Analysis and Applications in MGWR

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Content

- MGWR Introduction
- Literature selection & overall condition
- Taxonomy
  - Converge Standard
  - Data Preprocessing
  - Goodness of fit
  - Overfit Condition
  - Combined algorithms

Models

- OLS
- GWR

$$y_i = \sum_{j=0}^{k} \beta_j(u_i, v_i)x_{i,j} + \varepsilon_i$$

- MGWR

$$y_i = \sum_{j=0}^{k} \beta_{bwj}(u_i, v_i)x_{i,j} + \varepsilon_i$$

Literature selection & overall condition

high	medium	low
6, 7, 9, 10, 12, 14, 15, 16, 17, 18, 20, 21	8, 11, 13	1, 2, 3, 4, 5, 19

Only literatures with ‘high’ priority are analysed.

Application area

6,7 population estimation

9,16,17 Environmental protection

10,18,20 financial/business analysis

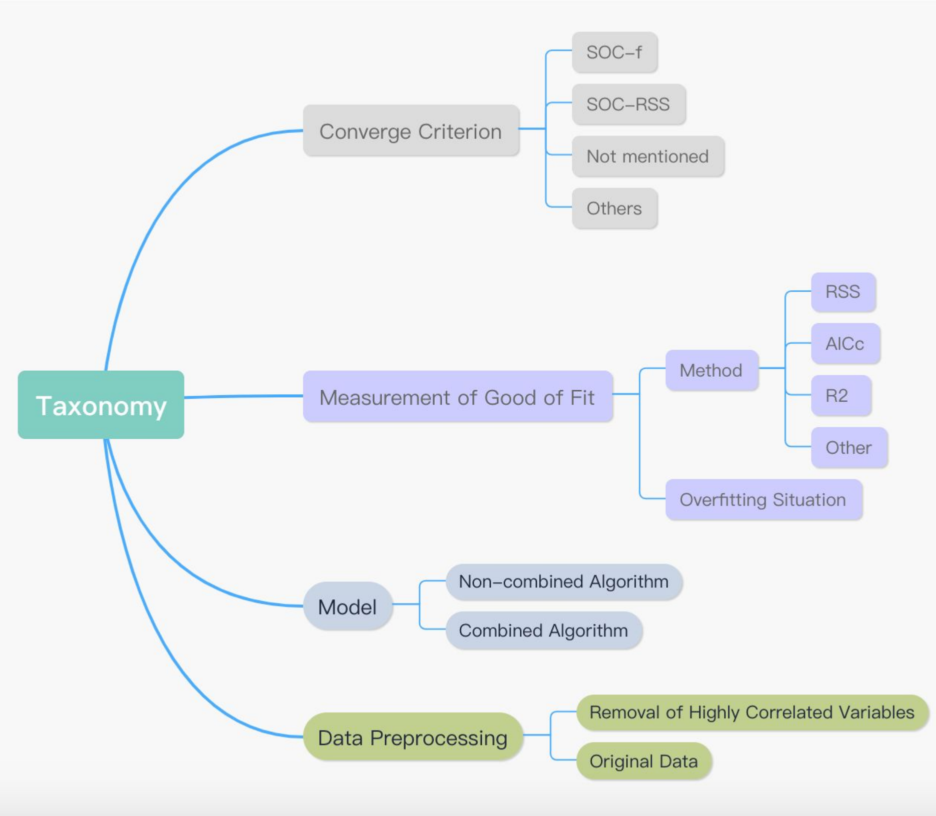
12 software for analysis (paper 15, 18 use this Python based package!)

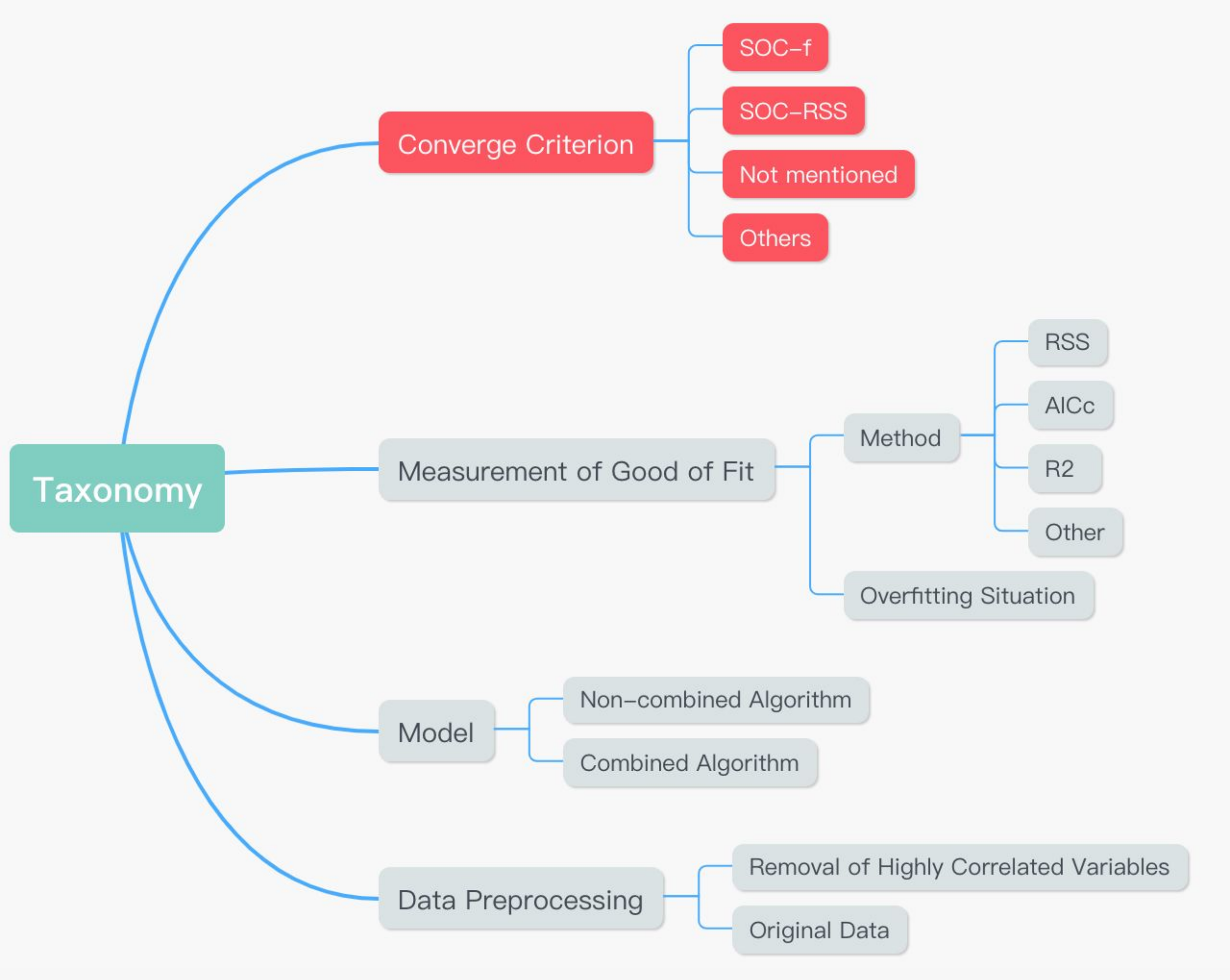
14 Transportation

15 Mortality Rates

21 Guns and Homicides

Taxonomy Construction

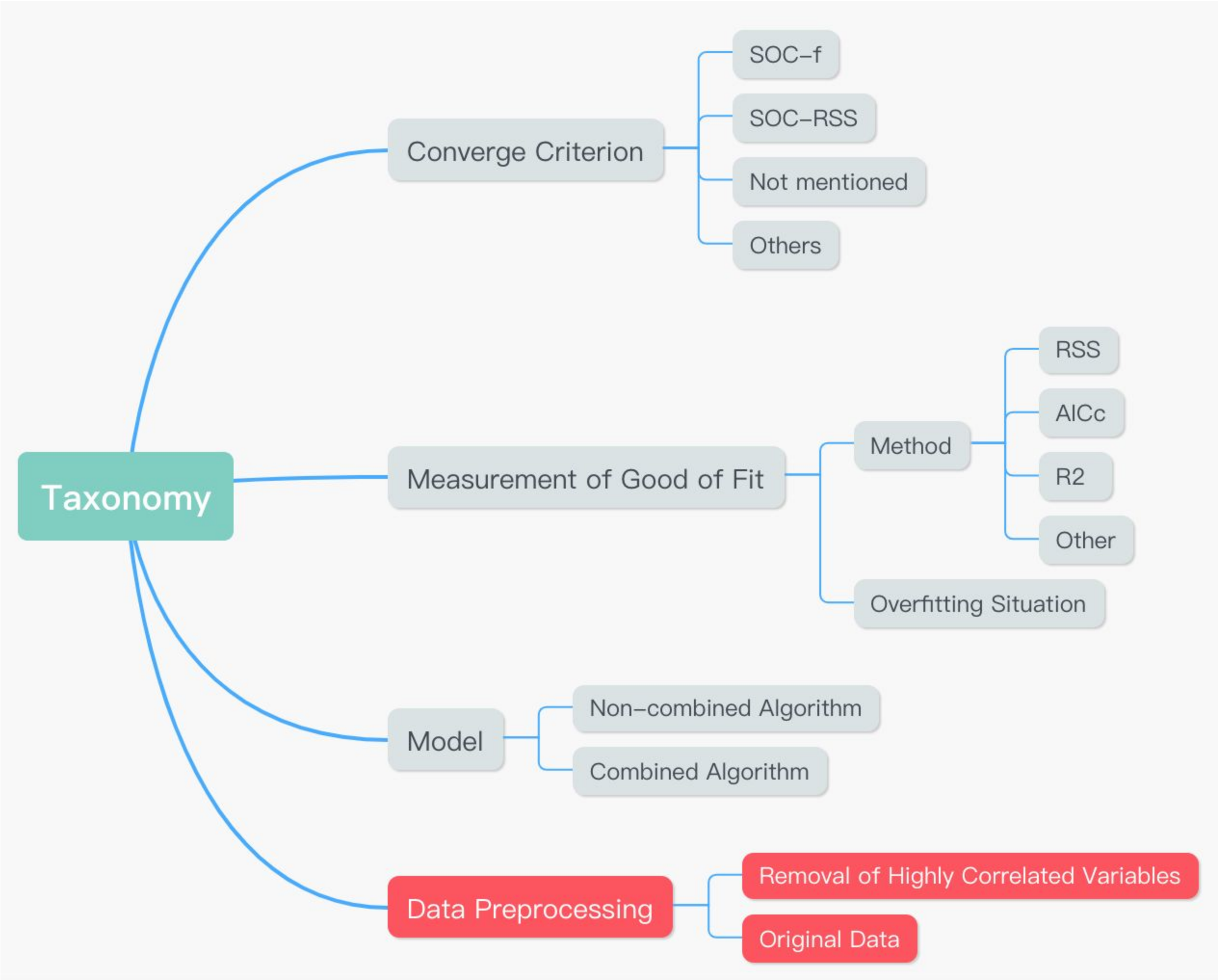



Taxonomy
Converge Criterion
SOC–f
SOC–RSS
Not mentioned
Others
Measurement of Good of Fit
Method
RSS
AICc
R2
Other
Overfitting Situation
Model
Non–combined Algorithm
Combined Algorithm
Data Preprocessing
Removal of Highly Correlated Variables
Original Data

1.Converge Standard

- SOC-RSS: more focused on overall model fit
- SOC-f: has the advantage of being focused on the relative changes of the additive terms
- Cross Vaidation(CV)
- Out-of-bag estimation error(OOB)
- COS-RSS combined with iteration number and threshold presetted
- AICc

SOC-RSS	SOC-f	Not mentioned	Others
None	7; 9; 14; 18	6; 8; 12; 15; 17	10(CV); 16(OOB); 20(COS-RSS); 21(AICc)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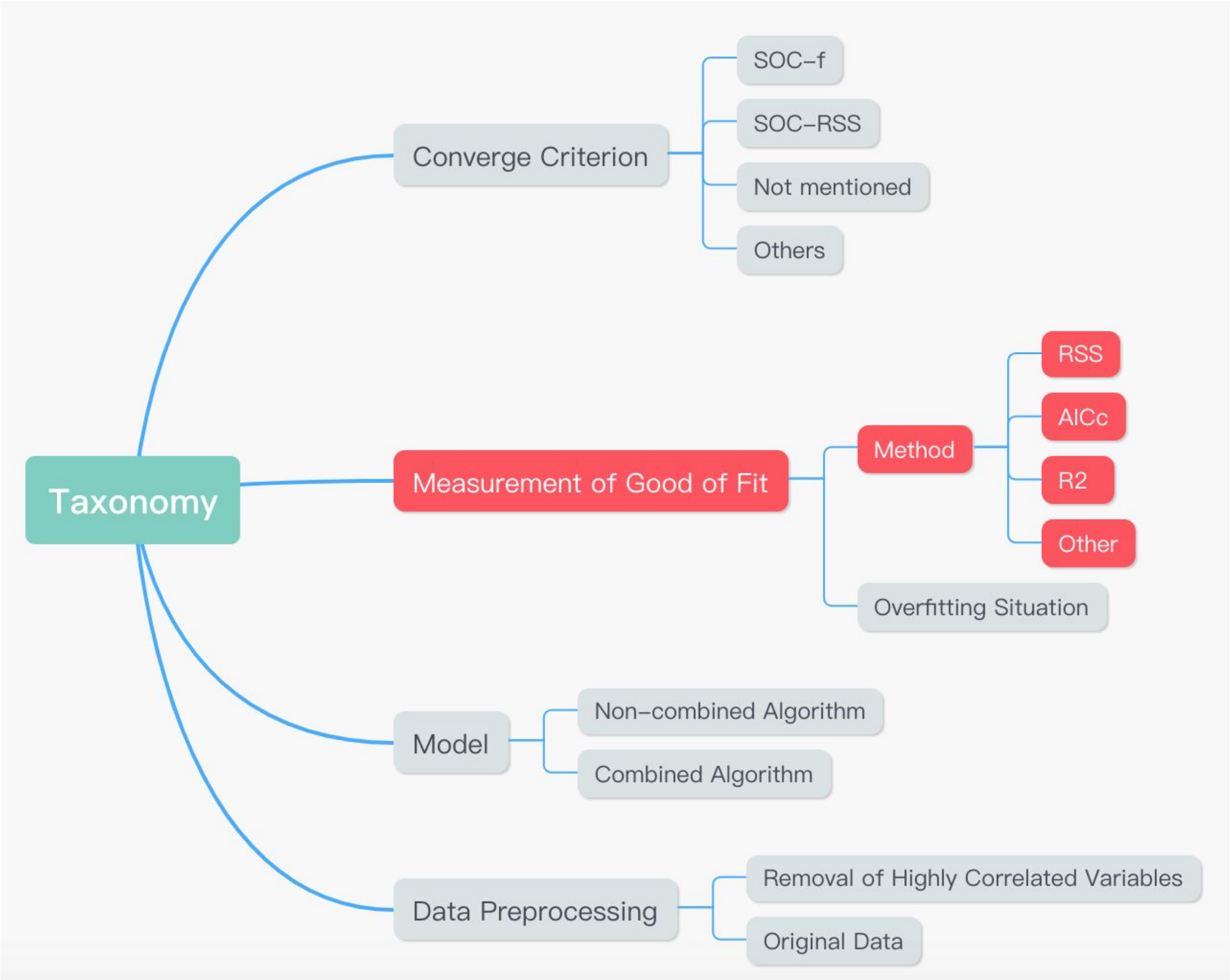
2.Data Preprocessing

- Removal of selected variables:
  - Reduce factors that have strong correlations to increase the accuracy of regression model (6)
  - Fit regression model better (15)
  - Satisfy the result of goodness of fit (16)

Removal of Selected Variables	No	Not mentioned
6; 15; 16	7; 8; 9; 10; 12; 17; 18; 21	14; 20



Taxonomy
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Others
Measurement of Good of Fit
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RSS
AICc
R2
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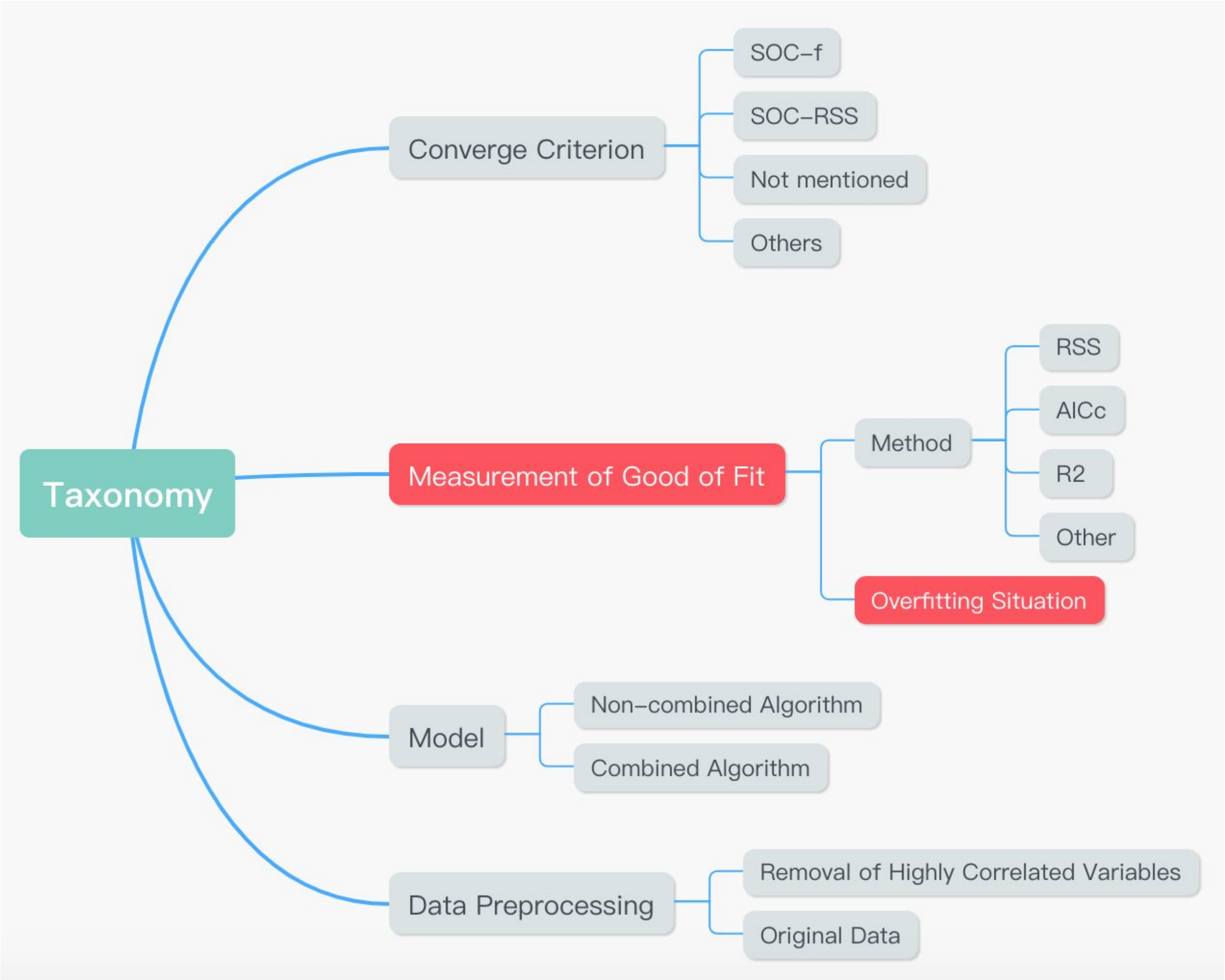
3.Measurement of Goodness of Fit

doc#	R2	RSS	AICc	other
6	√			
7		√		
9	√	√		√(MAE)
10	√		√	
12			√	

Measurement of Goodness of Fit (ctd)

doc#	R2	RSS	AICc	other
14	√	√	√	√(ENP,AIC)
15	√	√	√	
16	√			√(RMSE)
17		√	√	
18	√	√	√	
20	√		√	√(RMSE)
21			√	


Taxonomy
Converge Criterion
SOC–f
SOC–RSS
Not mentioned
Others
Measurement of Good of Fit
Method
RSS
AICc
R2
Other
Overfitting Situation
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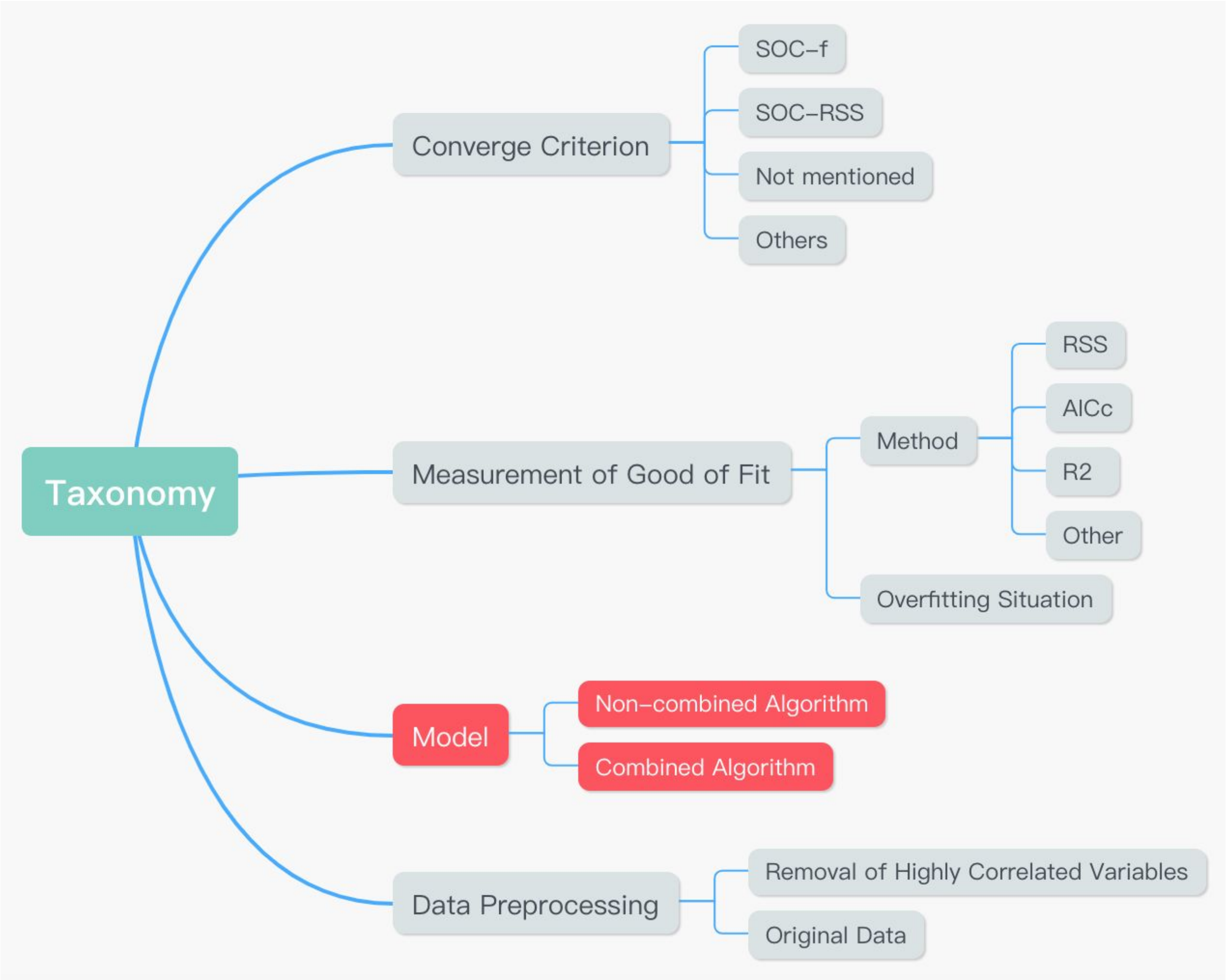
Original Data

4.Occurrence of Overfit condition

Yes	No	Not mentioned/ Not applicable
7	6, 9, 10, 14, 15, 16, 17, 18, 20	8, 12, 21


Taxonomy
Converge Criterion
SOC–f
SOC–RSS
Not mentioned
Others
Measurement of Good of Fit
Method
RSS
AICc
R2
Other
Overfitting Situation
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Removal of Highly Correlated Variables
Original Data

5. Integrate MGWR with other algorithm

❖

Yes	No
6, 9, 14, 16, 20, 21	7, 10, 12, 15, 17, 18,

Thank you

Site specific crop management

Group #2:

Anish Sekar

Prajnya Prabhu

Yogesh Singh

Outline

- Introduction
- Application goals
- Technologies Used
- Progress
- Conclusion/ Future work

Introduction

- **Site specific crop management** (SSCM) is a farming management concept which is based upon observing, measuring and responding to multiple variables.
- SSCM is required as farmers can get better yield, soil will be least disturbed, and it will avoid depletion of minerals.
- It is also known as Precision agriculture.
- Farmers who use SSCM practices, they use weather data, humidity, soil temperature, growth and other factors for crop rotation.

Agriculture parameters considered

- Soil temperature
- Temperature
- Soil pH
- Humidity
- Crop type

Application Goals

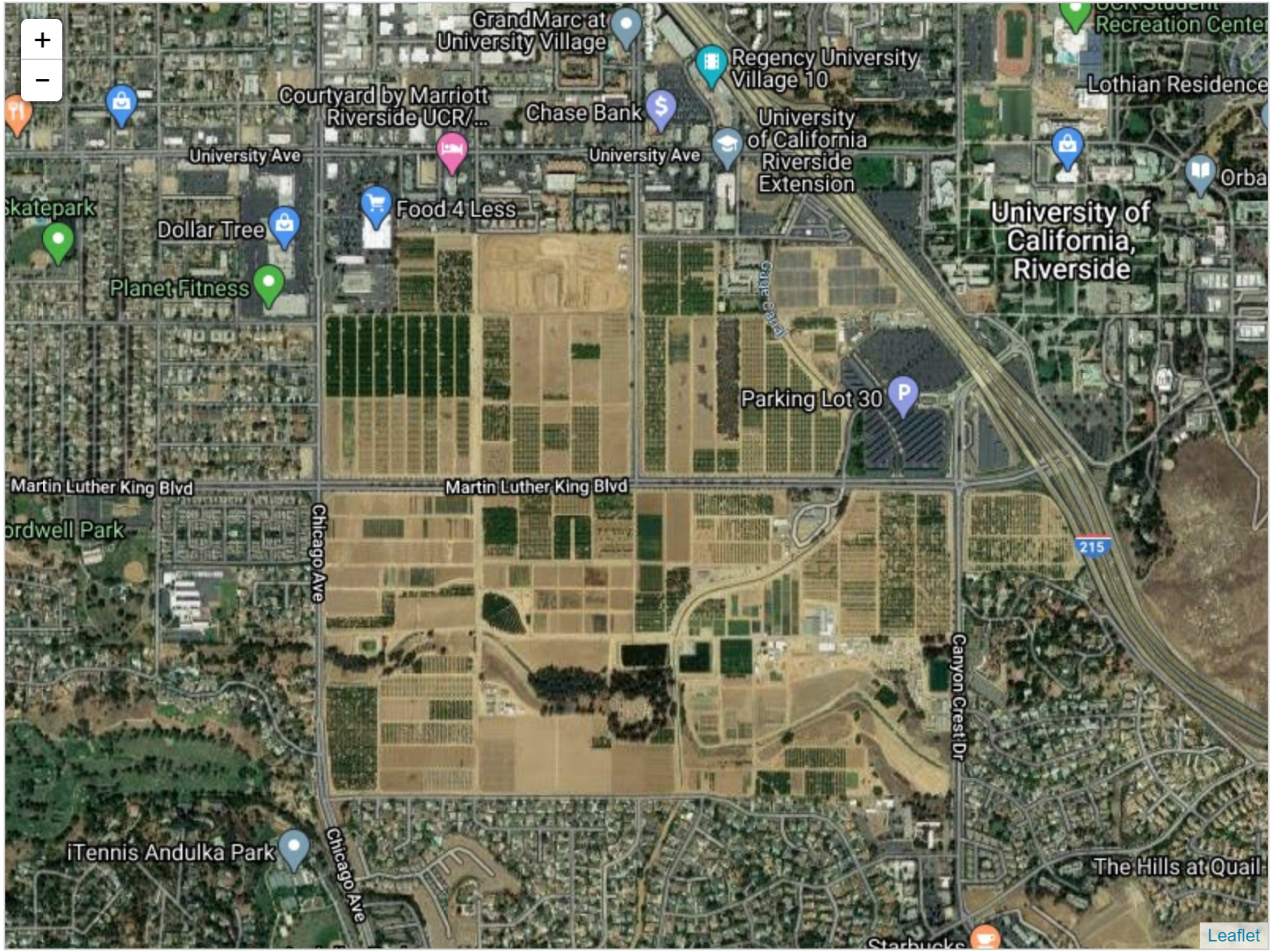
- The data generated from sensors such as air temperature, soil temperature, moisture (humidity), soil pH will be periodically mapped to the appropriate crop regions.
- The user will have various controls on the dashboard to control which data is displayed on the map. This information can now be used to better manage crops in the following ways.
  - Identify poorly irrigated zones
  - Identifying temperature anomalies
  - Identify soil acidity
  - Light intensity (future work)

Technologies

- Leaflet Api is used for this project.
- MongoDB is used to store data.
- Bootstrap, HTML, CSS, JavaScript are used for front end.

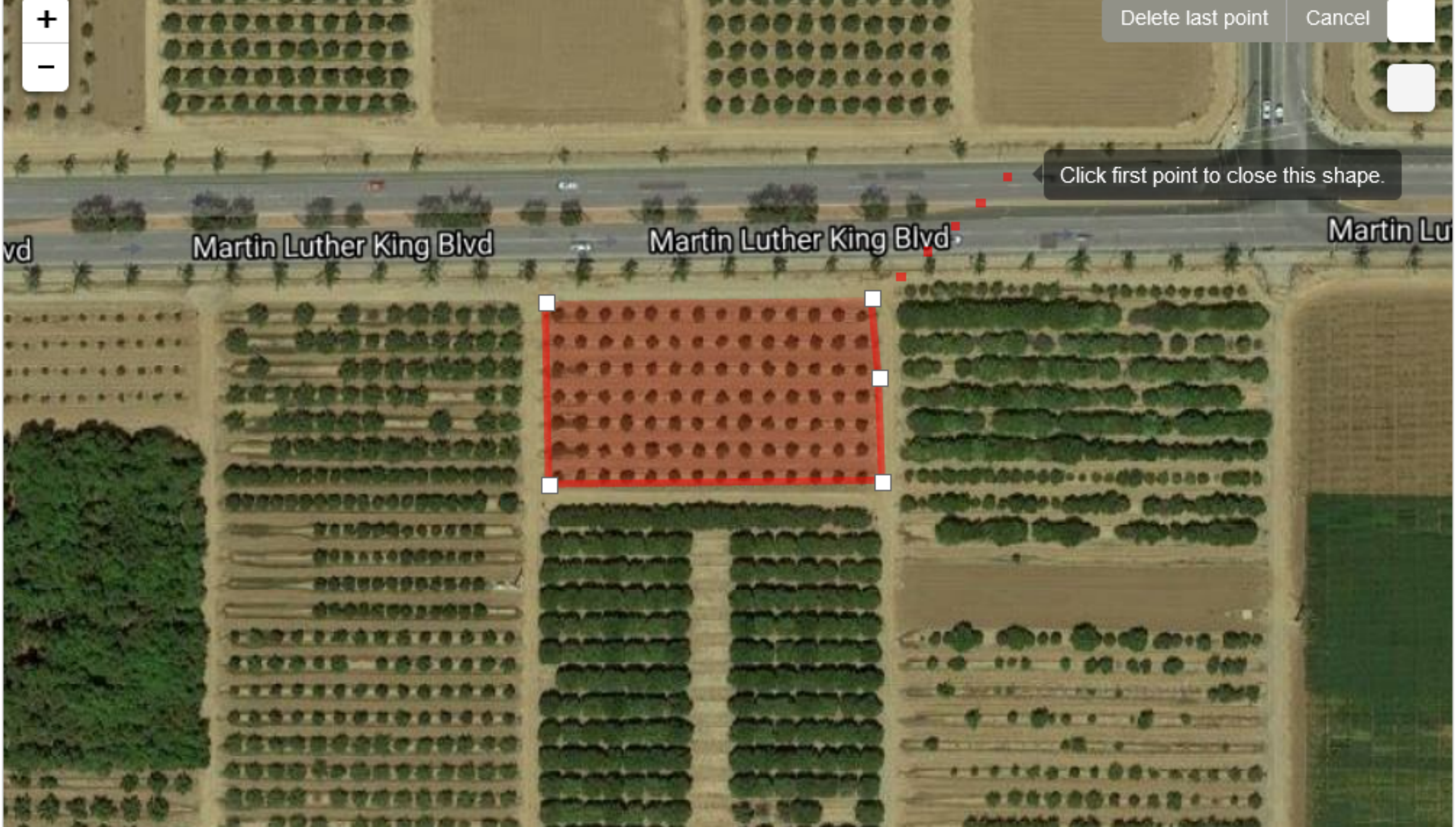
Spatial View Customize

SELECT AREA TO ZOOM

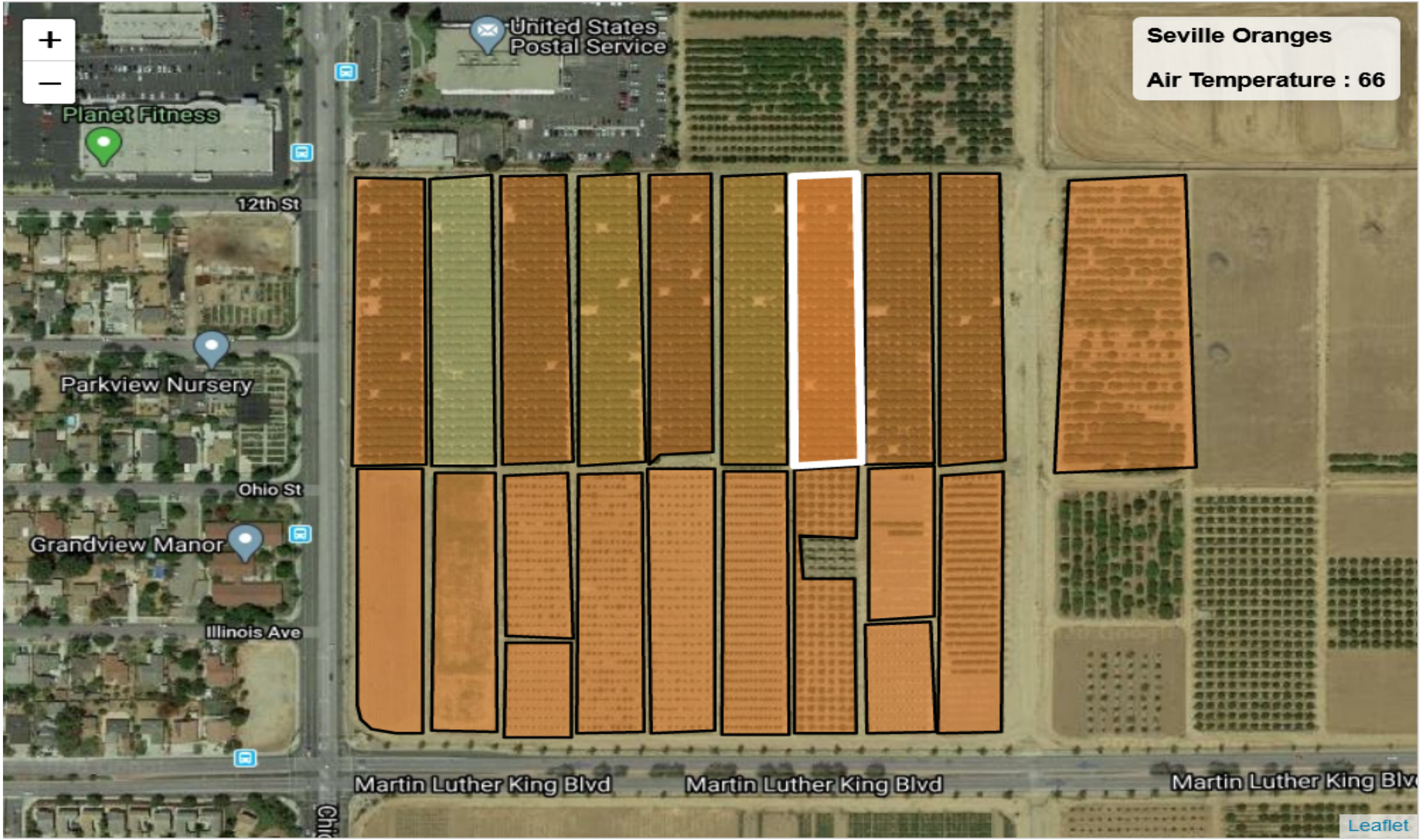


Color

EDIT MODE



Delete last point
Cancel
Click first point to close this shape.
Martin Luther King Blvd
Martin Luther King Blvd



+
−
United States Postal Service
Seville Oranges
Air Temperature : 66
Planet Fitness
12th St
Parkview Nursery
Ohio St
Grandview Manor
Illinois Ave
Martin Luther King Blvd
Martin Luther King Blvd
Leaflet

Tangerine Orange
Humidity (%) : 10
United States
Postal Service
Planet Fitness
12th St
Parkview Nursery
Ohio St
Grandview Manor
Illinois Ave
Martin Luther King Blvd
Martin Luther King Blvd
Leaflet

Future work

- Organize data on User Interface
- Predict the next crop for crop rotation based on the condition of the current plot.
- Include more features.

Thank you

LITERATURE SURVEY
SPATIAL APPLICATIONS ON MGWR

Kexin Wang, Qiguang Xie, Xu Chen, Yifan Zhao

WHAT IS MGWR

- MGWR refers to **Multi-scale Geographically Weighted Regression**

- Geographically Weighted Regression(GWR) model is a kind of data analysis model widely used in spatial data analysis, and multi-scale geographic weighted regression model(MGWR) is an extension of GWR model, which can accurately reflect the nature of spatial data in many practical problems.

THE USAGE OF MGWR

- This techniques can be used in many areas, like geography and agriculture
- We can find many articles based on this techniques

Open Access Article

mgwr: A *Python* Implementation of Multiscale Geographically Weighted Regression for Investigating Process Spatial Heterogeneity and Scale

by Taylor M. Oshan [1,*], Ziqi Li [2], Wei Kang [3], Levi J. Wolf [4] and A. Stewart Fotheringham [2]

[1] Center for Geospatial Information Science, Department of Geographical Sciences, University of Maryland, College Park, MD 20740, USA
[2] Spatial Analysis Research Center, School of Geographical Sciences an Urban Planning, Arizona State University, Tempe, AZ 85281, USA
[3] Center for Geospatial Sciences, School of Public Policy, University of California, Riverside, CA 92521, USA
[4] School of Geographical Sciences, University of Bristol, Bristol BS8 1SS, UK
[*] Author to whom correspondence should be addressed.

ISPRS Int. J. Geo-Inf. **2019**, *8*(6), 269; https://doi.org/10.3390/ijgi8060269

Received: 16 April 2019 / Revised: 23 May 2019 / Accepted: 5 June 2019 / Published: 8 June 2019

(This article belongs to the Special Issue Free and Open Source Tools for Geospatial Analysis and Mapping)

PAPER • OPEN ACCESS

Mixed geographically weighted regression (MGWR) model with weighted adaptive bi-square for case of dengue hemorrhagic fever (DHF) in Surakarta

H N Astuti[1], D R S Saputro[1] and Y Susanti[1]

Published under licence by IOP Publishing Ltd
Journal of Physics: Conference Series, Volume 855, International Conference on Mathematics: Education, Theory and Application 6–7 December 2016, Surakarta, Indonesia

Theoretical research of MGWR

- **limitation of GWR:**all of the spatially varying parameters are assumed to arise from processes operating at the same spatial scale
- **MGWR** allows the conditional relationships between the response variable and the different predictor variables to vary at different spatial scales

Methods, Models, and GIS

Multiscale Geographically Weighted Regression (MGWR)

A. Stewart Fotheringham, Wenbai Yang & Wei Kang

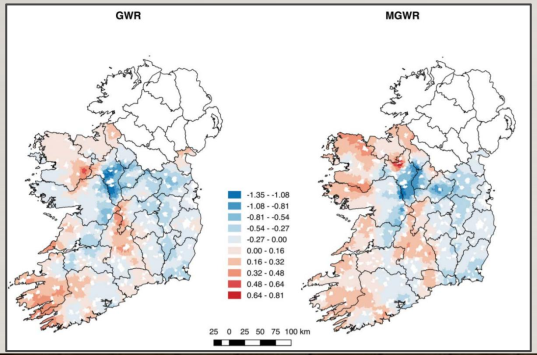
Pages 1247-1265 | Received 01 May 2016, Accepted 01 May 2017, Published online: 28 Aug 2017

Download citation https://doi.org/10.1080/24694452.2017.1352480 Check for updates

Theoretical research of MGWR

Advantages of MGWR

- accurately discriminate parameter surfaces with high spatial heterogeneity from those with low spatial heterogeneity
- produce similar bandwidths for processes that operate at the same spatial scale.



Original Article

Inference in Multiscale Geographically Weighted Regression

Hanchen Yu, A. Stewart Fotheringham, Ziqi Li, Taylor Oshan, Wei Kang, Levi Jo

First published:22 January 2019 | https://doi.org/10.1111/gean.12189 | Citations

Measuring Bandwidth Uncertainty in Multi Geographically Weighted Regression Using Weights

Ziqi Li, A. Stewart Fotheringham, Taylor M. Oshan & Levi John Wolf

Received 06 Aug 2019, Accepted 30 Oct 2019, Published online: 11 Feb 2020

Research Article

Computational improvements to multi-scale geographically weighted regression

Ziqi Li & A. Stewart Fotheringham

Received 15 Jun 2019, Accepted 21 Jan 2020, Published online: 06 Feb 2020

Download citation https://doi.org/10.1080/13658816.2020.1720692 Check for updates

WHAT WE HAVE DONE

- We have found 60 literatures on MGWR.
- We have summarized their general contents.
- We have worked out a refined literature taxonomy to classify each document with reference to its general contents.

WHAT WE HAVE DONE

Theoretical	Experimental
[1] Brunsdon, Chris, A. Stewart Fotheringham, and Martin E. Charlton. "Geographically weighted regression: a method for exploring spatial nonstationarity." Geographical analysis 28.4 (1996): 281-298.	[2] Oshan, Taylor M., et al. "mgwr: A Python implementation of multiscale geographically weighted regression for investigating process spatial heterogeneity and scale." ISPRS International Journal of Geo-Information 8.6 (2019): 269.
[3]Fotheringham, A. Stewart, Wenbai Yang, and Wei Kang. "Multiscale geographically weighted regression (mgwr)." Annals of the American Association of Geographers 107.6 (2017): 1247-1265.	[4] Leung, Yee, Chang-Lin Mei, and Wen-Xiu Zhang. "Statistical tests for spatial nonstationarity based on the geographically weighted regression model." Environment and Planning A 32.1 (2000): 9-32.

[1]In this paper, a technique is developed, termed geographically weighted regression, which attempts to capture this variation by calibrating a multiple regression model which allows different relationships to exist at different points in space.

[2]This paper introduces mgwr, and provide two case studies using mgwr, in addition to reviewing core concepts of local models.

[3]We compare the performance of GWR and MGWR by applying both frameworks to two simulated data sets with known properties and to an empirical data set on Irish famine.

[4]authors focus mainly on the development of statistical testing methods relating to GWR.

[5]The Model of Mixed Geographically Weighted Regression (MGWR) for Poverty Rate in Central Java

[6]Determination of the statistical test is Use the method of Maximum Likelihood Ratio Test (MLRT) to decide statistical test of MGWR.

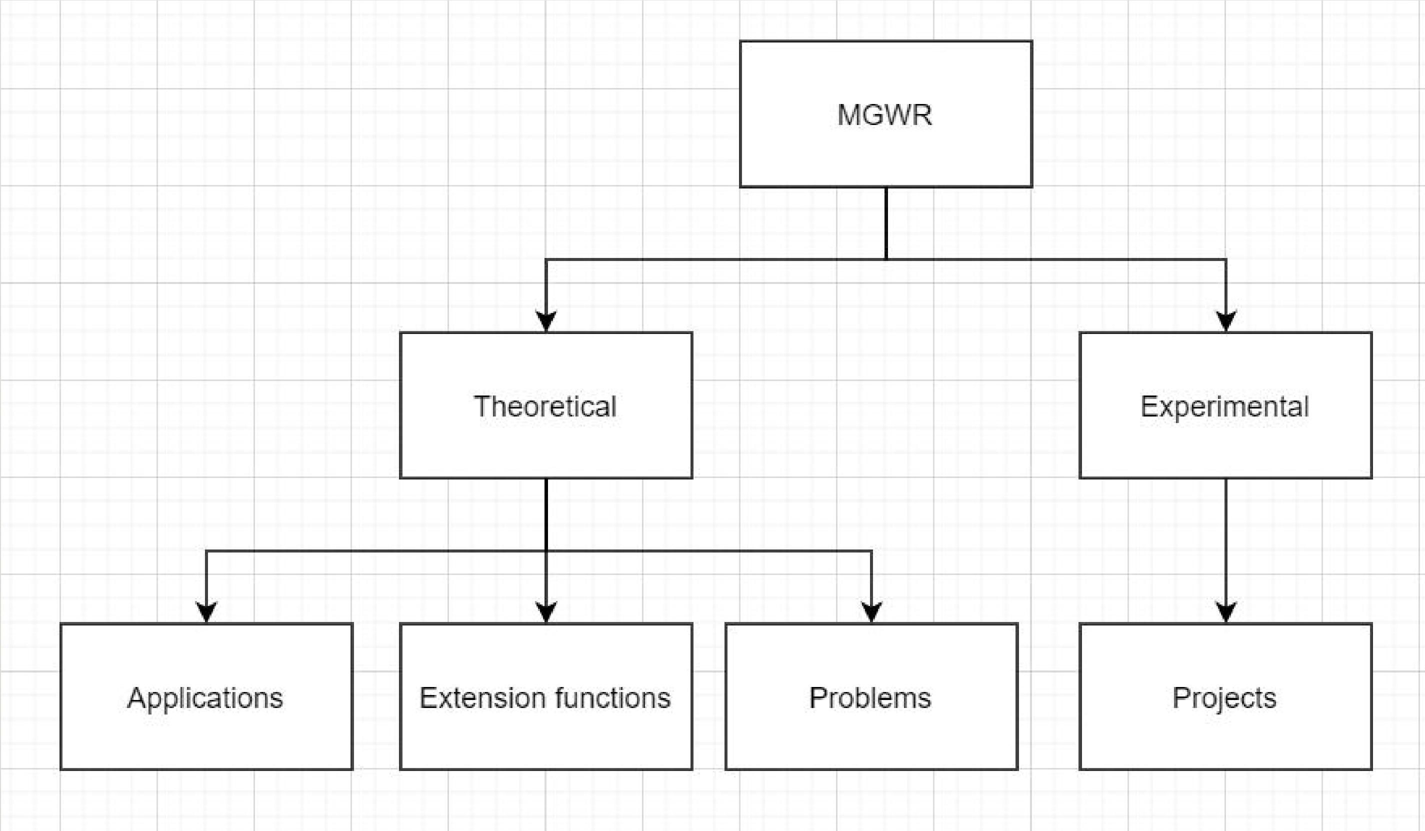
[7]In this research, we applied MGWR model with weighted adaptive bi-square for case of DHF in Surakarta based on 10 factors (variables) that is supposed to influence the number of people with DHF.

[8]some work of GWR are summarized.

[9]we proposed a modeling methodology from the perspective of spatial poverty, integrating BP and MGWR-SL that correspond to population estimation and poverty incidence estimation, respectively, to explore a more accurate and detailed village-level poor population distribution.

[10]Modeled by global linear regression, and then continued to use GWR and MGWR models to estimate factors with spatial influence.

TAXONOMY


MGWR
Theoretical
Experimental
Applications
Extension functions
Problems
Projects

CONCLUSION

- applications of existing technology

[13]Mulley, Corinne, and Michael Tanner. Vehicle Kilometres Travelled (VKT) by Private Car: A Spatial Analysis Using Geographically Weighted Regression. Transport NSW, 2009.

- extension functions of the existing technology

[11]Paramita, AsharinaDwi. Estimasi Model Mixed Geographically Weighted Regression (Mgwr) Menggunakan Fungsi Pembobot Fixed Kernel Pada Data Spasial. Diss. Universitas Brawijaya, 2014.

- discover the problems found based on the technology of MGWR

[4] Leung, Yee, Chang-Lin Mei, and Wen-Xiu Zhang. "Statistical tests for spatial nonstationarity based on the geographically weighted regression model." Environment and Planning A 32.1 (2000):

SHORTCOMING

- The choice of material
- Classification bias due to insufficient expertise
- Scientific nature of division of labor

THANK YOU!

Kexin Wang, Qiguang Xie, Xu Chen, Yifan Zhao

California Fire Risk Assessment and Prediction

Spatial Computing

Presented by:
Abhijit Taneja
Rithika A R

UNIVERSITY OF CALIFORNIA, RIVERSIDE

Problem

- Forest Fires are uncontrollable and untamable.
- It is out of our hand.
- Can we predict if the fire is going to take place

https://www.reddit.com/r/pics/comments/1i6xut/mythbusting_minions_by_lars_of_looking_for_group/

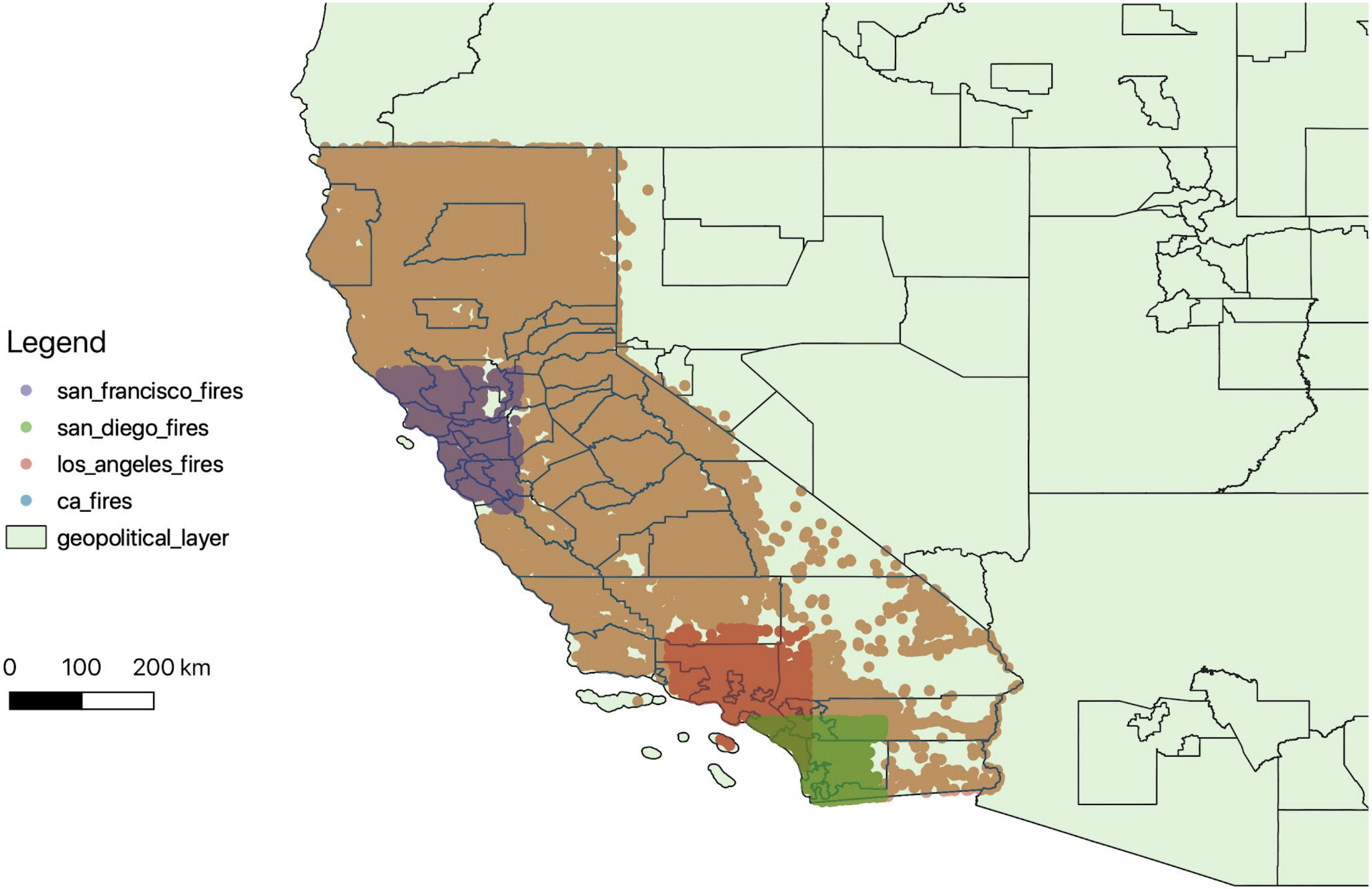
Outline

- Problem
- Preprocessing
  - GIS plot of final dataset.
- Sampling
  - Distribution
- Classifier Model
  - SVM
  - Random Forest Classifier
- Cross Validation
  - SVM stratified K fold validation
  - Random Forest stratified K fold validation
- Class Imbalance
  - Oversampling
  - Graph
- Observations

Preprocessing

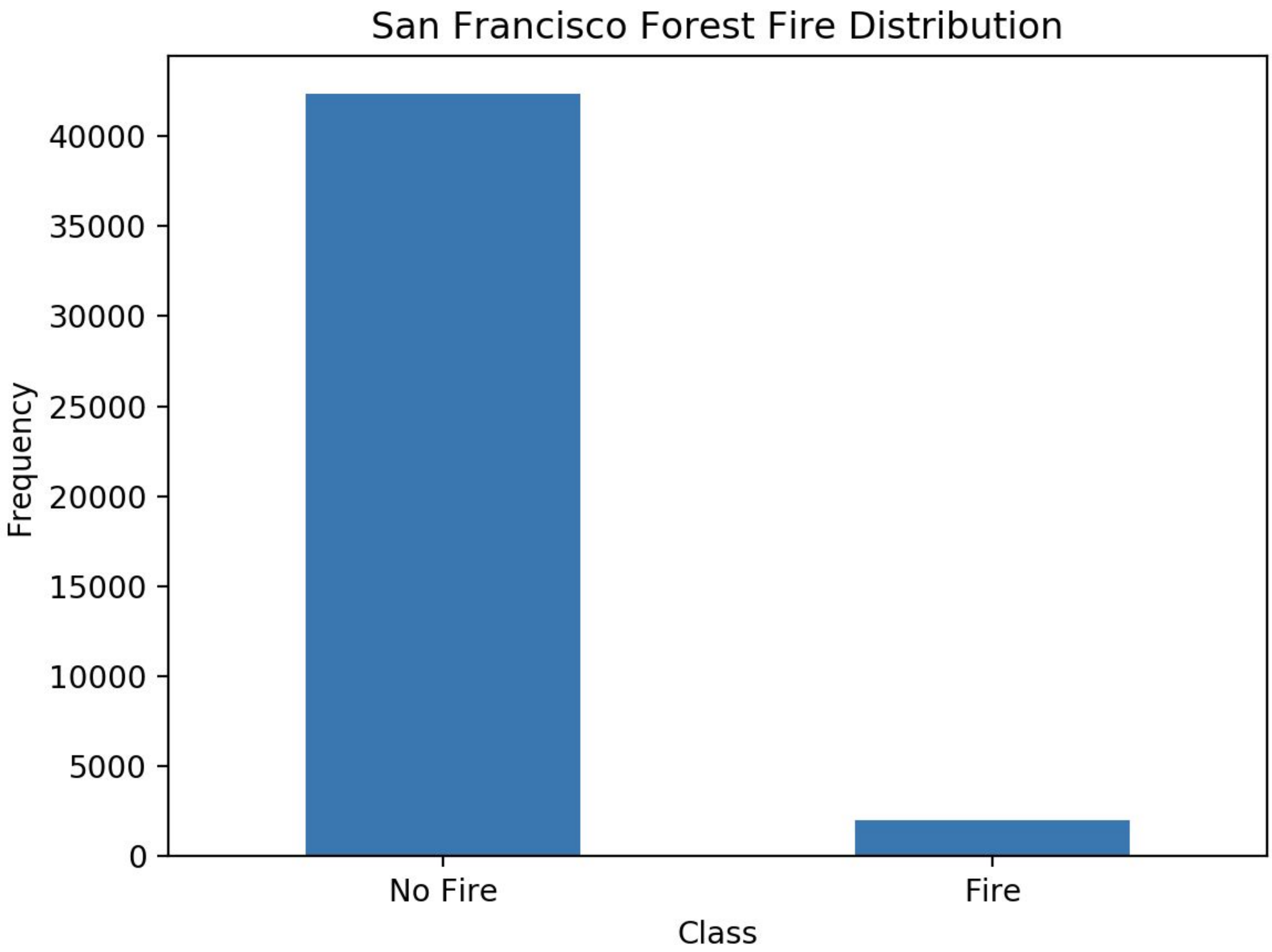
Final Dataset

California Forest Fires from 1992 to 2015



Sampling

Distribution



Classifier Model

Support Vector Machine

Stratified Sampling				
	Precision	Recall	F1	Support
T	0.09	0.09	0.09	54
F	0.96	0.96	0.96	1146

Reservoir Sampling				
	Precision	Recall	F1	Support
T	0.06	0.05	0.06	60
F	0.95	0.96	0.96	1140

Random Forest Classifier

Stratified Sampling				
	Precision	**Recall**	**F1**	**Support**
T	**0.00**	**0.00**	**0.00**	**54**
F	**0.95**	**1**	**0.98**	**1146**

Reservoir Sampling				
	Precision	**Recall**	**F1**	**Support**
T	**0.33**	**0.02**	**0.03**	**60**
F	**0.95**	**1**	**0.97**	**1140**

Cross Validation

SVM Stratified K fold

Stratified K fold cross validation on SVM trained model with 10 n splits

Stratified Sample				
	Precision	Recall	F1	Accuracy
T	0.21	0.21	0.21	0.80

Reservoir Sample				
	Precision	Recall	F1	Accuracy
T	0.21	0.21	0.21	0.80

RFC Stratified K fold

Stratified K fold cross validation on Random Forest trained model with 10 n splits

Stratified Sample				
	Precision	Recall	F1	Accuracy
T	0	0	0	0.95

Random Sample				
	Precision	Recall	F1	Accuracy
T	0.22	0.01	0.02	0.95

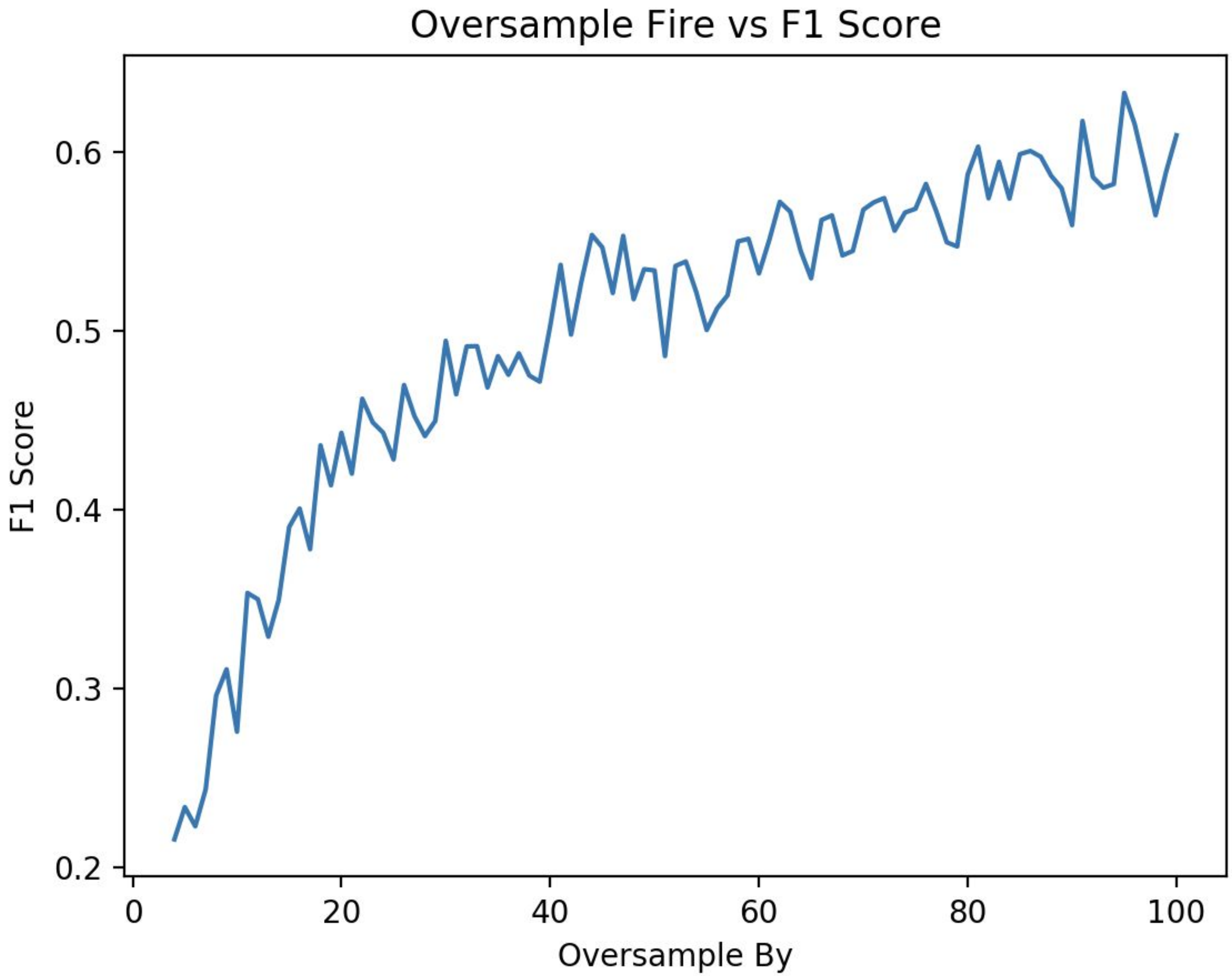
Class Imbalance

Oversampling

Classification Report				
	Precision	Recall	F1	Support
T	0.26	0.24	0.25	160
F	0.88	0.89	0.89	1040

Stratified K Fold Cross Validation				
	Precision	Recall	F1	Accuracy
T	0.21	0.21	0.21	0.80

Graph



Oversample Fire vs F1 Score
F1 Score
0.2
0.3
0.4
0.5
0.6
0
20
40
60
80
100
Oversample By

Observations

Observations

- Stratified Sampling gave must better F1 Score for imbalanced data.
- Stratified K Fold cross validation does not fare very well for imbalanced data.
- Oversampling held improve F1 score and recall.
- Temperature, Humidity, Pressure and Wind have more impact on Fires.
- If we are presented with the predicted data of the above feature we can make a viable prediction.
- We need a much more data to have a better model.

Spatial Interpolation on Scattered Data: A Survey

Group 6 Members:

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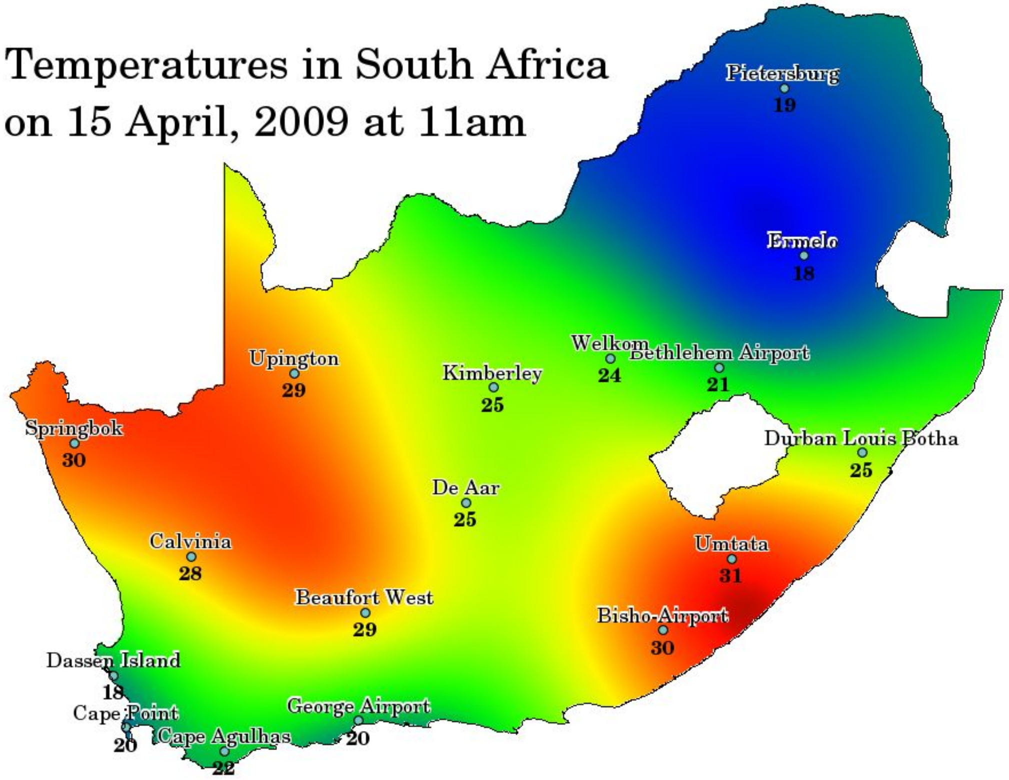
Kuan-Chie Hsu: 862188621
Yeqing Wang: 862186226
Tianyu Liu: 681358

Outline

1. introduction
2. Classification & Characteristics
3. Local-based Algorithms
4. Global-based Algorithms
5. Comparisons
6. Conclusion
7. Reference

Introduction



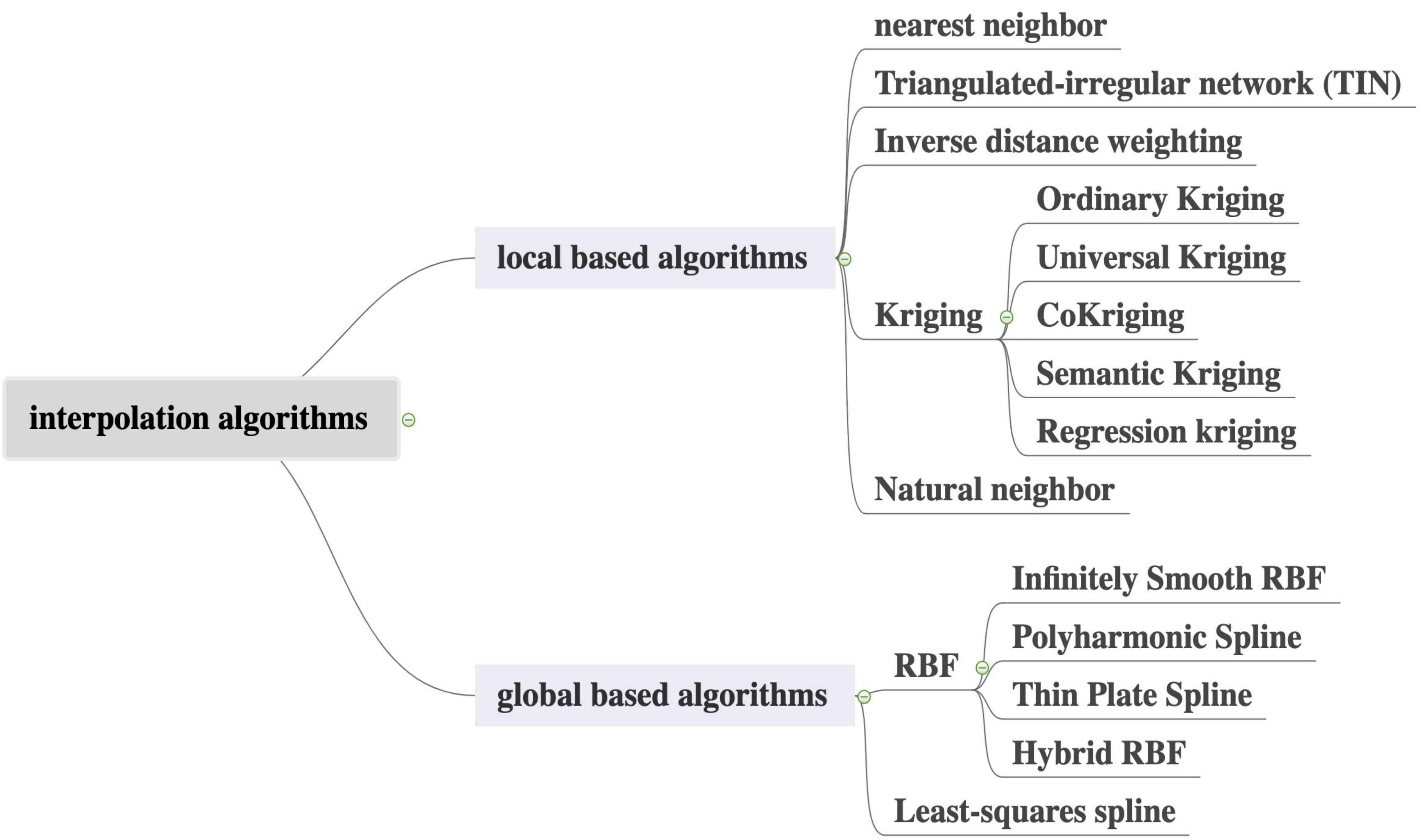
source: https://docs.qgis.org/3.4/en/docs/gentle_gis_introduction/spatial_analysis_interpolation.html

- target at spatial applications / multidisciplinary research
    - geography, medicine, physics...
- available data points in space are scattered in nature.
    - measurement cost
- closer points in space have stronger relation.
    - nature assumption

Classification & Characteristics

1. Interpolation algorithm taxonomy

2. 6 characteristics


interpolation algorithms
local based algorithms
nearest neighbor
Triangulated-irregular network (TIN)
Inverse distance weighting
Kriging
Ordinary Kriging
Universal Kriging
CoKriging
Semantic Kriging
Regression kriging
Natural neighbor
global based algorithms
RBF
Infinitely Smooth RBF
Polyharmonic Spline
Thin Plate Spline
Hybrid RBF
Least-squares spline

Characteristics

1. **Computational Complexity**

   Low Computational Complexity means the proposed interpolation method is easy to implement.

2. **Time Cost**

   The execution time of the interpolation process.

3. **Accuracy**

   RSME (root mean square error)

4. **Scalability**

   Good scalability represents that the stableness and accuracy of the data could be maintained with the increasement of the datasets.

Characteristics

5. Multidimension

The interpolation algorithms can be applied to 3 dimension or higher dimension data.

6. Generalization

The interpolation algorthms can be used in several area, such as geography, medical science, etc.

Local-Based Interpolation Algorithms

- Nearest-neighbor
- Triangulated-irregular network
- Inverse distance weighting
- Kriging
    - Ordinary kriging
    - Universal kriging
    - Cokriging
    - Semantic kriging
    - Regression kriging

- **Nearest-neighbor**

  Assign the nearest sampled point value to the target point value.

- **Triangulated-irregular network**
  Using vector-based data representation, the set of vertices are triangulated. Also, the vertex set has to satisfy the Delaunay triangle criterion, which no other vertex is located within the circumcircle of any triangles in the network.

- **Inverse distance weighting**

  Use the measured values surrounding the prediction location to predict a value for any unmeasured location. The measured values closest to the prediction location have more influence on the predicted value than those farther away. IDW assumes that each measured point has a local influence that diminishes with distance. It gives greater weights to points closest to the prediction location, and the weights diminish as a function of distance.

Kriging - Spatial Variability

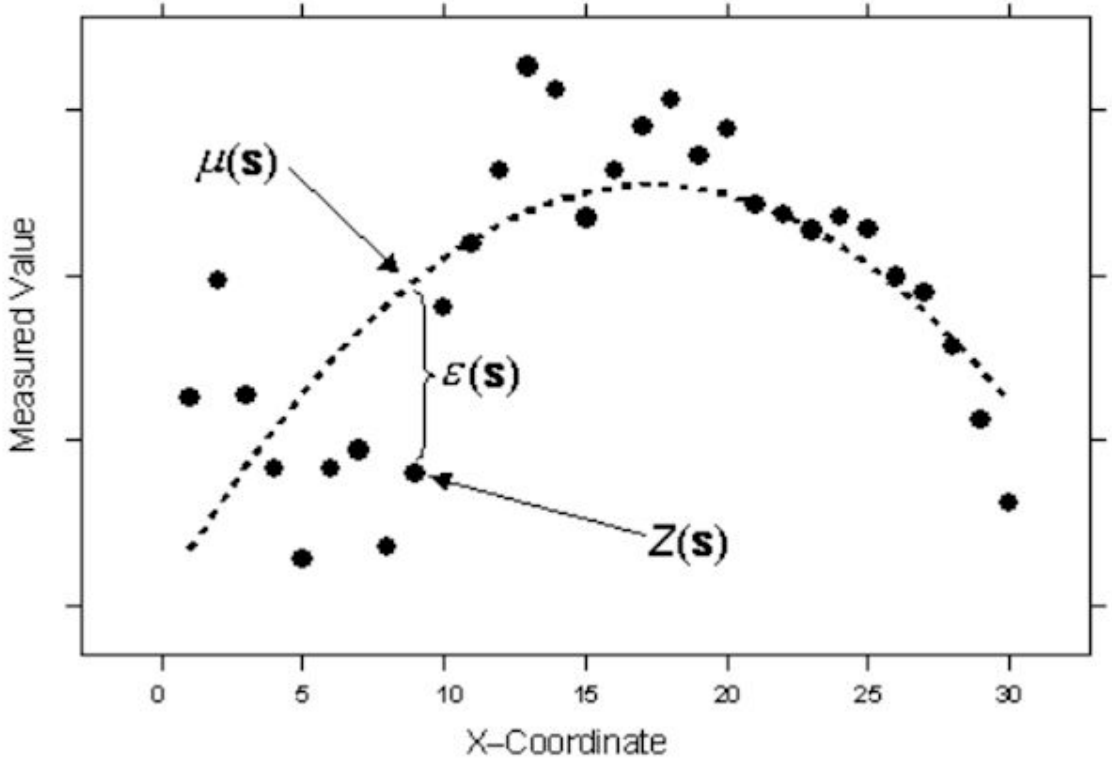
- Two components:
  - Large scale variation (trend)
  - small scale spatial autocorrelation (error)

- $Z(s) = \mu(s) + \varepsilon(s)$

Reference: https://www.youtube.com/watch?v=AoIUcE0vvq8

Types of Kriging

- Ordinary kriging
  - $Z(s) = m + \varepsilon(s)$
- Universal kriging
  - $Z(s) = \mu(s) + \varepsilon(s)$



Global-Based Interpolation Algorithms

- RBF
  - Infinitely Smooth Surface
  - Polyharmonic Spline
  - Thin Plate Spline
  - Hybrid RBFs
- Least-Square Spline

RBF- Infintely Smooth RBFs

- Ohtake, Yutaka, Alexander Belyaev, and H-P. Seidel. "3D scattered data approximation with adaptive compactly supported radial basis functions." *Proceedings Shape Modeling Applications, 2004.*. IEEE, 2004.

$$\underbrace{\sum_{\mathbf{c}_i \in \mathcal{C}} g_i(\mathbf{x}) \Phi_{\sigma_i}(\|\mathbf{x} - \mathbf{c}_i\|)}_{\text{adaptive PU}} + \underbrace{\sum_{\mathbf{c}_i \in \mathcal{C}} \lambda_i \Phi_{\sigma_i}(\|\mathbf{x} - \mathbf{c}_i\|)}_{\text{normalized RBF}} = 0 \quad (5)$$

1) High quality in data reconstruction
2) Failed in multi-dimensions

RBF- Polyharmonic Spline

- Fasshauer, Gregory E. "Solving differential equations with radial basis functions: multilevel methods and smoothing." *Advances in computational mathematics* 11.2-3 (1999): 139-159.

Table 4

Convergence rates for algorithm 2 with and without smoothing.

Mesh	B	w/o smoothing		w/ smoothing	
		ℓ_2-error	rate	ℓ_2-error	rate
5	17	3.637579×10^{-4}		1.513479×10^{-3}	
9	17	1.674853×10^{-5}	4.44	2.359495×10^{-5}	6.00
17	19	1.390688×10^{-6}	3.59	1.551685×10^{-6}	3.93
33	21	2.839726×10^{-7}	2.29	2.719340×10^{-7}	2.51
65	25	1.350834×10^{-7}	1.07	1.111654×10^{-7}	1.29
129	31	9.582244×10^{-8}	0.50	7.087024×10^{-8}	0.65
257	41	7.905540×10^{-8}	0.28	5.717555×10^{-8}	0.31
513	55	6.895165×10^{-8}	0.20	4.818539×10^{-8}	0.25
1025	79	6.072093×10^{-8}	0.18	4.163330×10^{-8}	0.21
2049	113	5.200779×10^{-8}	0.22	3.529323×10^{-8}	0.24

RBF- Thin Plate Spline

- Franke, Richard. "Smooth interpolation of scattered data by local thin plate splines." *Computers & mathematics with applications* 8.4 (1982): 273-281.
  1. Choosing A weight Function

     Change the boundaries of all existing rectangles.

  2. Selecting Local Approximations

     the approximations interpolate the appropriate points, and that they have continuous first derivatives to assure a smooth interpolant

RBF- Hybrid RBFs

- Yu, L. I. U., G. U. O. Zheng, and L. I. U. Jun. "RBFs-MSA hybrid method for mesh deformation." *Chinese Journal of Aeronautics* 25.4 (2012): 500-507.
  1) RBFs ------ A very simple and robust method to deform the mesh

     ------The memory storage limits to apply in multidimensions

  2) MSA ------ Could handle the memory limitations

     ------ The performance depends on the background mesh

  3) RBFs-MSA ------ Suitable for unsteady flow simulation which refers to boundaries movement

Least-Square Spline

- A way to generate a smooth surface without a huge amount of basic functions and coefficients.
- It aims to find the best coefficients in the global area to give a spline approximation.

Comparsion

1. Kriging
2. RBF
3. Local-based Algorithms & Global-based Algorithms

		Paper	Low computational complexity	Low Time cost	High Accuracy	Scalability	Multidimension	generalization
Kriging	Ordinary Kriging	[51]			✓			✓
		[52]			✓			
		[2]			✓			✓
		[53]			✓	✓		
	Universal Kriging	[20]			✓			✓
		[22]			✓			✓
		[23]		✓		✓		✓
	CoKriging	[24]			✓		✓	
	Semantic Kriging	[25]			✓	✓		
	Regression Kriging	[26]			✓			

		Paper	Low computational complexity	Low Time cost	High Accuracy	Scalability	Multidimensions	generalization
RBF	Infinitely Smooth RBFs	[29]					✓	
		[30]		✓	✓	✓	✓	
		[31]	✓			✓		
		[32]	✓	✓			✓	
		[33]				✓	✓	
	Polyharmonic Spline	[34]	✓	✓				
		[35]				✓	✓	
		[36]					✓	
		[37]		✓		✓	✓	✓
		[38]				✓	✓	✓
	Thin Plate Spline	[39]	✓	✓				
		[40]			✓		✓	✓
		[41]					✓	
		[42]			✓		✓	
		[43]	✓					
	Hybrid RBFs	[47]			✓	✓	✓	
		[46]		✓				✓
		[44]	✓	✓				
		[49]			✓			✓
		[45]			✓	✓		

	Unit of factor		Low Computational complexity	Low Time cost	High Accuracy	Scalability	Multidimensions	Generalization
Local Based interpolation algorithm	Nearest-neighbor		✓	✓		✓	✓	✓
	Triangulated-irregular network(TIN)				✓			
	Inverse distance weighting		✓	✓			✓	✓
	Kriging	Ordinary Kriging			✓			✓
		Universal Kriging			✓			✓
		Cokriging		✓		✓		✓
		Semantic Kriging			✓			
		Regression Kriging			✓			
	Natural neighbor interpolation				✓	✓	✓	✓
Global Based interpolation algorithm	RBF	Infinitely Smooth RBFs	✓	✓		✓	✓	
		Polyharmonic Spline		✓		✓	✓	✓
		Thin Plate Spline			✓		✓	
		Hybrid RBFs		✓	✓	✓		✓
	Least-Square Spline						✓	

Conclusion

1. Main contributions

2. Future directions

Main contributions

- Summarize some of the most used interpolation techniques on spatial scattered data
- Make classification for the spatial interpolation algorithms
- Detailed definitions
- Make comparison for the Kriging, RBFs and local-based & global-based algorithms

Future direction:

1. Focus on low-complexity interpolation methods which still can maintain high-accuracy
2. Make more combinations for algorithms to improve the multiple performances

References:

[1]. Franke, Richard. "Scattered data interpolation: tests of some methods." Mathematics of computation 38.157 (1982): 181-200.

[2] Ohtake, Yutaka, Alexander Belyaev, and H-P. Seidel. "3D scattered data approximation with adaptive compactly supported radial basis functions." Proceedings Shape Modeling Applications, 2004.. IEEE, 2004.

[3]. Fasshauer, Gregory E. "Solving differential equations with radial basis functions: multilevel methods and smoothing." Advances in computational mathematics 11.2-3 (1999): 139-159.

[4] Yu, L. I. U., G. U. O. Zheng, and L. I. U. Jun. "RBFs-MSA hybrid method for mesh deformation." Chinese Journal of Aeronautics 25.4 (2012): 500-507.

Weather Routing on Road Networks

CS 225 Project: Winter 2020

Group: 07
Andrew Lvovsky
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Jonathan Peng

Outline

- Introduction/Motivation
- Related Work
- System Architecture
- Weather Router Implementation
  - Back End
  - Front End
- Conclusion and Future Work

Introduction/Motivation

- Aimed towards long-range travel
  - Roadtrippers
  - Truck drivers
- Currently bothersome to look up weather on your route
  - individual weather look-ups
  - unsafe while driving
- What if there was a way to do this during routing?

Related Works

- In literature,
    - Most of the research works
        - are done on ship trips and ocean transportation system.
        - focus on the weather routing optimization problem
            - detects a optimized route depending on weather status
    - A few are done on weather routing forecast for marine systems
    - No existing work on weather routing forecast on road networks

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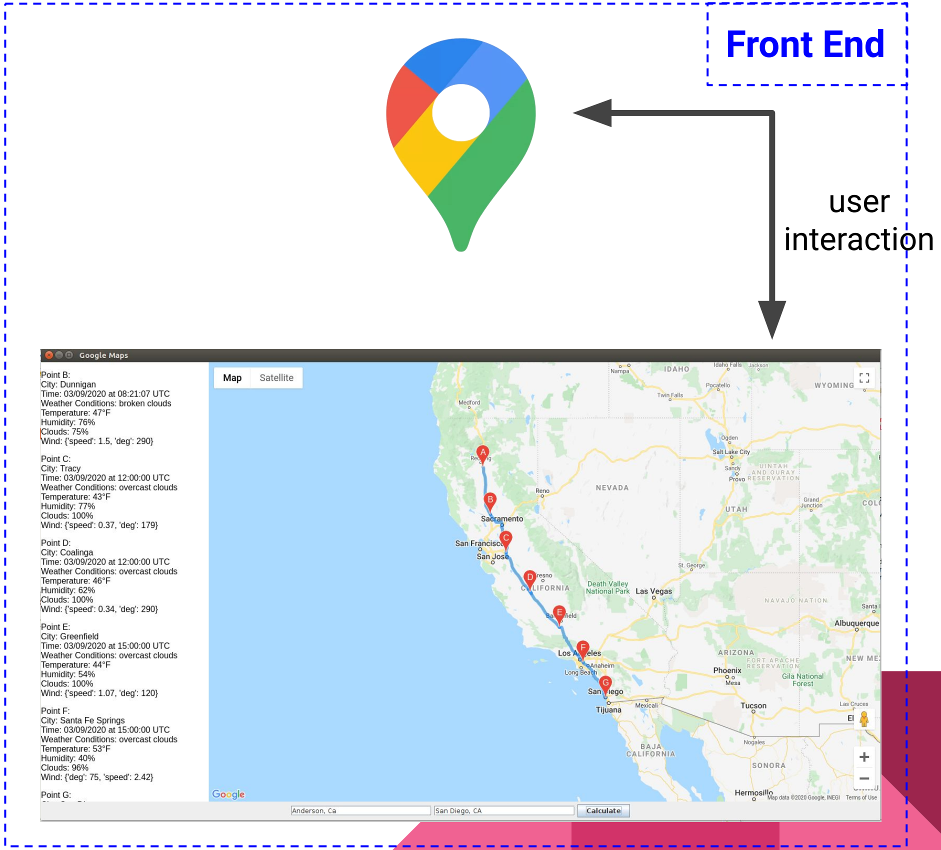
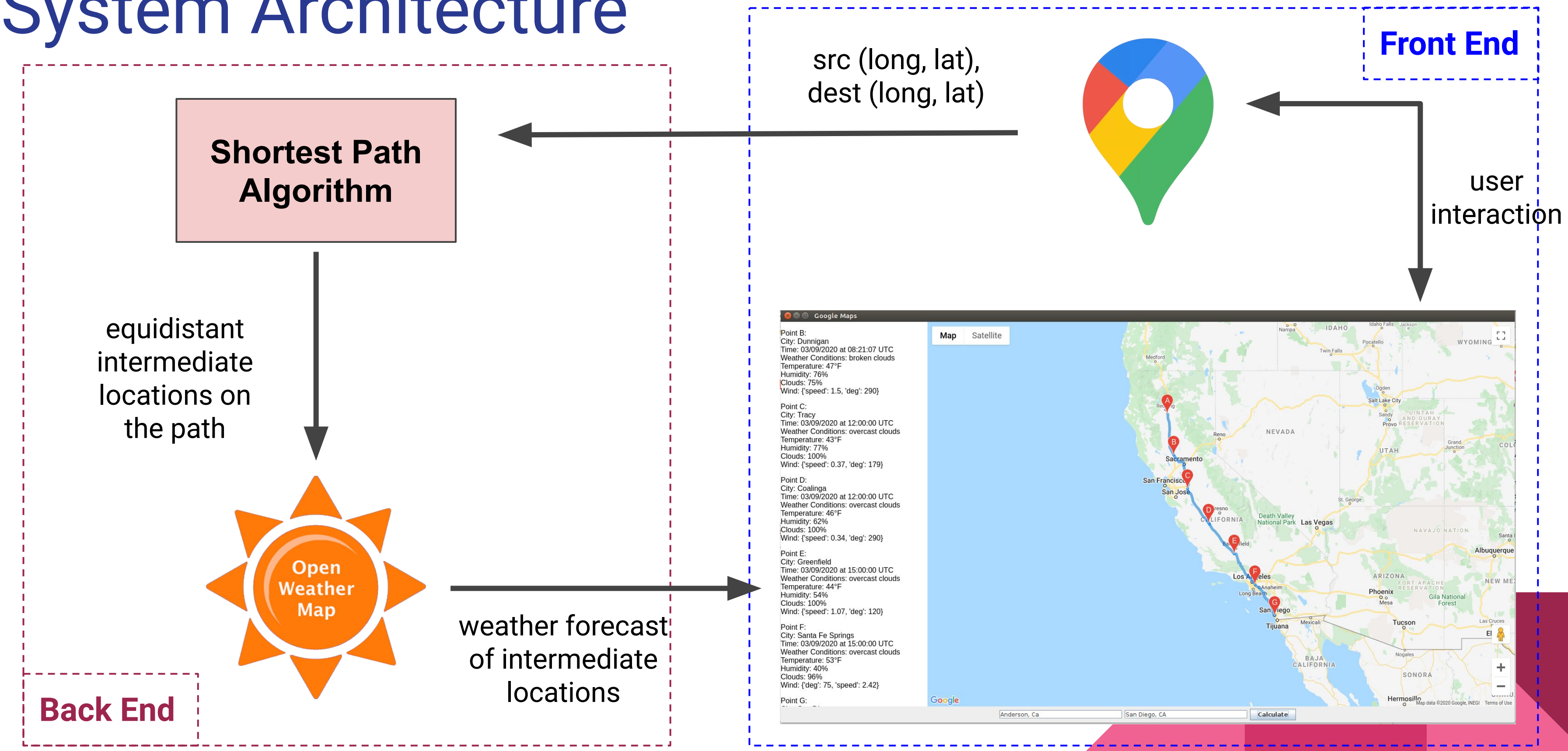
  - No existing work on weather routing forecast on road networks

- Existing applications
  - Area Road Conditions
  - Safe Travel USA
  - Highway Weather

System Architecture



System Architecture



Weather Router: Back End

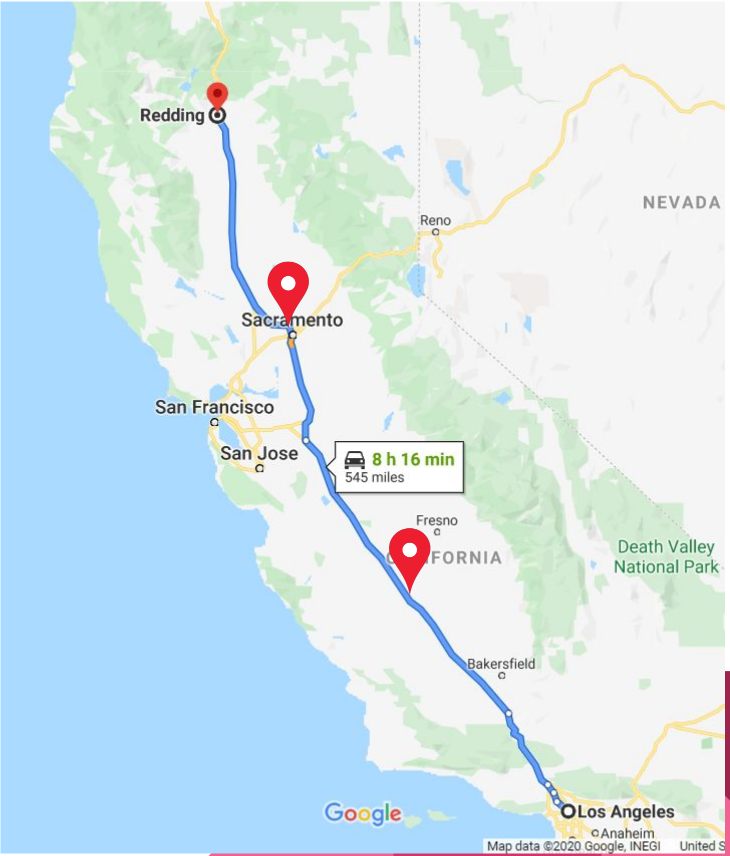
- Road network
  - California state road network*
  - 21047 nodes, 21692 road segments
  - Node format: (longitude, latitude)

- Euclidean distance
  - Does not provide us the real distance
- Haversine distance (Great circle distance)
  - Distance between two points on the Earth
  - Considers the radius of Earth (~3959 miles)

*binds us to the California State only

Weather Router: Back End

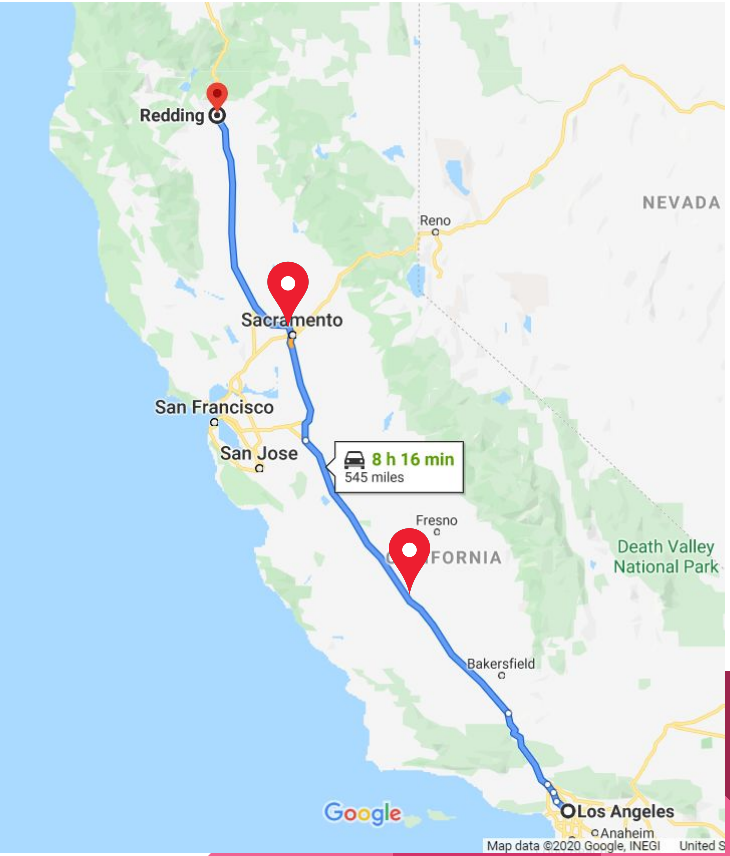
- Shortest path distance
  - Dijkstra's algorithm
  - Equi-distant locations on the shortest path
  - Time depends on the speed limit



Weather Router: Back End

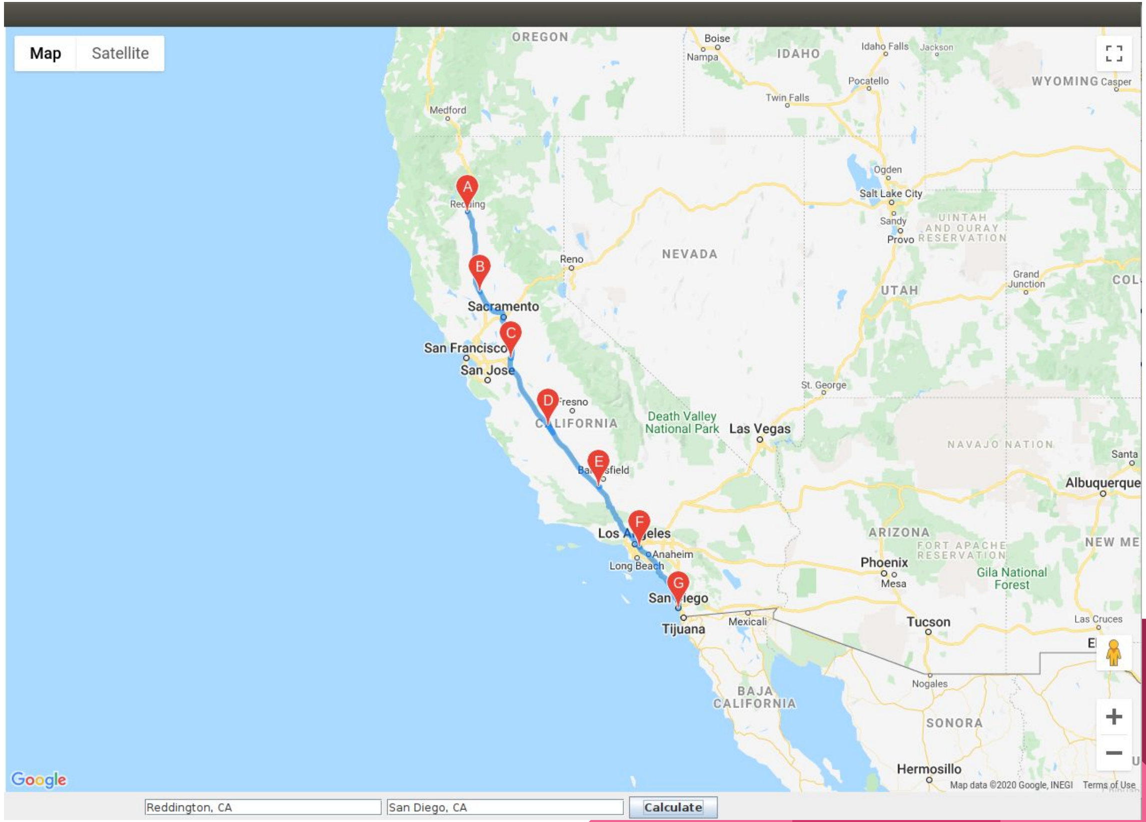
- Shortest path distance
  - Dijkstra’s algorithm
  - Equi-distant locations on the shortest path
  - Time depends on the speed limit

- OpenWeatherMap (OWM) - Weather API
  - Provides current weather and 3-hour (5-day) forecasts for free
  - pyowm for API calls
    - Python wrapper for OWM
  - Weather status at multiple points on the shortest path

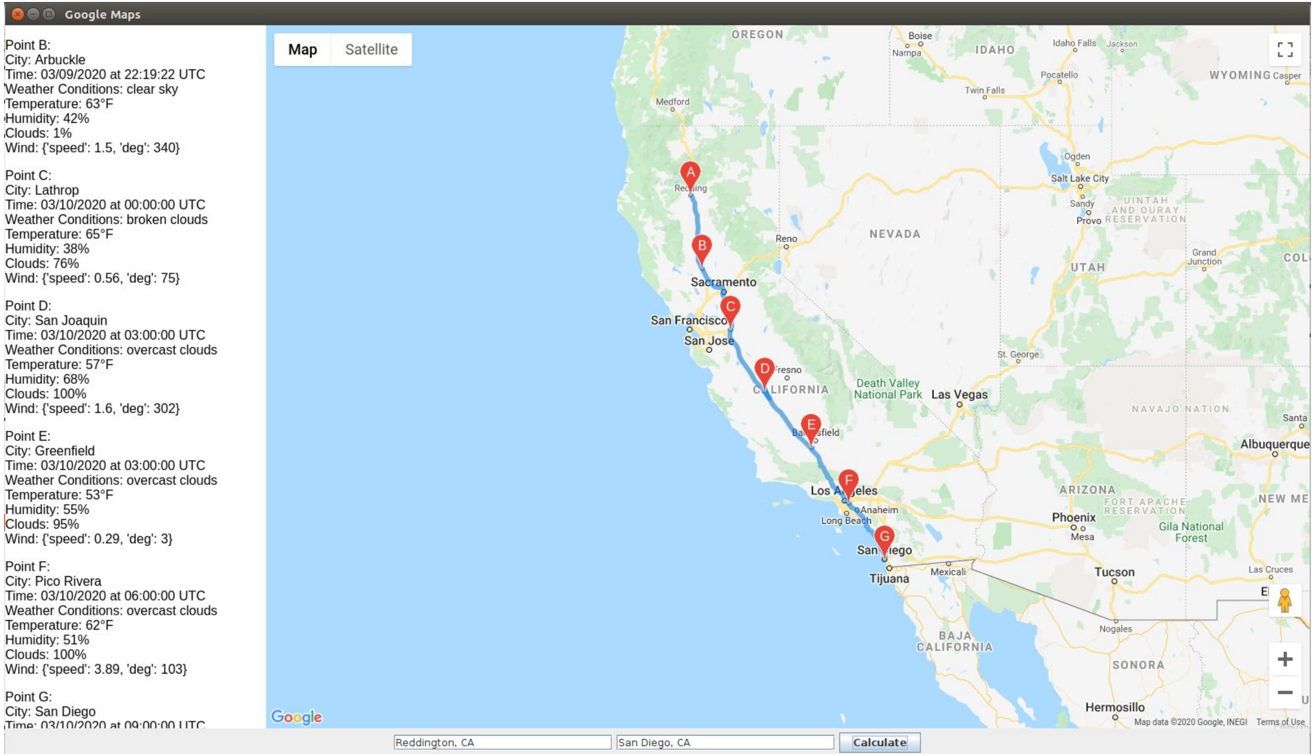


Weather Router: Front End

- Google Map Service API:
  - Display customized Google Map
- Google Direction API :
  - Search Original and Destination Location
  - Efficient path between two locations
  - Set up waypoints



Weather Router: Front End



- Enter departing and arriving addresses
- Wait a few seconds…
- Route is displayed with intermediate points
- Closest predicted weather at each point

Conclusion and Future Work

- Our web application
  - Takes source and destination locations from users
  - Detects equi-distant locations on the shortest path
  - Fetches and displays the weather forecast at these locations on Google Maps
  - Helps users to plan ideally a long trip ahead of time

- Future Work
  - Extend the back end (California) road network so that it can be applicable in the US
  - Scale app to work for mobile devices

Thank you

Questions?