Regression Models for Tree Trunk Temperature for Energy Harvesting

Yajun An

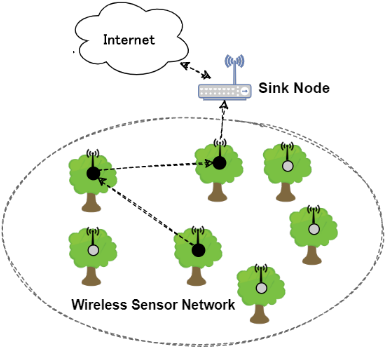
School of Interdisciplinary Arts & Sciences
University of Washington, Tacoma

April 3, 2024

Background

- Recent years, there have been increased influx of tourists that endangers the ecosystem through the pollution of the environment and the damage of protected areas.
- We aim to obtain environmental data to inform policy makers about the severity of the environmental impact of tourism.
- We develop wireless sensor networks (WSN) to gather environmental data in large areas, which are special network composed of sensor nodes with wireless communication capabilities

Smart trees: An Example of WSN application



WSNs require several parameters, including the amount and type of sensors, network topology, communication technology, and energy power supply for the sensors.

Not ideal: batteries

- inconvenient in remote areas
- environmentally unfriendly

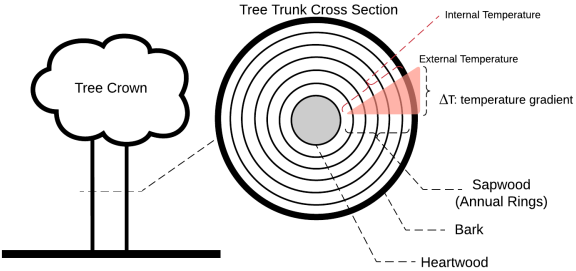
Better alternative: energy harvesting from trees

- collects energy on site
- electricity energy can feed low-power electronic devices

Installing sensors and TEGs

Device being installed on young mango trees (left); Device on the tree

Tree stem cross section



- Trees store a large amount of heat in their trunks.
- Annual rings in a tree trunk can be treated as isothermal sub-volumes.
- Temperature gradient varies with some time delay as the environment varies.

Energy harvesting from tree trunks

- Let $\Delta T :=$ radial temperature difference in tree trunk
- If $\Delta T > 0$, then electrical energy is generated by Thermoelectric Generators (TEG). The voltage (V) is proportional to ΔT based on the Seebeck Effect
- To infer the amount of electrical energy that can be generated, we study the temperature distribution within a tree trunk
- We present a few regression models to find the temperature distribution within a tree trunk based on measured weather conditions

Temperature and weather data collection

Data collected onsite in Brazil, over a 7 day period, in August of 2022

- Tree temperature: measured in 10 different position on the tree trunk, varying in direction, height, and depths
- Average wind speed in m/s measured by a anemometer
- Average humidity in % measured by a Hygrometer
- Average air temperature in Celsius measured by a Hygrometer
- Average air pressure in hPa measured by a Barometer
- Average Direct Normal Irradiance (DNI) in W/m^2 measured by a Pyrheliometer.

Problem set up

Assume $Y = f(\mathbf{X}) + \epsilon$

- Y : response
  temperature in tree trunk
- $\mathbf{X} = [X_1, ..., X_n]$: features, or predictors
  weather condition, bark and core temperatures
- ϵ : random error term
- Estimate f :
  - understand the relation between weather conditions with tree temperature
  - predict the tree temperature given future weather condition
- Data usage
  - training data: August 21
  - testing data: August 22, August 26

How to estimate f

Parametric method

- Linear regression
  - Assume $Y = f(\mathbf{X}) = \beta_0 + \beta_1 X_1 + ... + \beta_n X_n$
  - We determine β_j values

Non parametric methods

- K-nearest neighbors (KNN) regression
- Decision tree regression

KNN regression

Input:

- K : number of interest neighbors
- x_0 : point at which a value y_0 is predicted

Algorithm:

1. Identify K training observations that are closest to x_0 (represent by $\mathcal{N}_0$)
2. Estimate $\hat{y}_0 = \hat{f}(x_0) = \frac{1}{K} \sum_{x_i \in \mathcal{N}_0} y_i$ (the average of all the training responses in $\mathcal{N}_0$)

KNN regression for heat modeling

Input:

- K : number of similar weather observations
- x_0 : weather condition at which a tree trunk temperature y_0 is predicted

Algorithm:

1. Identify K training weather observations that are closest to x_0 (represent by $\mathcal{N}_0$)
2. Estimate tree temperature $\hat{y}_0 = \hat{f}(x_0) = \frac{1}{K} \sum_{x_i \in \mathcal{N}_0} y_i$ (the average of all the training tree temperature responses in $\mathcal{N}_0$)

Experiments are done on Google Colab: here

KNN regression: experiments and results

Test on various K values

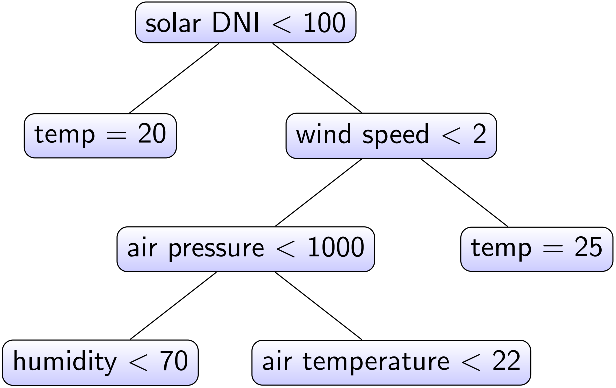
- small K: flexible fit; low *bias* but high *variance*
- big K: smoother (low *variance*), but might mask structure (high *bias*)

Variance and bias of a statistical learning method

- Variance: the amount by which $\hat{f}$ would change if we estimate it using a different training data set
- Bias: the error that is introduced by approximating a real-life problem

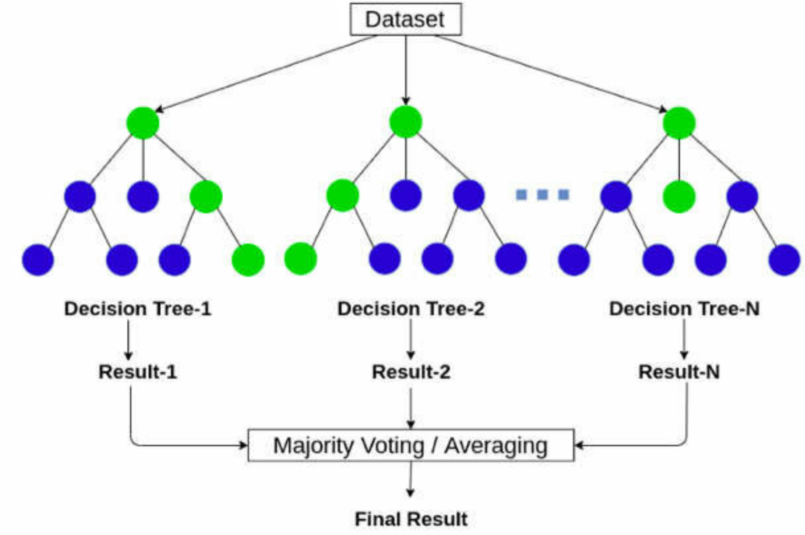
Decision tree regression

- segments the predictor space into a number of simple regions
- assign mean response value of the region to the point



Random Forest regression

Ensemble of multiple trees, and final result is a combination of each tree



Tree and Forest: experiments and analysis

All experiments are performed on Google Colab, here

Parametric vs non parametric approaches

- Parametric approaches tend to outperform non-parametric approaches if the assumed parametric form is close to the true form of f

- True relation between tree trunk temperature and weather conditions are generally *linear*

Appx. Linear regression model for tree trunk temperature

Linear regression model

$$Y_{temperature} = \alpha_1 X_{bark_{temp}} + \alpha_2 X_{core_{temp}} + \alpha_3 X_{init_{temp}} + \alpha_4 X_{depth} + \sum_{j=5}^{k} \alpha_j X_{weather_j}$$

- $\sum_{j=5}^{k} \alpha_j X_{weather_j}$ is the sum of included weather conditions.
- Example: a model including wind speed, air temperature, and DNI is of the form

$$\sum_{j=5}^{k} \alpha_j X_{weather_j} = \alpha_5 \times \text{wind speed} + \alpha_6 \times \text{air temperature} + \alpha_7 \times \text{DNI}$$

Appx.Experiments, Results, and analysis

We experiment with several combinations of weather variables in the regression model

- Models are trained with data collected on August 21
- We train the regression model with various weather factor combinations
- We first test the trained regression models on data from August 22 to find best models
- We test the found best models from previous step with August 26 data

Appx.Example models: Tests 1, 2, 3, and 4

	Test 1	Test 2	Test 3	Test 4
Depth 9 cm	✓			
Depth 4.5 cm		✓	✓	✓
Wind speed	✓	✓	✓	✓
Air temp	✓	✓	✓	✓
Humidity			✓	
Inverse Humidity				✓
Air pressure				
Inverse Air pressure				
DNI	✓	✓	✓	✓

Table: Included parameters for linear regression model.

- Tests 1 and 2: efficiency of models for different depths;
- Tests 3 and 4: efficiency of models for humidity parameter
- Please see our paper for the remaining 5 models

Appx.Error comparison of all 9 regression models

	MSE	MAE	Maximum Error
Test 1	0.1097	0.2691	0.6156
Test 2	0.2466	0.4133	1.4130
Test 3	0.5396	0.6314	1.6343
Test 4	0.5646	0.6430	1.6884
Test 5	0.1439	0.3160	0.6840
Test 6	0.1082	0.2677	0.6102
Test 7	0.3722	0.5447	1.2723
Test 8	0.1495	0.3270	0.6810
Test 9	0.1445	0.3093	0.9158

Table: Error comparison of regression models

- Mean Square Error; Mean Absolute Error, and Maximum Error comparisons of models with data on August 22.

Appx.Analysis of test results

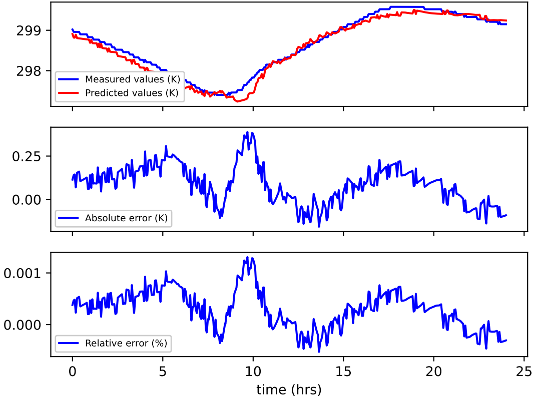
The smallest errors occur for Tests 1, 5, 6, 8, and 9. We further test these models with data collected on August 26.

	MSE	MAE	Maximum Error
Test 1.1	0.0188	0.1149	0.3828
Test 5.1	0.0195	0.1155	0.3891
Test 6.1	0.0181	0.1137	0.3683
Test 8.1	0.0170	0.1088	0.3493
Test 9.1	0.3212	0.4692	1.2553

Table: Error comparisons of models for data on August 26.

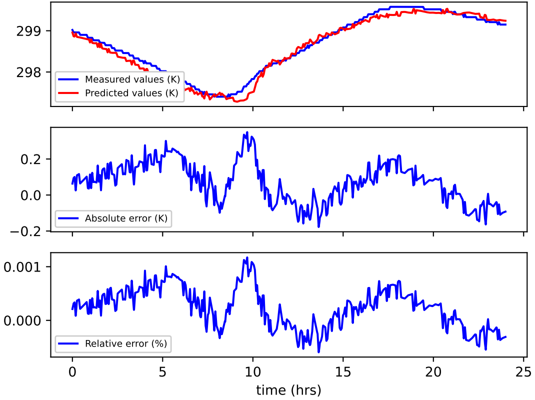
- We see that the best models tested with August 26 are models 1, 6, 8.

Appx.Examples of predicted temperatures- model 5



- Regression model including wind speed, air temperature, inverse humidity, and solar radiation.

Appx.Examples of predicted temperatures- model 8



- Regression model including wind speed, air temperature, inverse humidity, inverse air pressure, and solar radiation.

Conclusion and on going work

- We examine several linear regression models based on various weather conditions to model internal temperature distribution in tree trunks of young mango trees in Brazil
- We find that the linear regression models perform the best, and suspect that the relation is linear
- Other than wind speed, surrounding air temperature, and solar DNI, inverse air pressure and inverse humidity also improve the linear regression model
- Our model built with August 21 data can be used to predict temperature at later dates
- As weather conditions change between summer and winter, we plan to further investigate the validity of our linear regression models using data collected in February.
- We gain insight from the linear regression model to build other models (such as NN) for tree temperature modeling

Thank you!