Environmental Impacts on The Performance of Pavement Foundation Layers – Phase I

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Objective of the Study:

- Analyze the temperature and moisture data of soil at different location
- Clean and pre-process the soil temperature data
- To identify number of freeze thaw cycles at certain depths and frost depth isotherms over time
- Create a framework/tool to provide soil temperature and number of freeze-thaw cycles predictions

Data details:

Dataset 1 (of 2):

Temperature and moisture data of 6 different locations are available within 2-mile span of roadway at Monticello, Minnesota

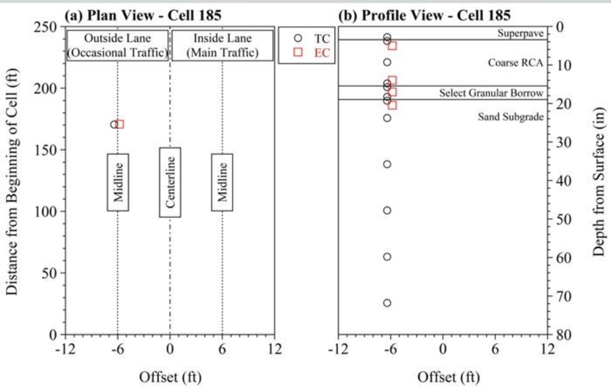
- Cell 185; Cell 186; Cell 188; Cell 189; Cell 127; Cell 728

Frequency: 15-minute time intervals

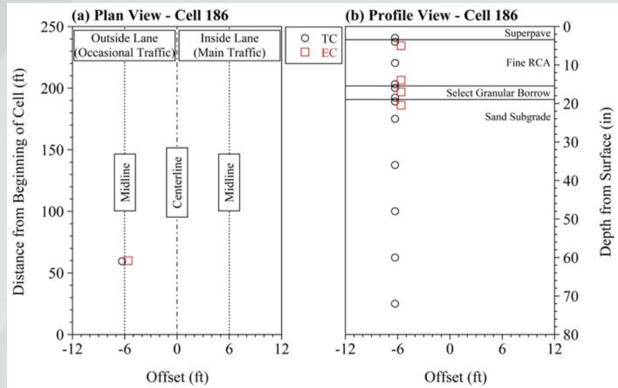
Time period: August 2017 to December 2019

Climate data: air temperature, relative humidity, wind speed, net radiation, precipitation

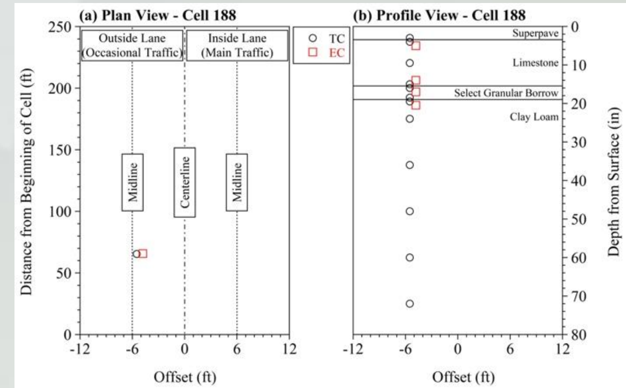
Soil profiles (Dataset 1):



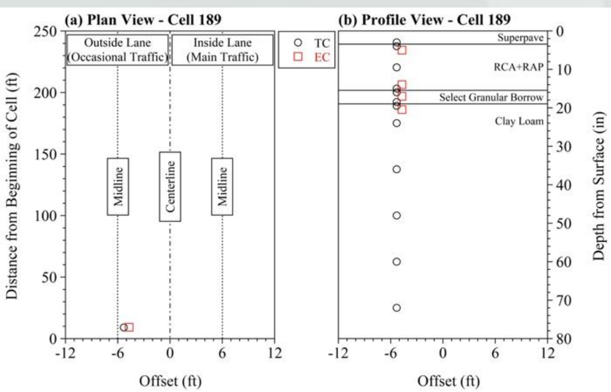
(a)



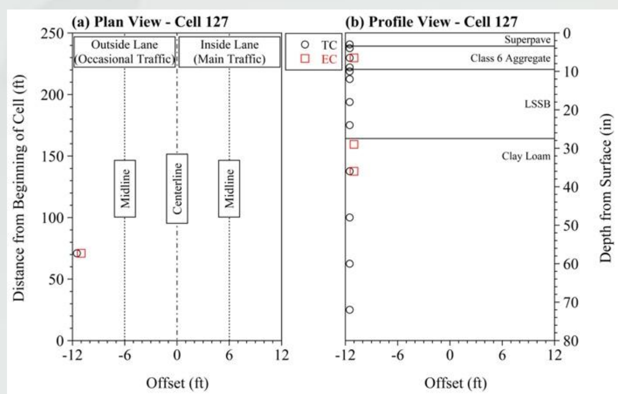
(b)



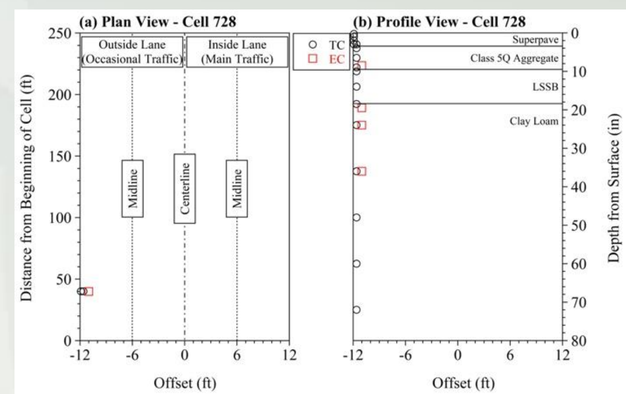
(c)



(d)



(e)



(f)

Schematic of the soil profiles for temperature and moisture data collection for the locations of (a) Cell 185; (b) Cell 186; (c) Cell 188; (d) Cell 189; (e) Cell 127; (f) Cell 728

Data details:

Dataset 2 (of 2):

Temperature and moisture data for 2 different counties in are Minnesota: Olmsted and Koochiching

Frequency: 1-hour time intervals

Time period: 2005-2012, 2012-2019 (Koochiching); 2000-2007, 2010-2017 (Olmsted)

Climate data (same as other dataset): air temperature, relative humidity, wind speed, net radiation, precipitation

Data details (Dataset 1):

Temperature data collected at 12 different depths for all stations

Cell no.	Cell 185	Cell 186	Cell 188	Cell 189	Cell 127	Cell 728
	Depth (in)					
TC_1	2.8	3	3	3	3	3
TC_2	3.8	4	4	4	4	4
TC_3	9.3	9.5	9.5	9.5	6.5	6.5
TC_4	14.8	15	15	15	9	9
TC_5	15.8	16	16	16	10	10
TC_6	18.3	18.5	18.5	18.5	12	14
TC_7	19.3	19.5	19.5	19.5	18	18.5
TC_8	23.8	24	24	24	24	24
TC_9	35.8	36	36	36	36	36
TC_10	47.8	48	48	48	48	48
TC_11	59.8	60	60	60	60	60
TC_12	71.8	72	72	72	72	72

Moisture data collected at 4 depths for all locations

Cell no.	Cell 185	Cell 186	Cell 188	Cell 189	Cell 127	Cell 728
	Depth (in)					
EC_1	5	5	5	5	6.5	8.5
EC_2	14	14	14	14	29	19.5
EC_3	17	17	17	17	36	24
EC_4	20.5	20.5	20.5	20.5		36

Data details (Dataset 2):

Temperature sensor locations for the two-time spans

Dataset location	Time span	Depth of temperature sensors
Koochiching	2005 to 2010	10; 40; 70; 90; 120; 180; 240; 300; 360; 420; 480; 540; 600; 720; 840; 960
	2012 to 2019	10; 30; 50; 80; 120; 150; 180; 210; 240; 300; 360; 420; 480; 540; 600; 640; 780; 910
Olmsted	2000 to 2007	25; 60; 90; 120; 180; 240; 300; 360; 420; 480; 600; 720; 840; 960; 1080
	2010 to 2017	10; 25; 50; 70; 130; 190; 250; 310; 370; 430; 490; 550; 610; 730; 850; 970

Dataset location	Time span	Depth of moisture sensors
Koochiching	2005 to 2010	NA
	2012 to 2019	80, 120, 150, 180, 210, 240, 300, 360, 420, 480, 540, 600, 780, 910
Olmsted	2000 to 2007	60, 90, 120, 180, 240, 300, 360, 420, 480, 600, 720, 840, 960, 1080
	2010 to 2017	70, 130, 190, 250, 310, 370, 430, 490, 550, 610, 730, 850, 970

Data preprocessing:

Dataset 1: Percent (%) missing temperature data

	TC1	TC2	TC3	TC4	TC5	TC6	TC7	TC8	TC9	TC10	TC11	TC12
Cell 185	2	2	2	2	2	2	2	2	12	2	87	2
Cell 186	< 1	< 1	< 1	< 1	< 1	< 1	< 1	< 1	11	< 1	< 1	< 1
Cell 188	< 1	< 1	0	0	0	0	0	0	0	0	0	0
Cell 189	< 1	< 1	0	0	0	0	0	0	NA	0	0	0
Cell 127	< 1	< 1	< 1	< 1	< 1	< 1	< 1	< 1	< 1	< 1	< 1	< 1
Cell 728	< 1	< 1	< 1	0	0	0	0	0	0	0	0	0

Outliers: identified and removed from the dataset

Missing Data:

- Number of missing elements were very small *(other than TC9 and TC11 in Dataset 1)*
- Data imputation was used to fill in missing elements as appropriate

Data preprocessing:

Dataset 2: Same procedure of data preprocessing is also used

Location	Timespan	Percentage of missing elements								
Koochiching	2005-2010	*TC1*	*TC2*	*TC3*	*TC4*	*TC5*	*TC6*	*TC7*	*TC8*	*TC9*
		<1	<1	<1	<1	58	<1	<1	<1	<1
		TC10	*TC11*	*TC12*	*TC13*	*TC14*	*TC15*	*TC16*	*TC17*	*TC18*
		<1	<1	<1	<1	<1	<1	<1	4	5
	2012-2019	*TC1*	*TC2*	*TC3*	*TC4*	*TC5*	*TC6*	*TC7*	*TC8*	*TC9*
		54	50	41	<1	<1	<1	<1	<1	<1
		TC10	*TC11*	*TC12*	*TC13*	*TC14*	*TC15*	*TC16*	*TC17*	*TC18*
		<1	<1	<1	<1	<1	<1	<1	<1	<1
Olmsted	2000-2007	*TC1*	*TC2*	*TC3*	*TC4*	*TC5*	*TC6*	*TC7*	*TC8*	*TC9*
		7	7	7	7	7	28	7	7	7
		TC10	*TC11*	*TC12*	*TC13*	*TC14*	*TC15*			
		7	7	9	7	7	7			
	2010-2017	*TC1*	*TC2*	*TC3*	*TC4*	*TC5*	*TC6*	*TC7*	*TC8*	*TC9*
		<1	<1	<1	<1	58	<1	<1	<1	<1
		TC10	*TC11*	*TC12*	*TC13*	*TC14*	*TC15*	*TC16*		
		<1	<1	<1	<1	58	<1	<1		

Freeze-thaw cycle calculations

Justification: Number of freeze-thaw cycles significantly impacts the soil properties

Number of freeze thaw cycles depends on:

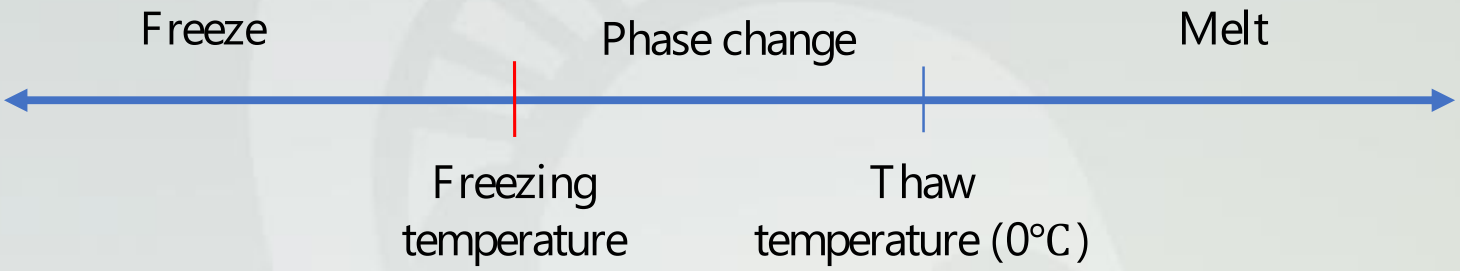
- Freezing temperature
- Thaw temperature (can be difference from freezing temperature)
- Time the soil temperature is lower than the freezing and higher than the thaw temperature

Based on these factors, three different approaches were considered to calculate the number of freeze-thaw cycles:

- Fixed freezing temperature
- Modified reference temperature
- Time delay method (including fixed freezing temperature)

Freeze-thaw cycles: Fixed freezing temperature

To undergo a complete freeze-thaw cycle, soil temperature needs to be higher than thaw temperature and then it needs to be lower than freezing temperature.



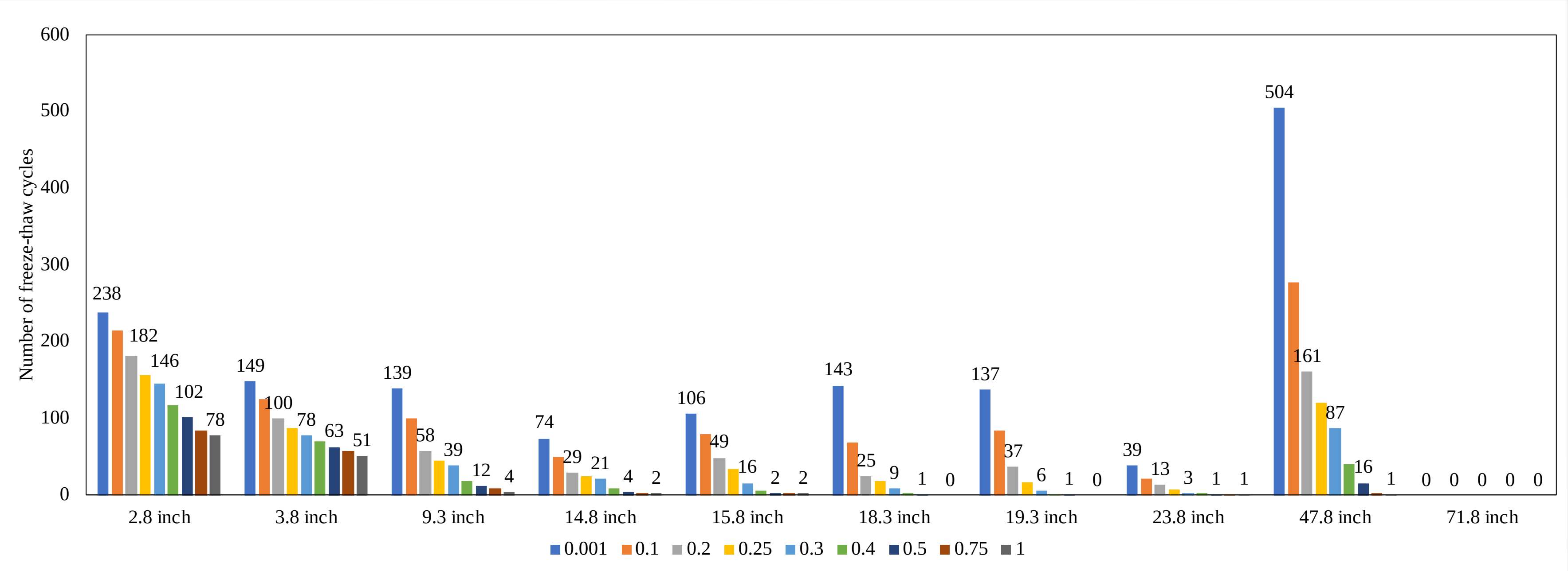
Thaw temperature is 0°C

9 different freezing temperatures are considered:

-0.001 °C, -0.1 °C, -0.2 °C, -0.25 °C, -0.3 °C, -0.4 °C, -0.5 °C, -0.75 °C, -1 °C

Freeze-thaw cycles: Fixed freezing temperature

The variation in number of cycles at different depth are shown below (Cell 185, Dataset 1, for 2018 January to December, similar data in other locations)



- increase freezing temperature, number of cycles reduces significantly
- If assume larger freezing temperatures, # of cycles reduces with depth; if assume smaller (makes sense), at deeper depths it increases increases significantly (doesn’t make sense)

Freeze-thaw cycles: Fixed freezing temperature

Summary:

- Selection of the freezing temperature plays an important role in the calculated number of freeze-thaw cycles
- Increasing the freezing temperature (up to **1℃**): reduces the number of freeze-thaw cycles calculated at different depths
- Temperature sensors error used in this study is **1℃**; the minimum freezing temperature that can be selected for this calculation should be at least **1℃**

Freeze-thaw cycles: Modified reference temperature

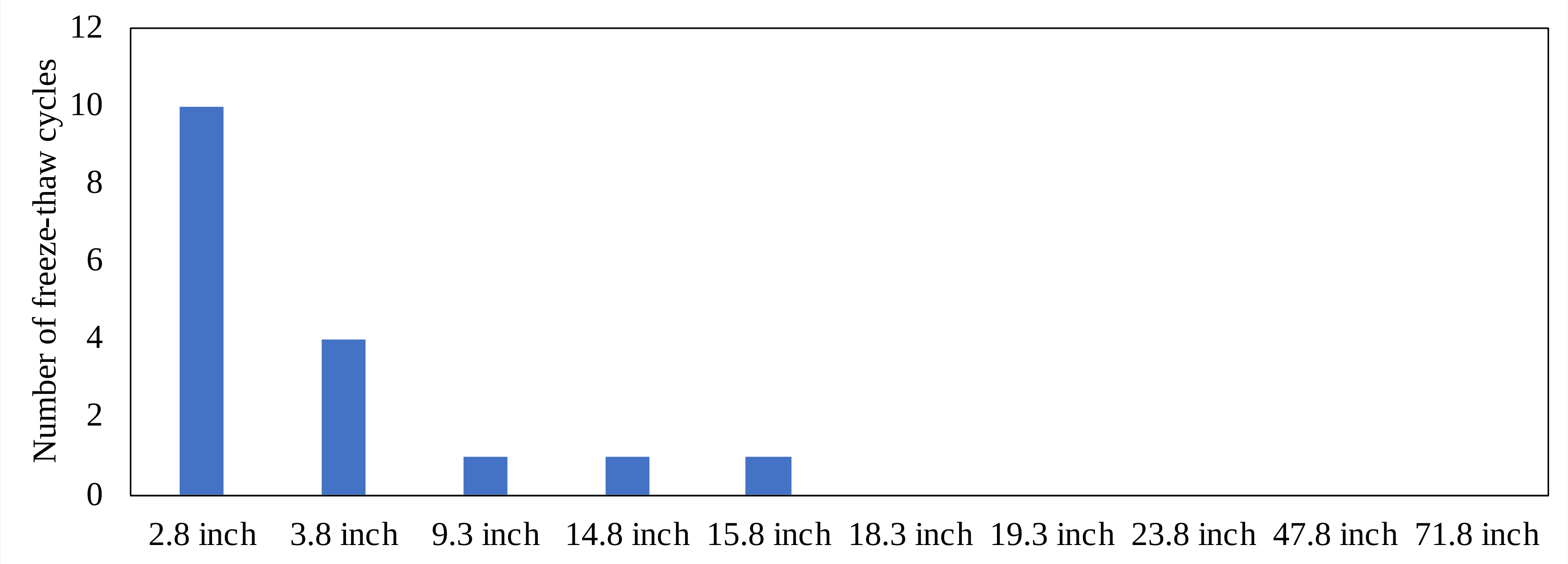
Similar to the previous method (i.e the fixed freezing method)
However, freezing point **varies** with respect to the time of year rather than a constant value

Date	Reference temperature (°C)	Modified reference temperature (°C)
January 1- January 31	0	-1.0
February 1- February 7	-1.5	-1.5
February 8- February 14	-2.0	-2.0
February 15- February 21	-2.5	-2.5
February 22- February 28	-3.0	-3.0
March 1 – March 7	-3.5	-3.5
March 8 – March 14	-4.0	-4.0
March 15 – March 21	-4.5	-4.5
March 22 – March 28	-5.0	-5.0
March 29 – April 4	-5.5	-5.5
April 5 - April 11	-6.0	-6.0
April 12 - April 18	-6.5	-6.5
April 19 - April 25	-7.0	-7.0
April 26 – May 2	-7.5	-7.5
May 3- May 9	-8.0	-8.0
May 10- May 16	-8.5	-8.5
May 107 May 23	-9.0	-9.0
May 24- May 30	-9.5	-9.5
June 1- December 31	0	-1.0

Ref: Technical Memorandum No. 14-10-MAT-02, MINNESOTA DEPARTMENT OF TRANSPORTATION, October 7, 2014

Freeze-thaw cycles: Modified reference temperature

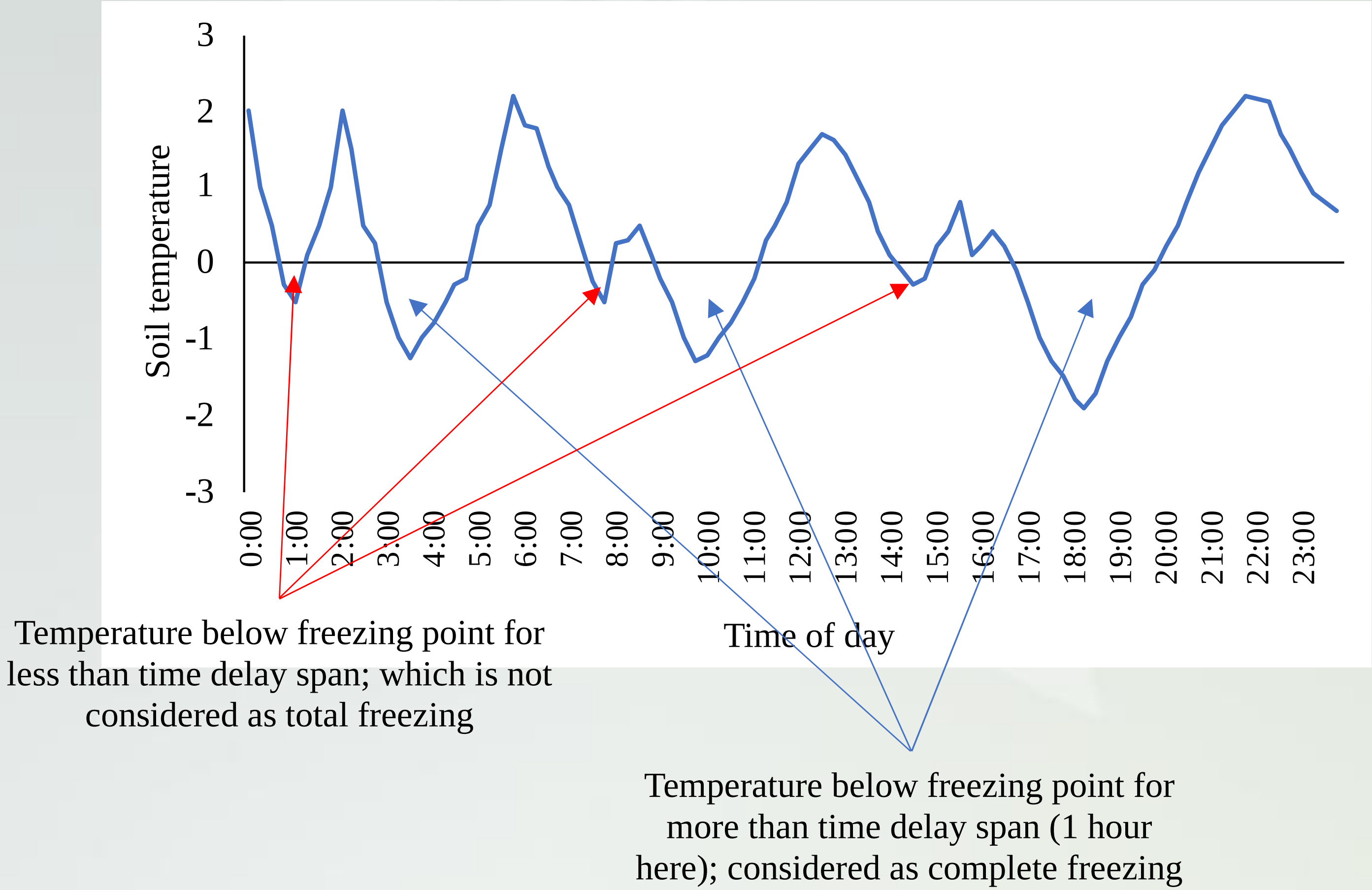
The variation in number of cycles at different depth are shown below (Cell 185, **Dataset 1**, for 2018 January to December)



The number of cycles calculated are much **less** compared to the fixed freezing temperature (previous) method

Freeze-thaw cycles: Time Delay

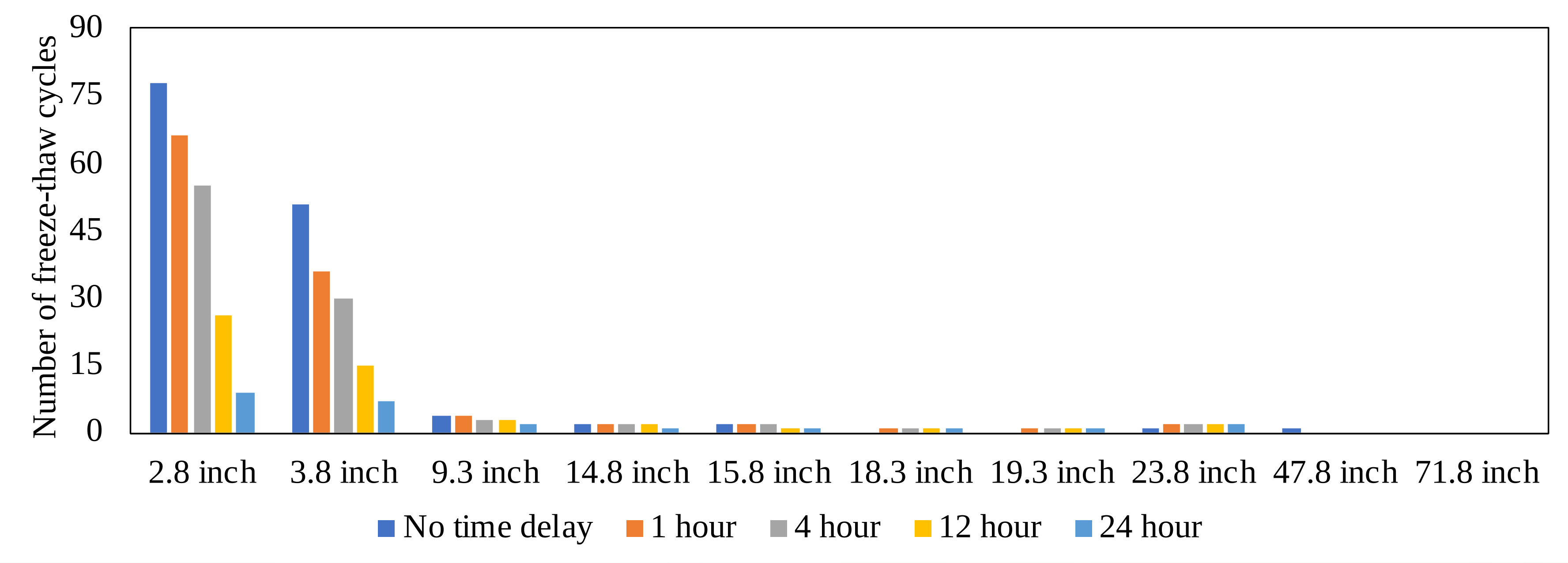
"Time delay" is defined as a minimum period of time required for a half of a freeze-thaw cycle to be completed in order for it to count as a F-T cycle



Freeze-thaw cycles: Time Delay

4 different time delays considered: 1-hour, 4-hour, 12-hour and 24-hour

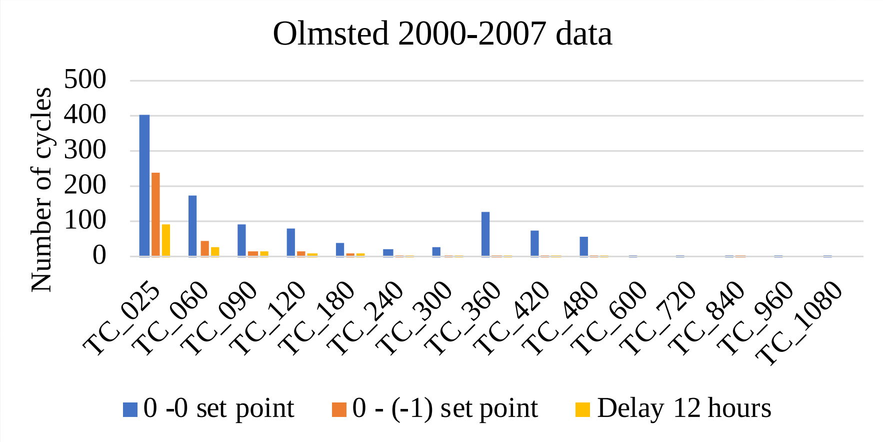
The variation in number of cycles at different depth are shown below (Cell 185, **Dataset 1,** for 2018 January to December)

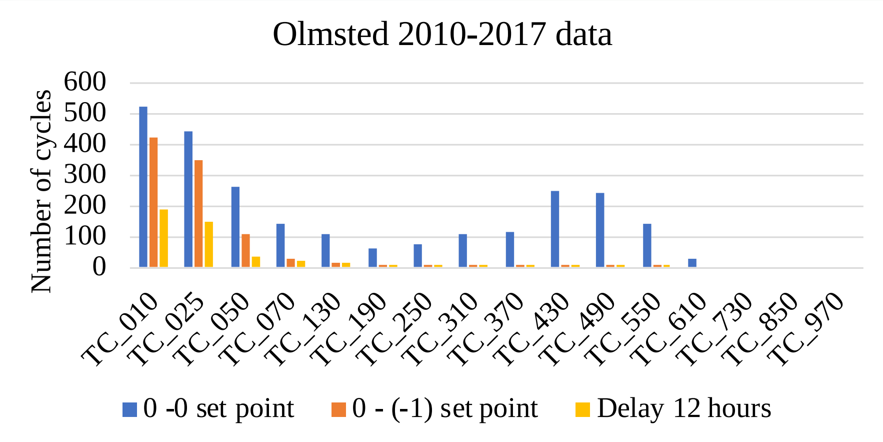


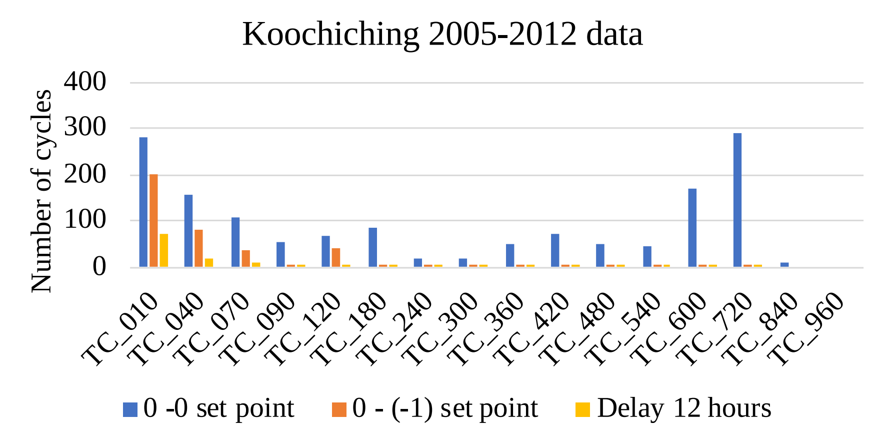
Increasing the time delay reduces the number of cycles calculated at shallower depths

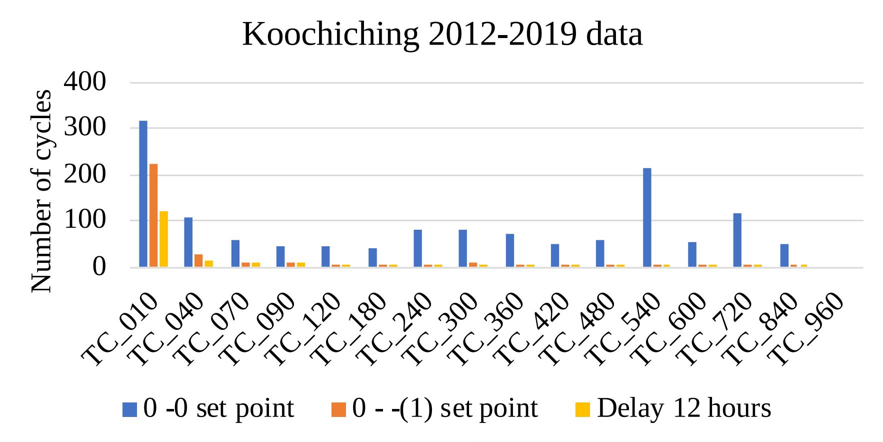
Freeze-thaw cycles:

A similar study for Dataset 2 using a **fixed freezing temperature** of **1 C** and **12-hour** time delay methods. Similar trends can be seen for this dataset



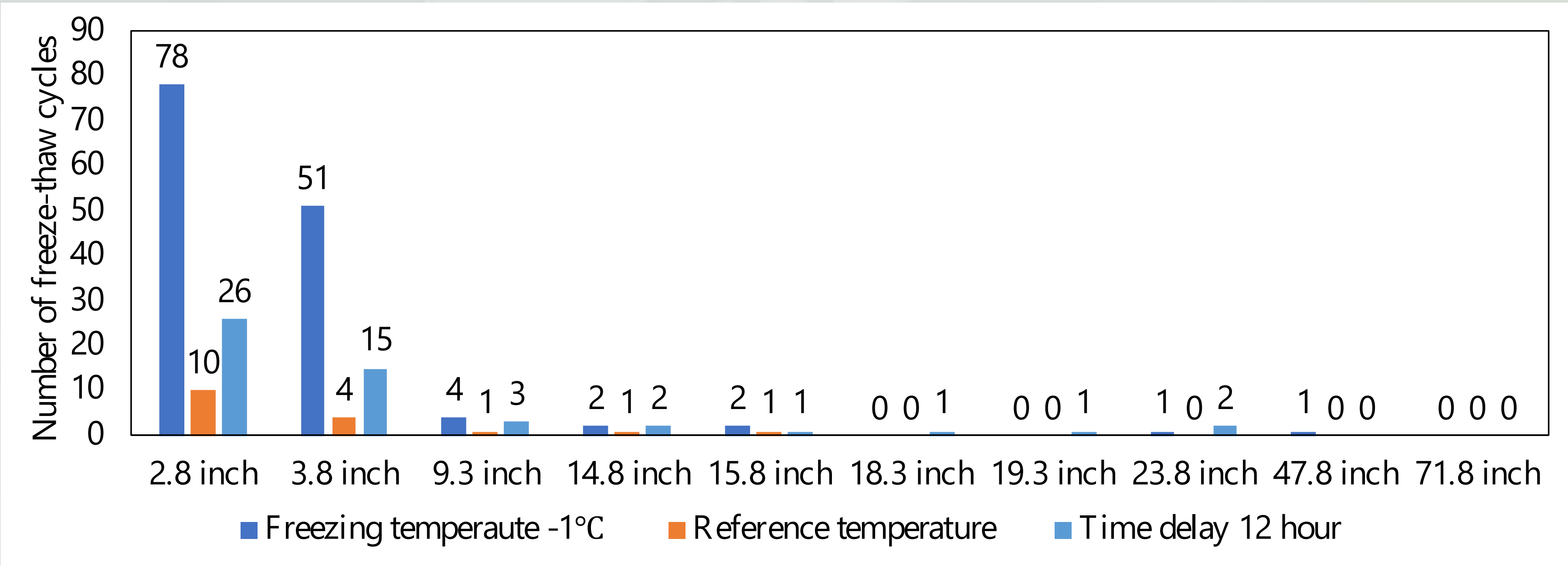






Questions for TAC :

Which of these three methods would be advised?



Soil temperature modeling approach

Previously we have discussed predicting soil temperature variations over time using different models:

- Linear regression methods,
- Polynomial regression methods,
- Vector auto regressive methods,

- Predictors used for these models:
  - climate parameters (air temperature, relative humidity, rainfall, wind speed)

Soil temperature modeling approach

There are several studies that used to predict soil surface temperatures:

1. Predict daily average temperature using superposition of two models: predict monthly average temperature and daily average temperature amplitude using *air temperature, solar radiation, wind speed, relative humidity and day of year* [Xing et al., 2018]

2. Estimate daily soil surface temperature using *mean, maximum and minimum air temperature, relative humidity, sunshine hours and solar radiation* [Talaee et al., 2013]

3. Predict daily soil surface temperature using parameters like *average air temperature, total solar radiation, average relative humidity, average dew point temperature, average wind speed and total potential evapotranspiration* [Kim et al., 2014]

Soil temperature modeling approach

Update:

- Solar radiation data has been used as an additional variable
- New variables created by modifying the climate data with respect to time
- 19 variables, based on combining time and climate variables (*see next slide*)

Modeling approach (updates):

The variables are

(a) Time variables

1. Week (1 to 52);
2. Month (1 to 12);
3. Day of year (1 to 365)
4. Timestep (1 to 96 for 15-minute and 1 to 24 for 1-hour data frequency)

(b) Climate variables (Air temperature, Relative humidity, Rain, Wind speed, Solar radiation)

1. Actual values
2. Daily average values
3. Variation in climate parameters for each timestep

Modeling approach (updates)

Stepwise regression to identify the most significant parameters

	Week	*Month*	*Day of Year*	*Timestep*	*Air Temperature*	*Rain*	*RH*	*Wind*	*Radiation*	*Variation Air Temperature*	*Variation Rain*	*Variation RH*	*Variation Wind*	*Variation Radiation*	*Average Air Temperature*	*Average Rain*	*Average RH*	*Average Wind*	*Average Radiation*
Week	1																		
Month	1	1																	
DayofYear	1	1	1																
Timestep	0	0	0	1															
AirTemp	0.22	0.21	0.22	0.11	1														
Rain	0.02	0.02	0.02	0.01	0.04	1													
RH	0.22	0.22	0.22	-0.25	-0.24	0.09	1												
Wind	-0.09	-0.09	-0.09	0.04	-0.11	0.01	-0.23	1											
rad	0	0	0	0.04	0.46	-0.03	-0.5	0.18	1										
varTemp	0	0	0	0.4	0.27	-0.01	-0.55	0.26	0.5	1									
varRain	0	0	0	0.01	0	0.96	0.03	0.02	-0.02	-0.01	1								
varRH	0	0	0	-0.36	-0.21	0.04	0.71	-0.27	-0.51	-0.78	0.04	1							
varWind	0	0	0	0.05	0.1	0.02	-0.27	0.71	0.35	0.37	0.02	-0.38	1						
varRad	0	0	0	0.04	0.15	-0.02	-0.4	0.28	0.91	0.55	-0.02	-0.56	0.39	1					
avgTemp	0.22	0.22	0.22	0	0.96	0.04	-0.09	-0.18	0.34	0	0	0	0	0	1				
avgRain	0.09	0.09	0.09	0	0.15	0.26	0.24	0	-0.04	0	0	0	0	0	0.16	1			
avgRH	0.31	0.31	0.31	0	-0.13	0.09	0.71	-0.06	-0.2	0	0	0	0	0	-0.13	0.34	1		
avgWind	-0.12	-0.12	-0.12	0	-0.25	0	-0.06	0.71	-0.11	0	0	0	0	0	-0.26	0	-0.08	1	
avgrad	-0.01	-0.01	-0.01	0	0.77	-0.02	-0.33	-0.18	0.42	0	0	0	0	0	0.8	-0.09	-0.46	-0.25	1

**NB: avg: average values for the whole day; var: variation values for each timestep; RH: relative humidity; Wind: wind speed*

Modeling approach

Stepwise regression method is used to:

1. Identify most significant variables for temperature prediction;
2. Remove highly correlated variables;

Correlation coefficient > 0.7 => High corelated variable

Correlation coefficient < 0.3 => Low corelated variable

Variables are selected where correlation coefficients are less than 0.3. In total 8 variables are obtained are obtained as the result of the regression analysis:

1. Day of year (1 to 365); 2. Timestep (1 to 4*24);

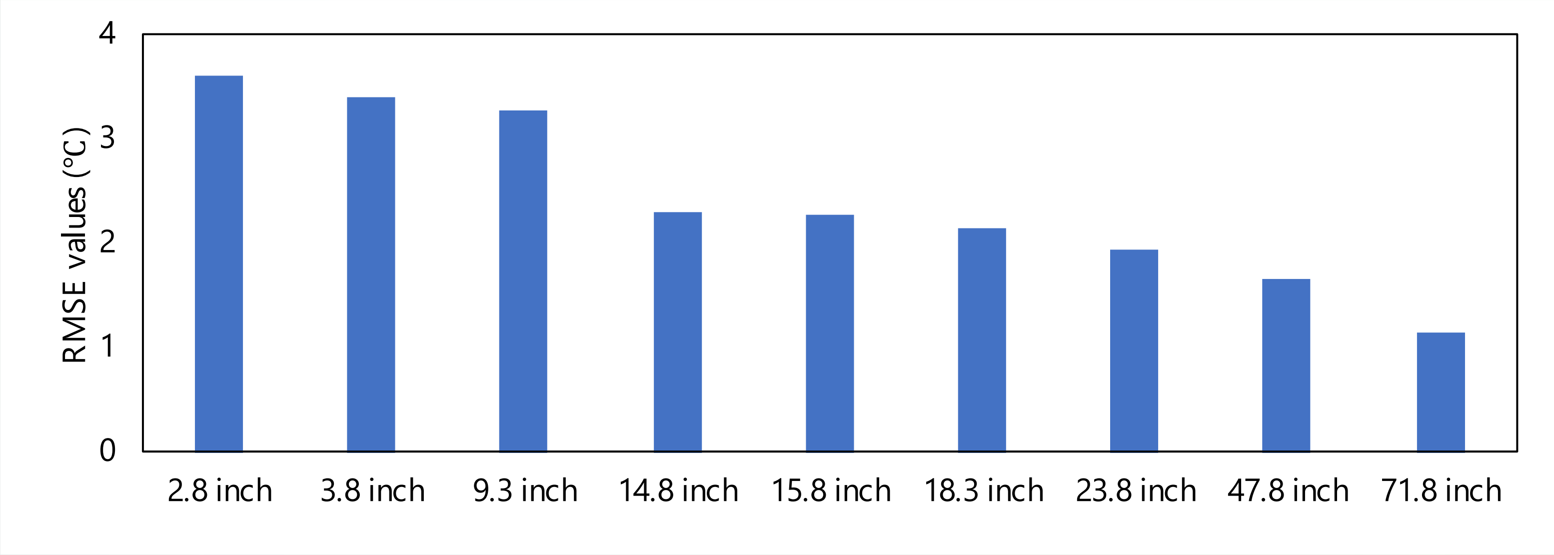
3. Air temperature; 4. Net radiation;

5. Variation in air temperature; 6. Variation in rain;

7. Variation in relative humidity; 8. Variation in windspeed;

Initial approach for modeling

- Fourth order polynomial regression analysis has been done
- Data of 2018 January to December has been used as training data and January 2019 to April 2019
- Root mean square errors (RMSE) are calculated for the predicted values and testing dataset
- Lower the RMSE values, better the model is
- RMSE values reduce with the increase in depth



Future steps

- Different models will be implemented to predict the soil temperature
- Number of freeze-thaw cycles will be predicted for different locations
- Which timestep should be used for the calculation:
  15-minute timestep or 1-hour timestep?

Reference:

- Barnard, John, and Xiao-Li Meng. "Applications of multiple imputation in medical studies: from AIDS to NHANES." Statistical methods in medical research 8, no. 1 (1999): 17-36.
- [2] Solaro, Nadia, Alessandro Barbiero, Giancarlo Manzi, and Pier Alda Ferrari. "A sequential distance-based approach for imputing missing data: Forward Imputation." Advances in Data Analysis and Classification 11, no. 2 (2017): 395-414.
- [3] Technical Memorandum No. 14-10-MAT-02, MINNESOTA DEPARTMENT OF TRANSPORTATION, October 7, 2014
- [4] Zegeye Teshale, Eyoab, Dai Shongtao, and Lubinda F. Walubita. "Evaluation of Unbound Aggregate Base Layers using Moisture Monitoring Data." Transportation Research Record 2673, no. 3 (2019): 399-409.
- Kim, Sungwon, and Vijay P. Singh. "Modeling daily soil temperature using data-driven models and spatial distribution." *Theoretical and applied climatology* 118, no. 3 (2014): 465-479.
- Talaee, P. Hosseinzadeh. "Daily soil temperature modeling using neuro-fuzzy approach." *Theoretical and applied climatology* 118, no. 3 (2014): 481-489.
- Xing, Lu, Liheng Li, Jiakang Gong, Chen Ren, Jiangyan Liu, and Huanxin Chen. "Daily soil temperatures predictions for various climates in United States using data-driven model." *Energy* 160 (2018): 430-440.