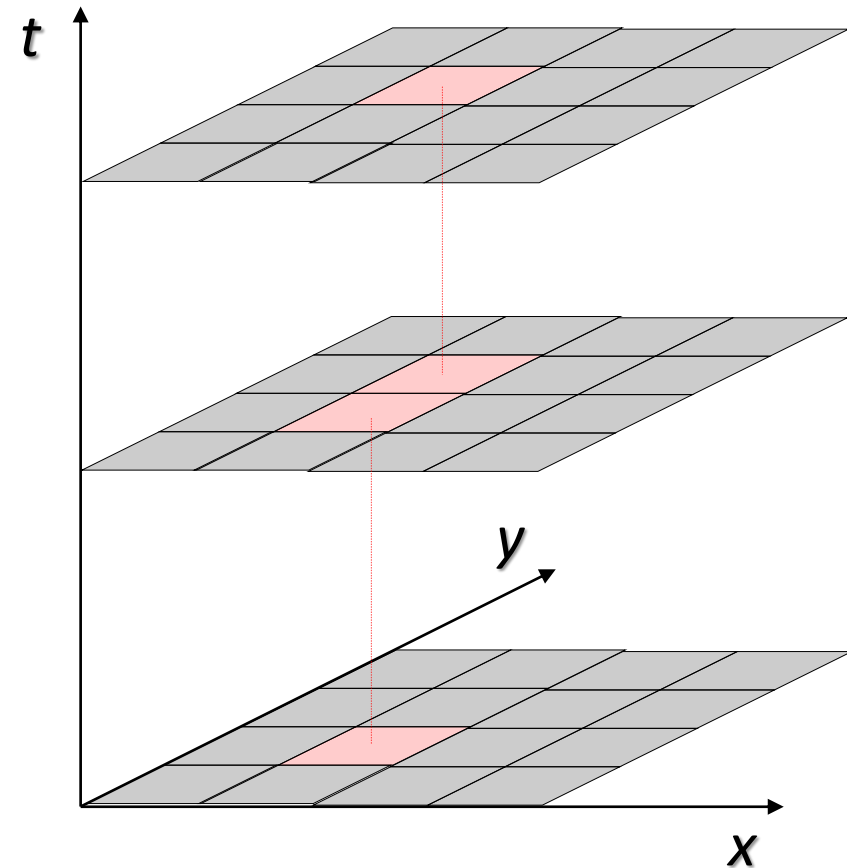


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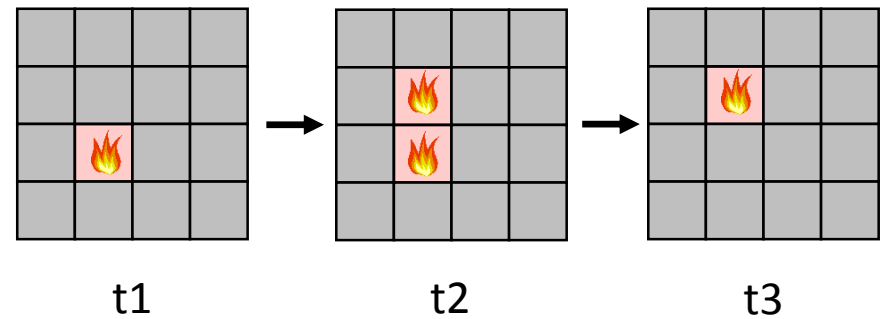


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Time Geography Representation (Raster)

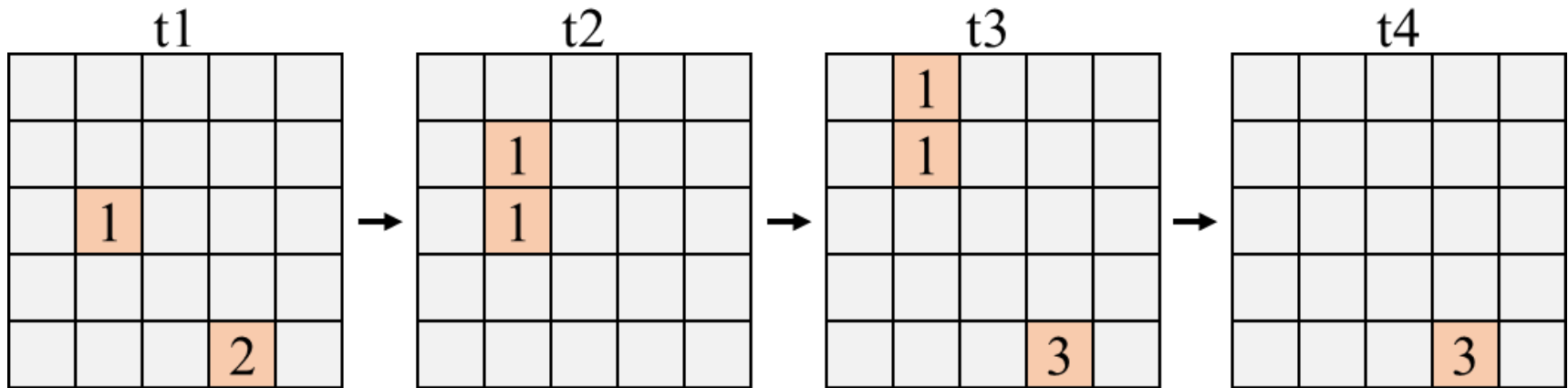


Single Spatiotemporal Event



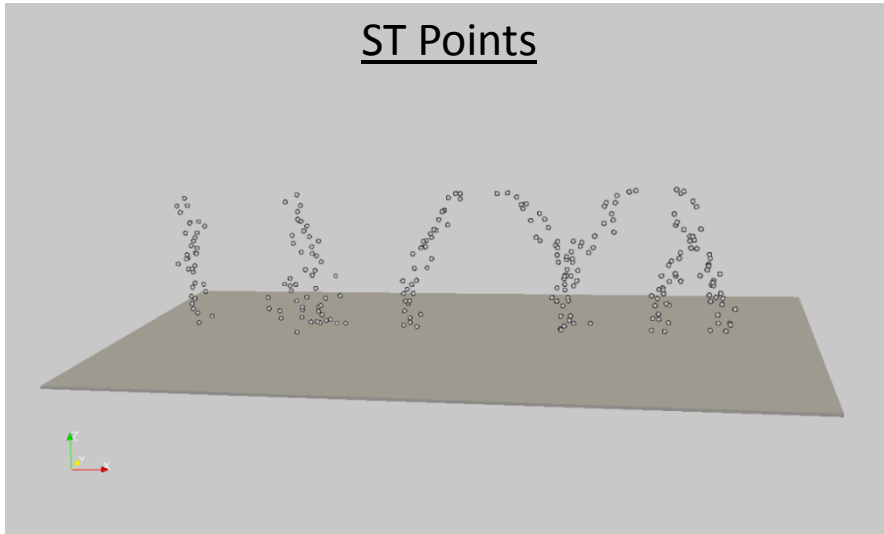
Time Geography Representation (Raster)

Three Spatiotemporal Events

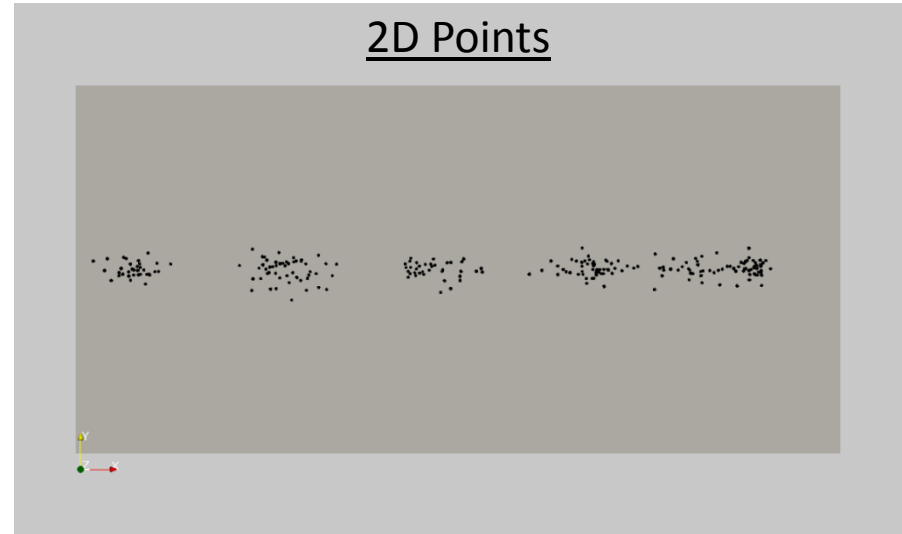


Introduction

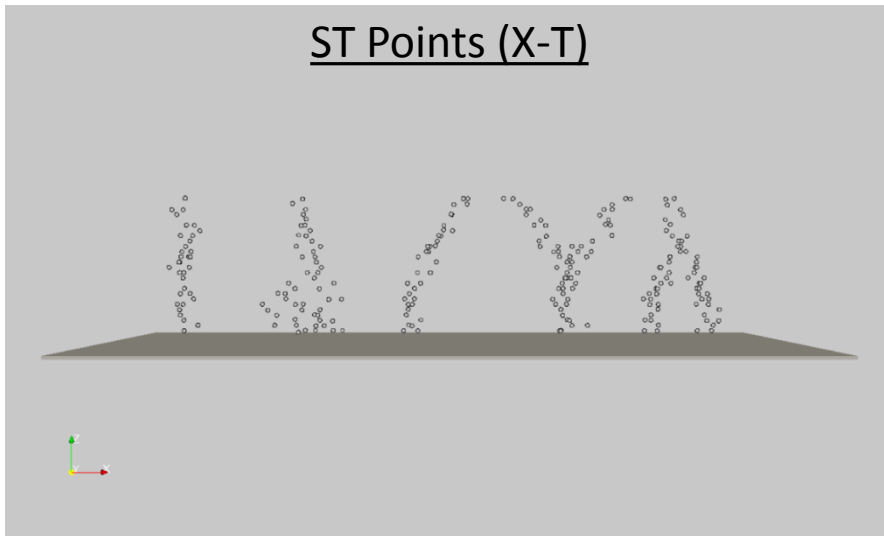
ST Points



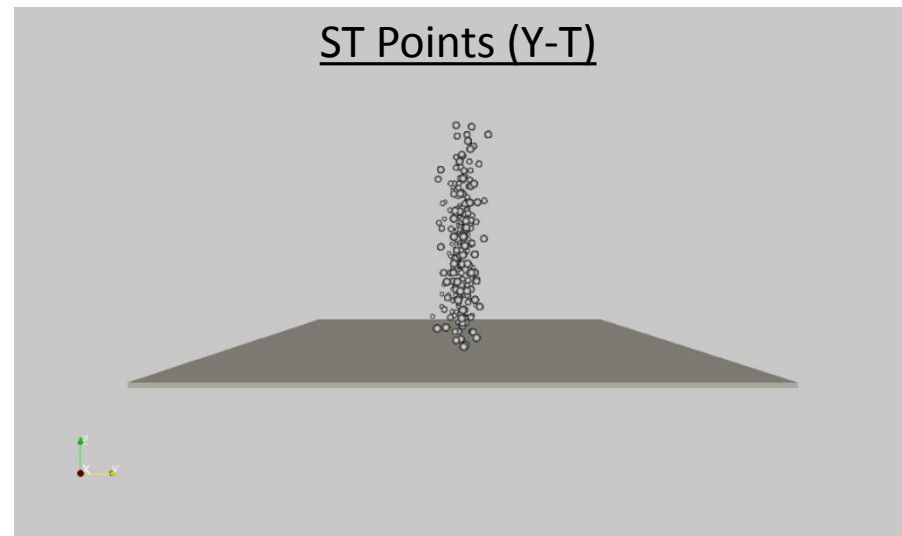
2D Points



ST Points (X-T)



ST Points (Y-T)



Collaborative work with **Dr. May Yuan**, U of Texas at Dallas



SAN DIEGO STATE
UNIVERSITY



HDMA
@SDSU

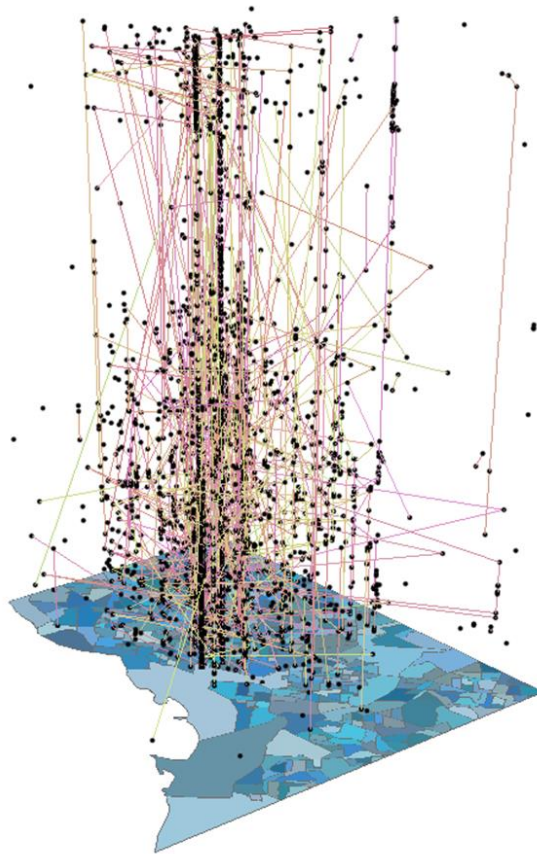


CALIFORNIA
AIR RESOURCES BOARD



Research Objective

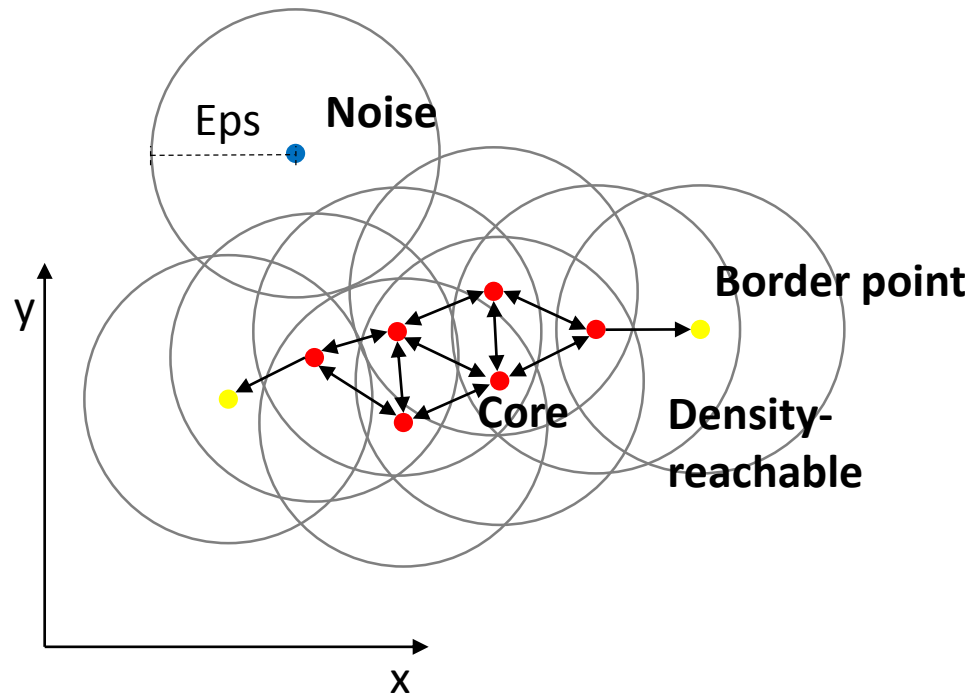
- Explore spatiotemporal trends of large event datasets effectively



- Develop a **parallel** implementation of **ST-DBSCAN** to identify spatiotemporal event clusters

DBSCAN

Min Points = 4



DBSCAN (2D)

DBSCAN

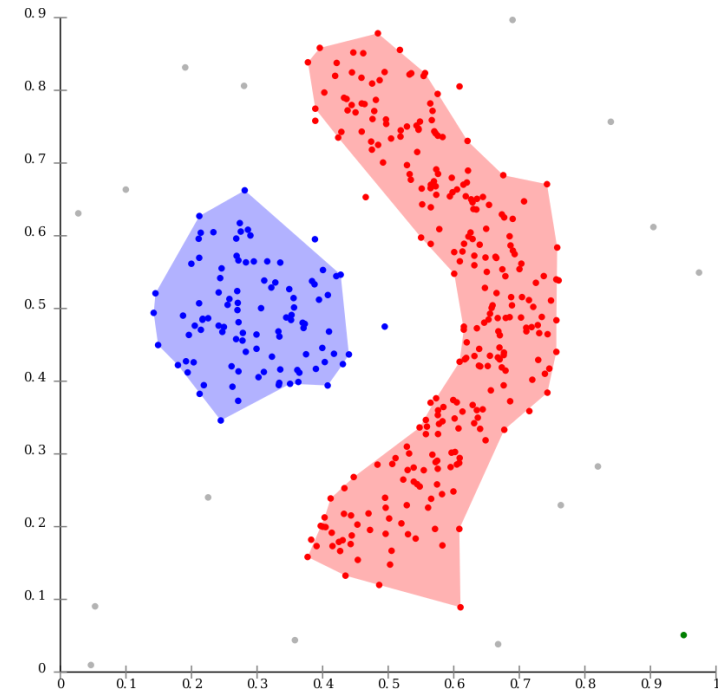
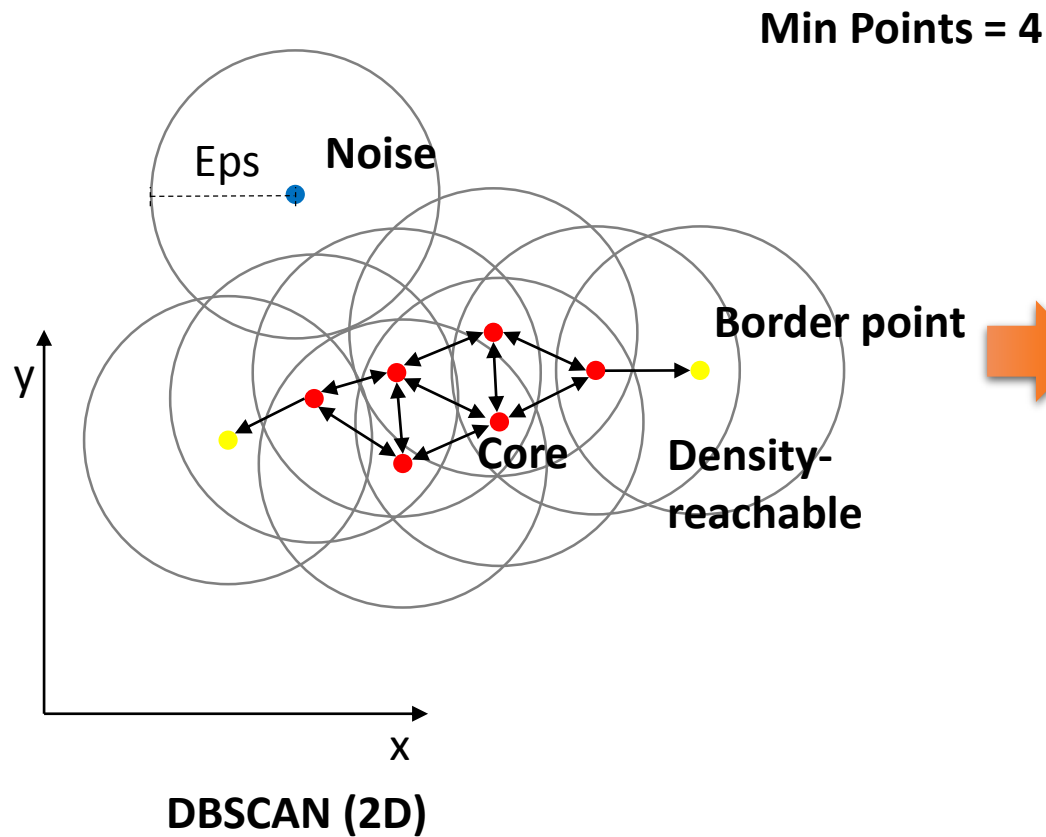
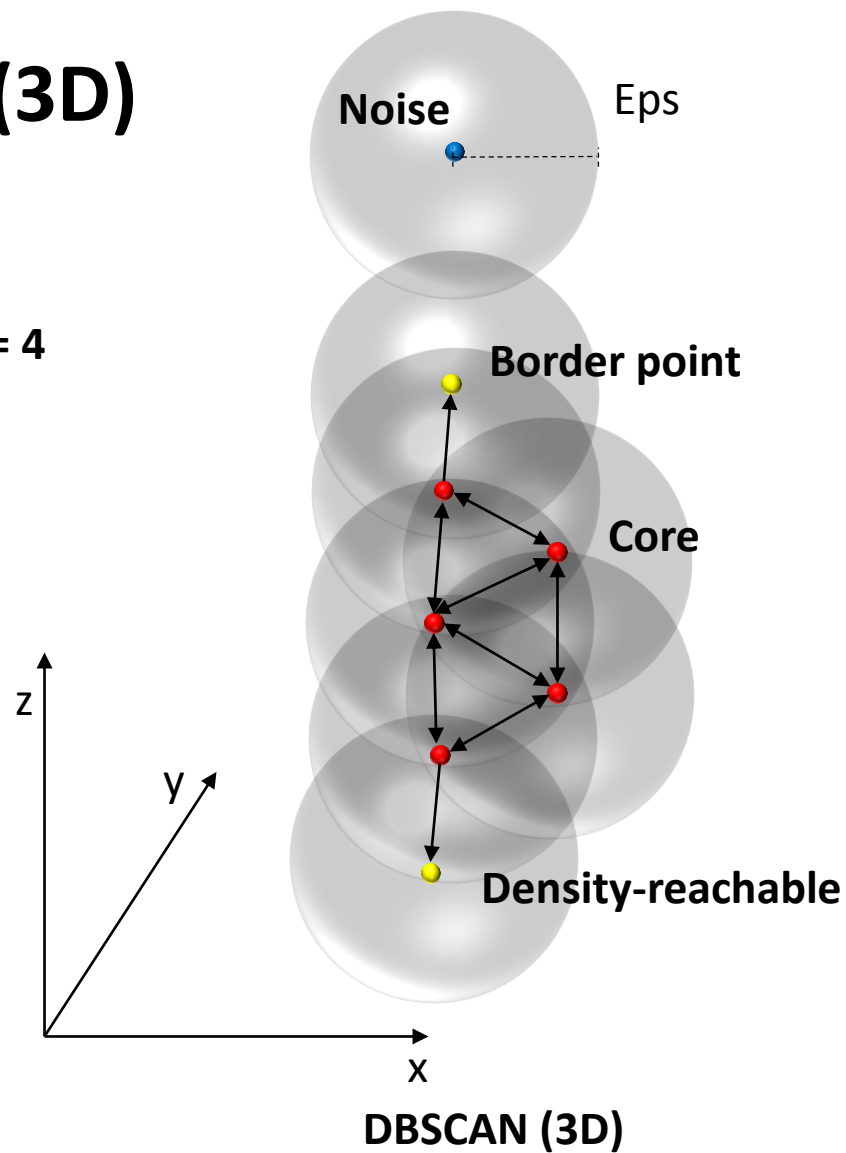
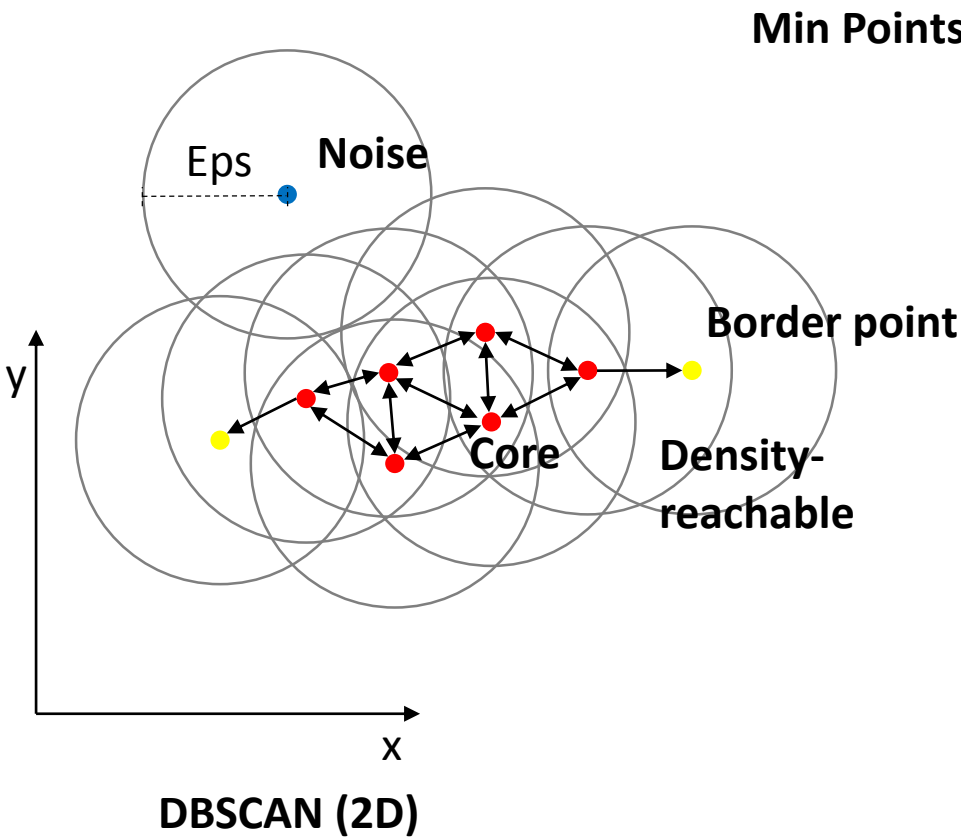


Image from Wikipedia

DBSCAN (3D)



DBSCAN Runtime Complexity

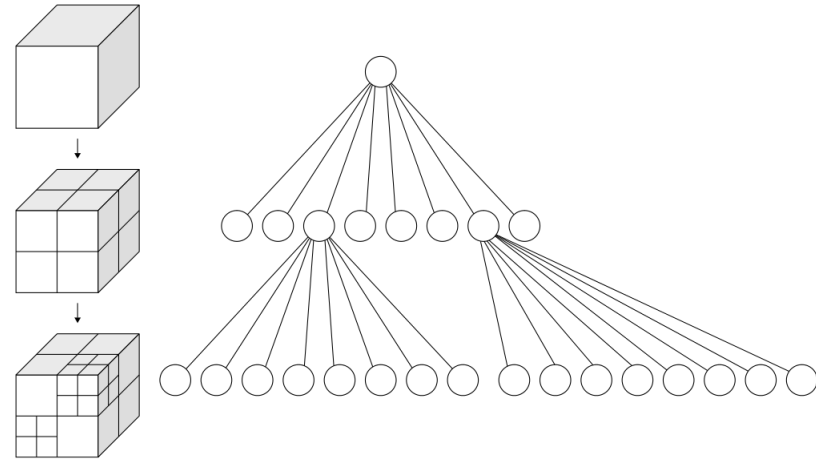
Average: $O(N \cdot \log(N))$

Worst case scenario: $O(N^2)$

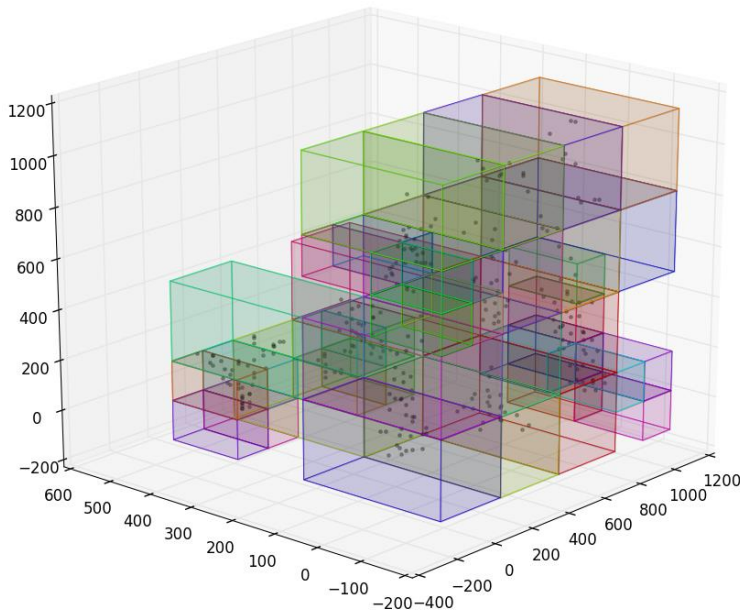
N: the size of the input data set

ST-DBSCAN Parallel Implementation

- Multi-core processing
- Partition data using Octree
- ST-DBSCAN on partitioned data
- Merge cluster results



Octree
(Image from Wikipedia)



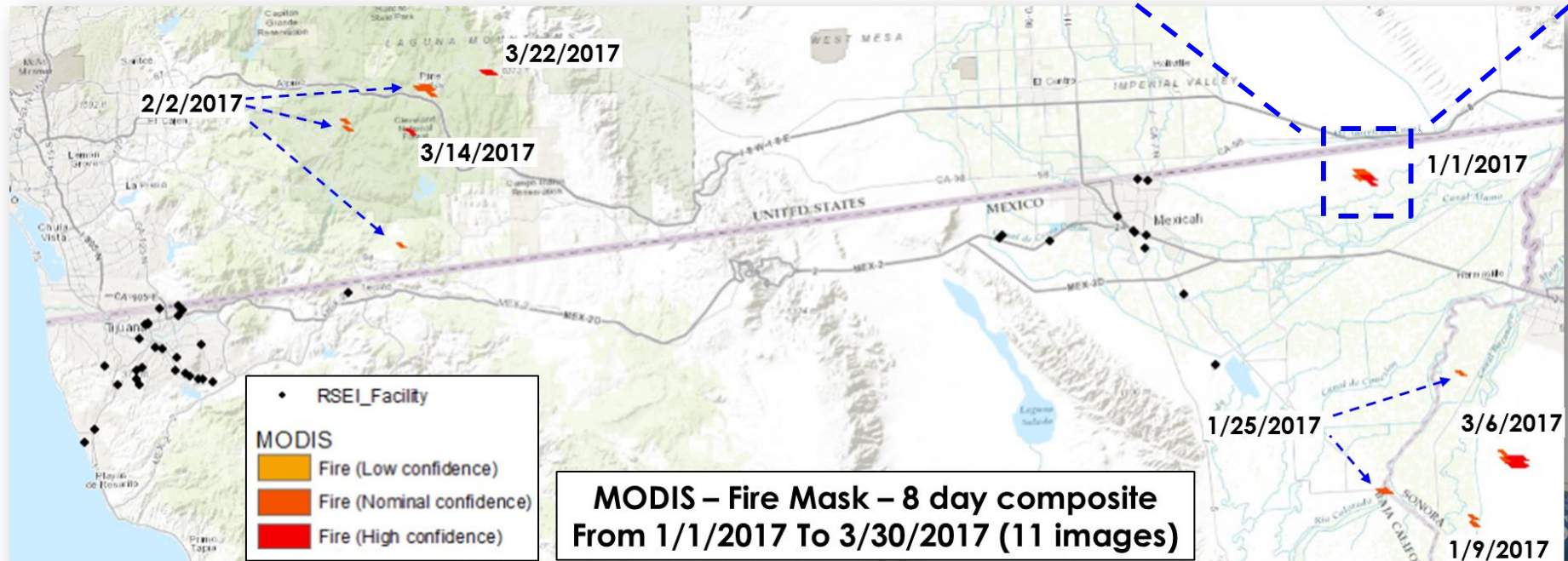
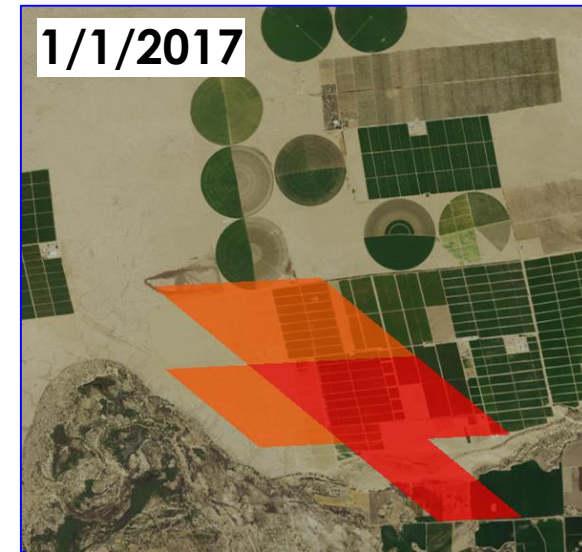
Octree Partition with a test datasets

Case Study

Find burning activities such as agricultural burns in the US-Mexico border area

Data Source: MODIS – Active Fire Product

- Thermal Anomalies & Fire
- Cell size: ~1,000m x ~1,000m
- Cycle: 1 day x 2 (Terra & Aqua)
- 1,545 HDF files from 2000 – 2018



Case Study

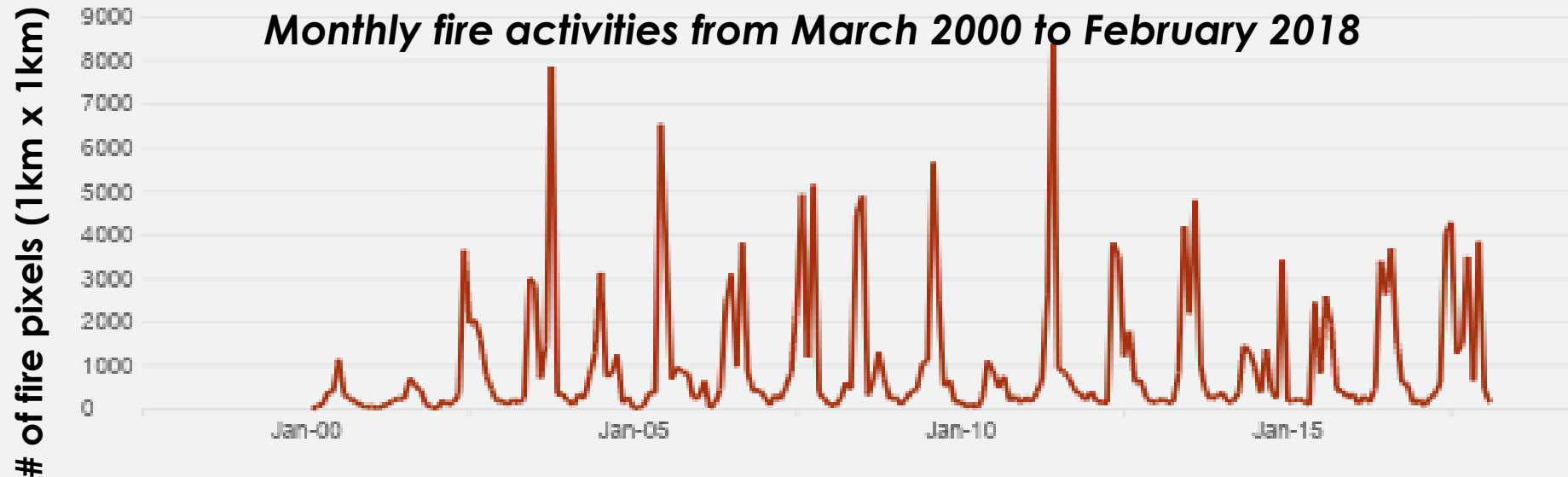
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50km buffers



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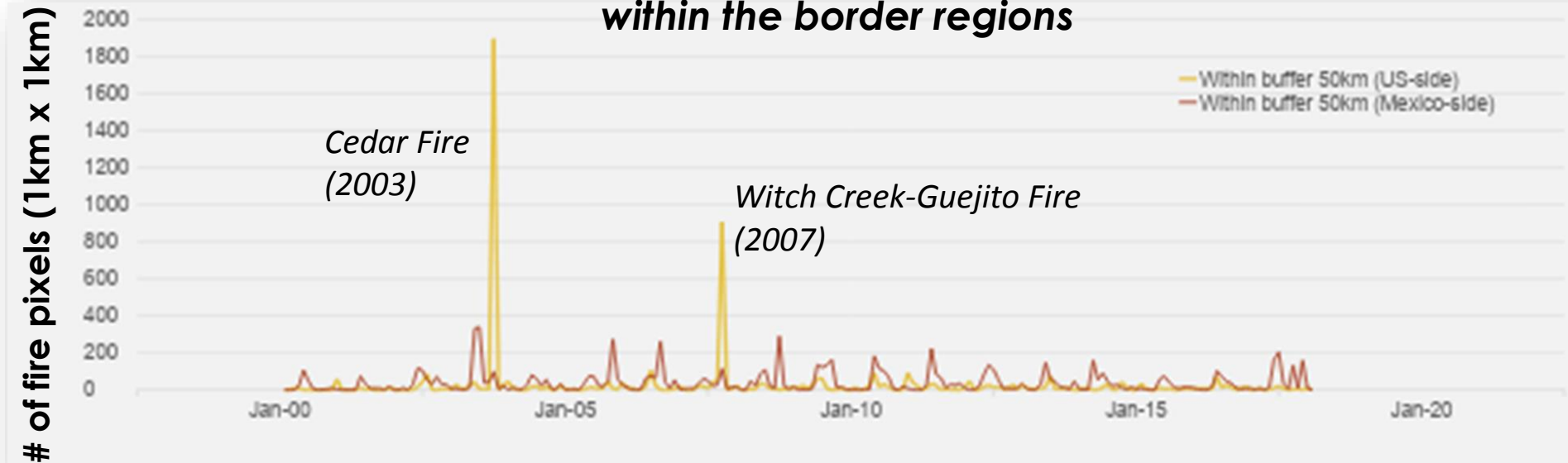
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Fire pixels within the border regions

**Monthly fire activities from March 2000 to February 2018
within the border regions**



Case Study

Find burning activities such as agricultural burns in the US-Mexico border area

Identify fire events using ST-DBSCAN

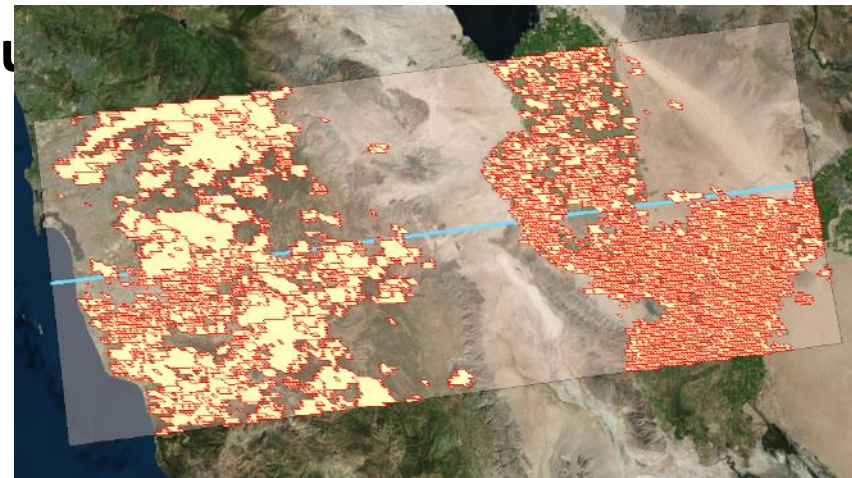
- $\text{eps-space} = 1,000 \text{ m}$
- $\text{eps-time} = 1 \text{ day}$
- $\text{min-points} = 1 \text{ pixel}$
- spatially and temporally contiguous fire pixels

Case Study

Find burning activities such as agricultural burns in the US-Mexico border area

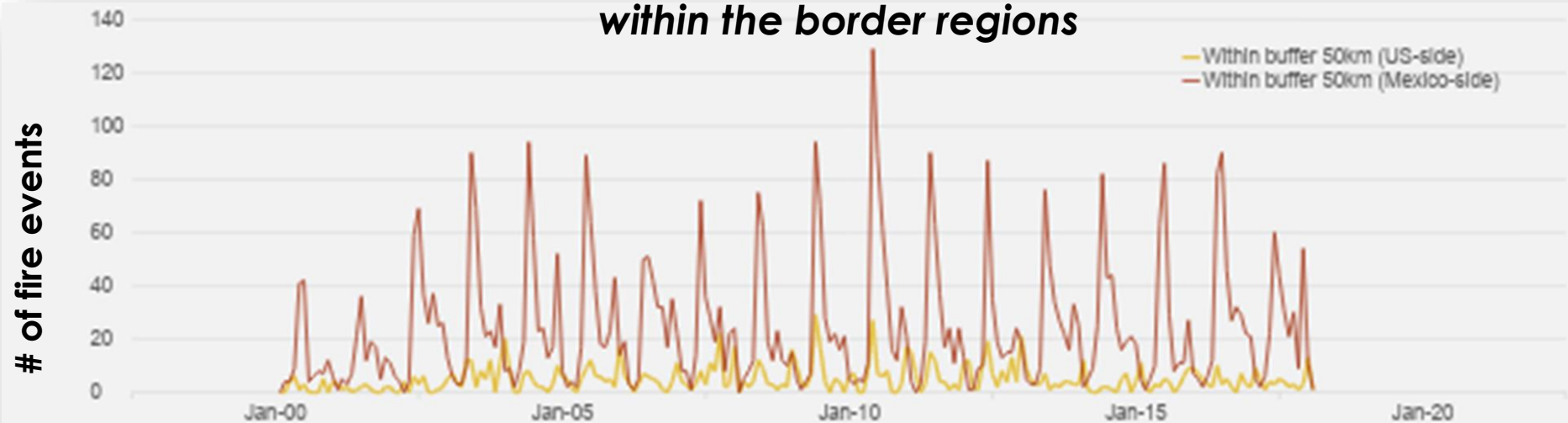
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Fire events within the border regions

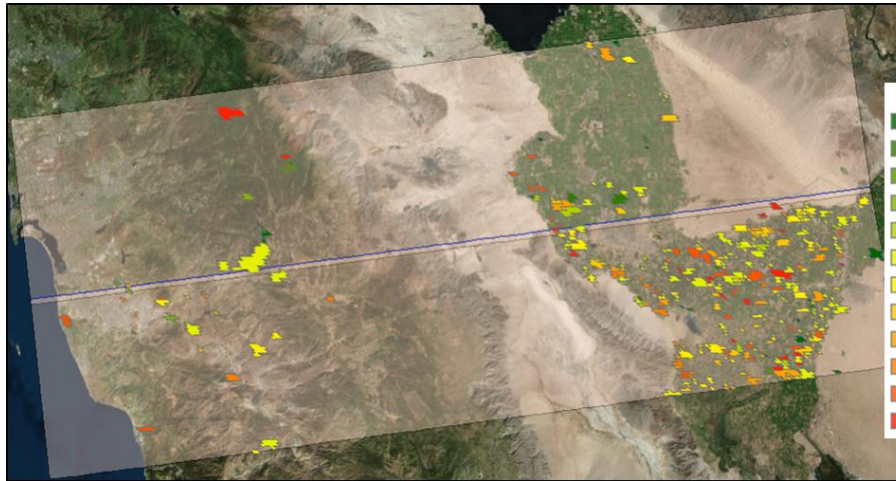
**Monthly fire activities from March 2000 to February 2018
within the border regions**



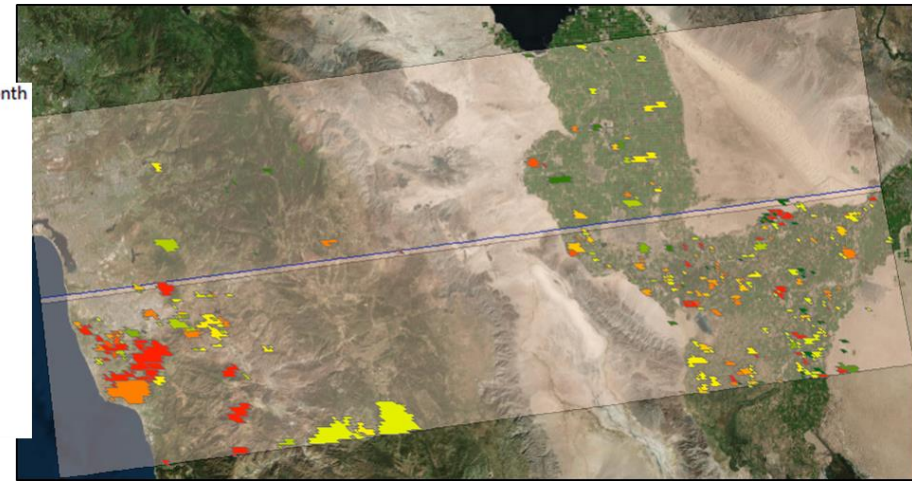
Case Study

Find burning activities such as agricultural burns in the US-Mexico border area

Fire Events



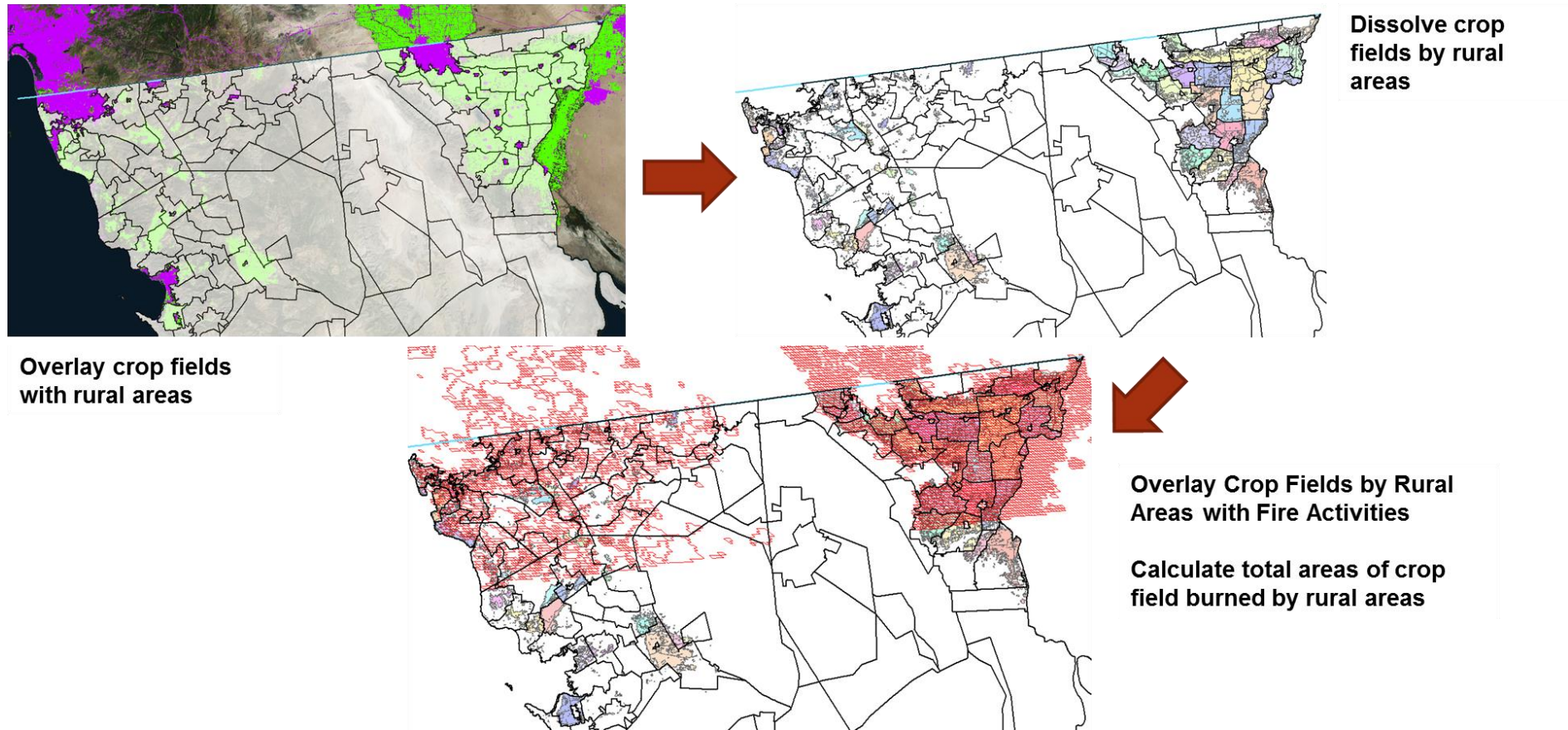
2016



2017

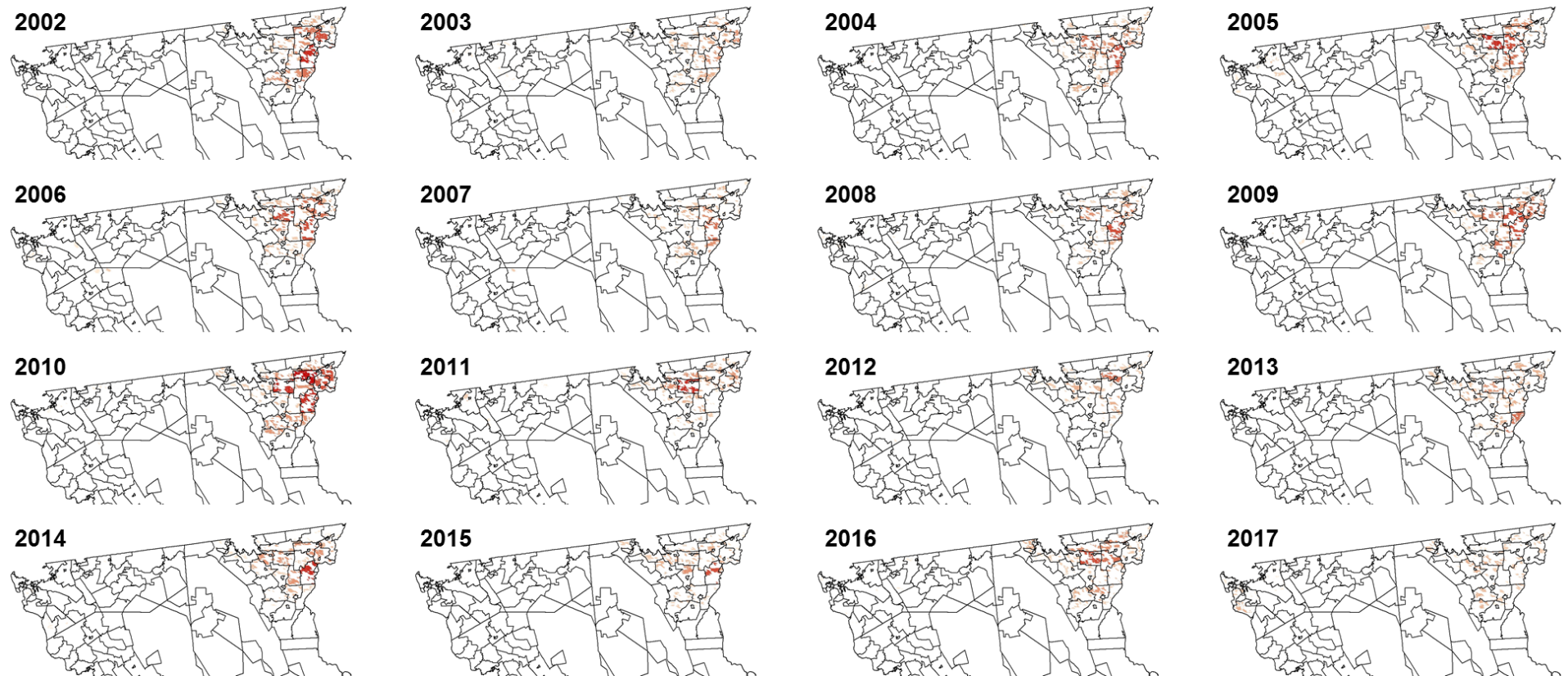
Case Study

Summarize agricultural burn events (fires on crop fields) by INEGI rural areas in BC



Case Study

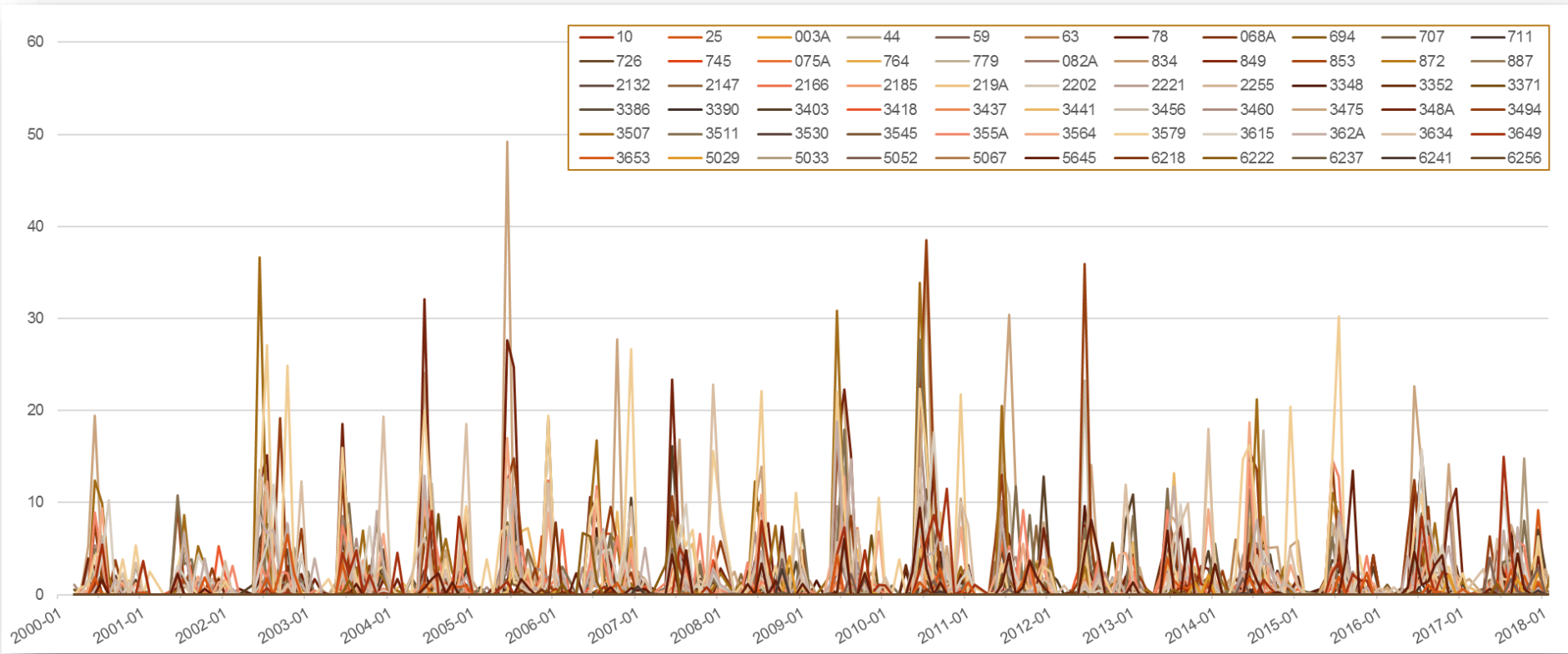
Summarize agricultural burn events (fires on crop fields) by INEGI rural areas in BC



Yearly total area of crop field with fire activities by INEGI rural area (km²)

Case Study

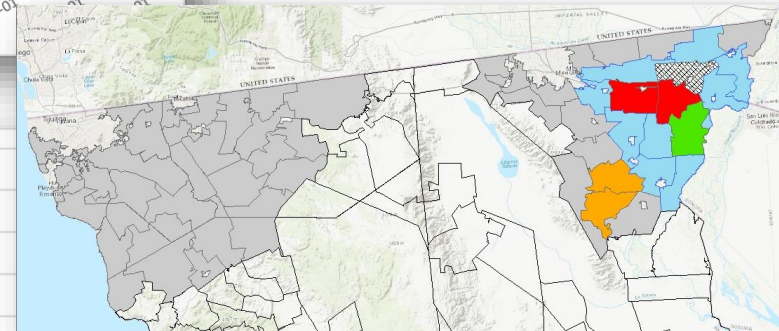
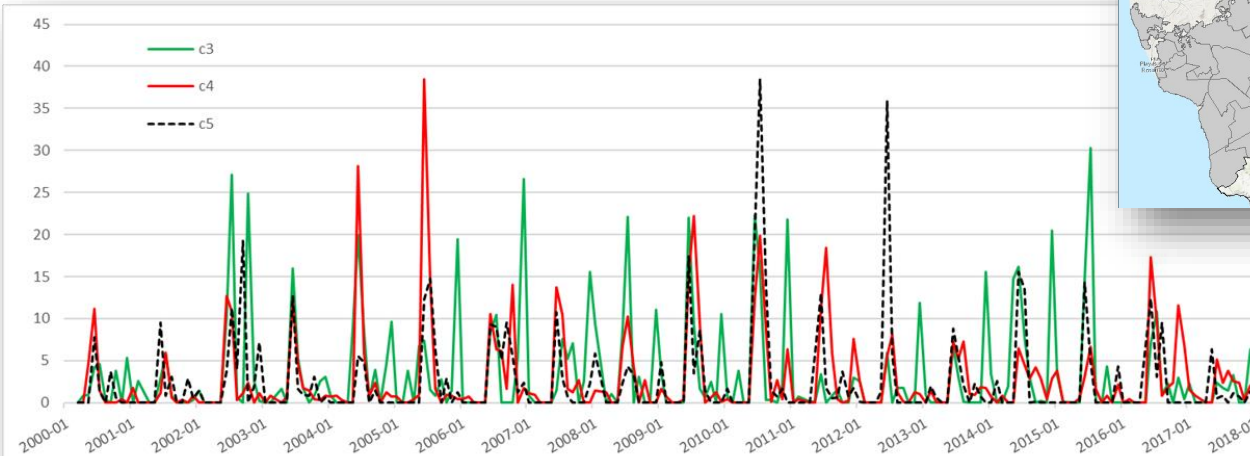
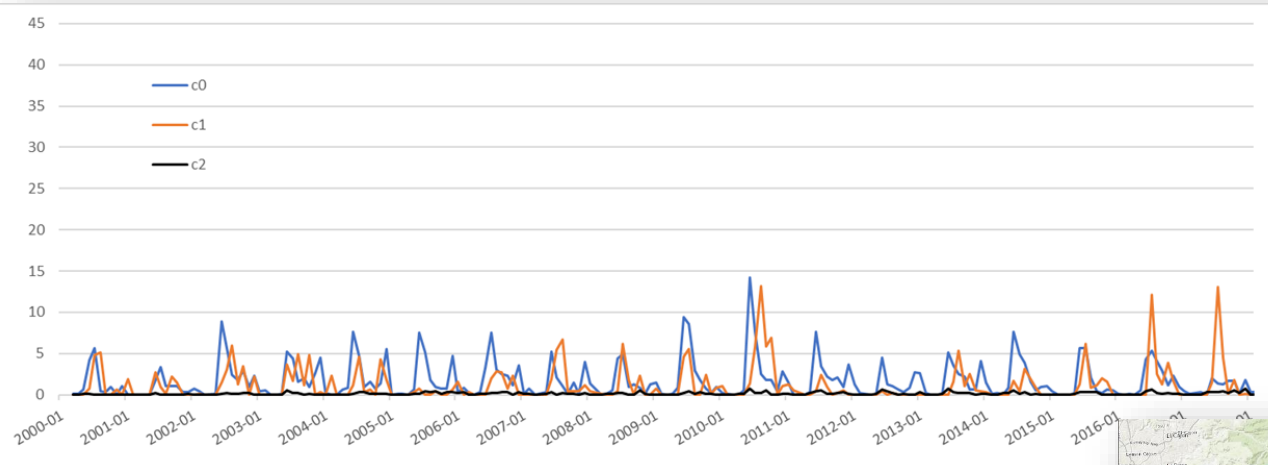
Summarize agricultural burn events (fires on crop fields) by INEGI rural areas in BC



Monthly total area of crop field with fire activities by INEGI rural area (km²)

Case Study

Time series clustering to find distinct time-space patterns of crop fields with fire activities (Monthly)



Future Works

- Verifying detected fire activities
- Explore non-agricultural urban fires
- Conduct a systematic performance test
- Apply ST-DBSCAN to other large event data
 - Crime Incidents
 - Social media
 - Transportation data

Acknowledgements

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- The Center for Human Dynamics at the Mobile Age at SDSU
- Dr. May Yuan, University of Texas at Dallas



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Thank you for participation

Any Questions?

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