Urban Air Temperature Model Using GOES-16 LST and a Diurnal Regressive NeuralNetwork Algorithm

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Abstract

An urban air temperature model is presented using GOES-16 land surface temperature. The Automated Surface Observing System (ASOS) serves as ground truth air temperature for calibration and testing of the model. The National Land Cover Database (NLCD) is used to calculate a weighted distribution of 20 land classifications for each satellite pixel surrounding a nearby ASOS station. A time-match algorithm aligns the ground and satellite measurements within 5-minutes of one another, and the resulting matched LST and air temperature are compared over nine months to investigate their cross-correlation. A model is constructed by fitting their difference using a gaussian profile. Landcover, latitude, longitude, local time, and elevation are inputted into an artificial regressive neural network to fit each unique GOES-16 pixel. Over 100 urban stations and satellite pixels throughout the continental U.S. are used to construct the diurnal gaussian model and approximate air temperature. Early statistics indicate favorable results, competing with other studies with more complicated and intensive calculations. The presentation of this model is intended to simplify the calculation of air temperature from satellite LST and create a successful model that performs well in urban environments. The improvement of urban air temperature calculations will also result in improved satellite land surface products such as relative humidity and heat index.

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Motivation

The GOES-R satellite is capable of producing 2-km spatial resolution land surface temperature (LST) at 5-minute time intervals. The high resolution temporal capability permits diurnal comparison against ground station measurements, which serve as the multi-point correlations between satellite LST and 2-m air temperature. The difference between LST and air temperature is fitted using a Gaussian function that uses the average pixel altitude, local time, geographic coordinates, and 20 National Land Cover Database (NLCD) classes. The model is trained using the Automated Surface Observing System (ASOS) to create coefficients used in the Gaussian function. The model is presented with the intention of creating air temperature data from remote sensed LST to improve models and weather prediction, specifically in urban areas. The creation of a satellite-derived air temperature product will also improve heat index calculations, something that will benefit society when predicting harmful extreme heat events.

Methods

The first step in comparing GOES-R LST and ground station air temperature began with analysis of diurnal variability between the two. Since the GOES-R temporal resolution permits 5-minute product resolution, we were able to create to build a multi-point correlation between LST and air temperature. The resulting temporal variability was analyzed and fitted using a Gaussian function with the following coefficients, derived for each satellite pixel:

$$T_{air} \approx T_{LST} + y_0 - Ae^{\frac{(x-x_0)^2}{2\sigma^2}}$$

Where T_{LST} is the GOES-R land surface temperature at the nearest pixel to the ground station (within 5-minutes from the ground station), x is the time-of-day input, x_0 is a time-of-day peak shift parameter, σ is a Gaussian width parameter, y_0 is a shift parameter, and A is an amplitude parameter.

The four parameters that were inputted into the regressive neural network were: y_0, A, x_0 and σ. A diagram outlining the methods for calculating the parameters in the Gaussian fit can be seen below:

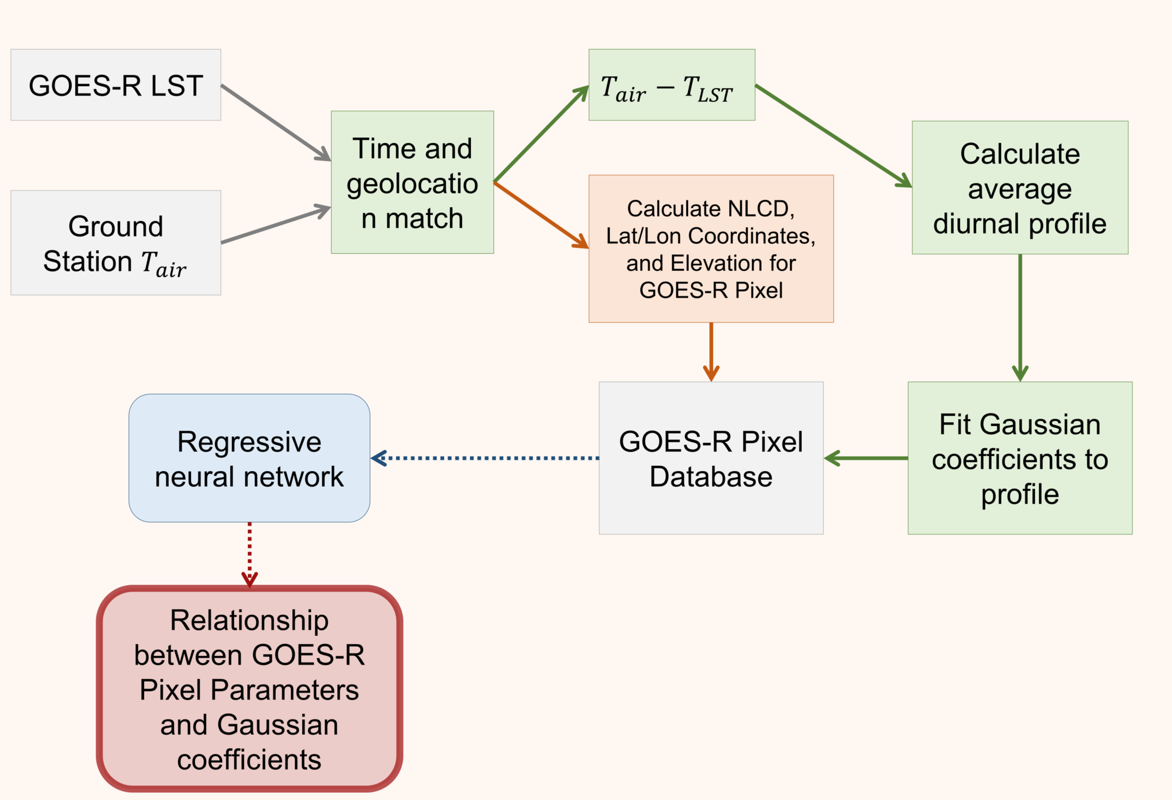

Figure 1: Flow diagram for calculating air temperature from GOES-R land surface temperature (LST) using a diurnal Gaussian model and a regressive neural network.

Results

-- Station Performance --

Information from 60 different GOES-R pixels in 20 cities was used to create a database containing coefficients for each respective diurnal Gaussian curve. The database was used to train the regressive neural network which established relationships between satellite land surface temperature (LST) and ground station air temperature (T_{air}). An **overall RMS of 3.0 K** was found for all stations in the study. The study trained with over six months of ground station air temperature, while testing was done for 3 months. An example can be seen in Figure 2 – demonstrating a 3-month correlation completely independent of the training data.

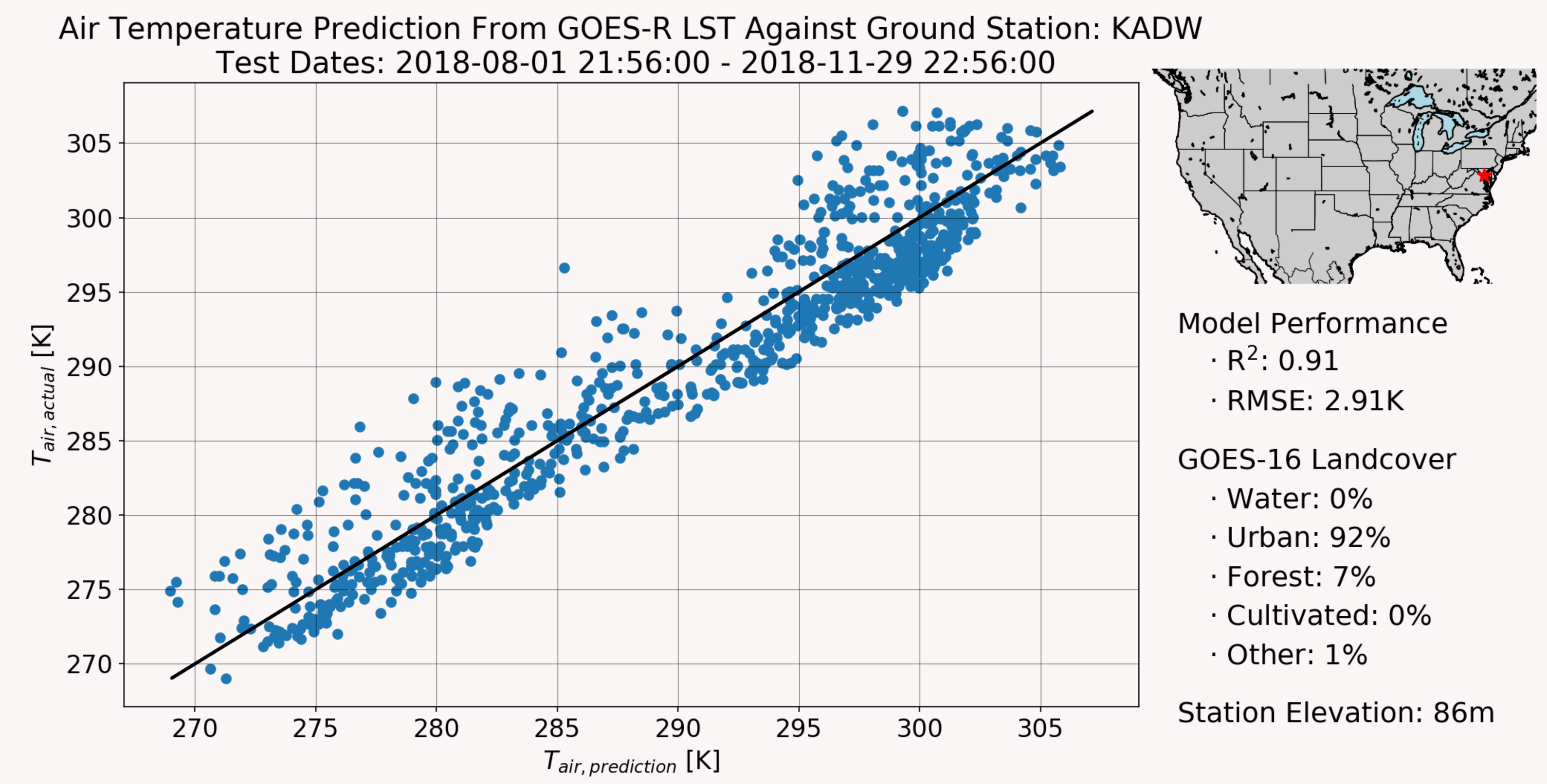

***Figure 2**: Air temperature model performance for a single station in Washington, DC. The city and station were independently tested, without training any nearby stations during the regressive neural network, indicating that the model performs well independent of city location.*

-- Nationwide Statistics --

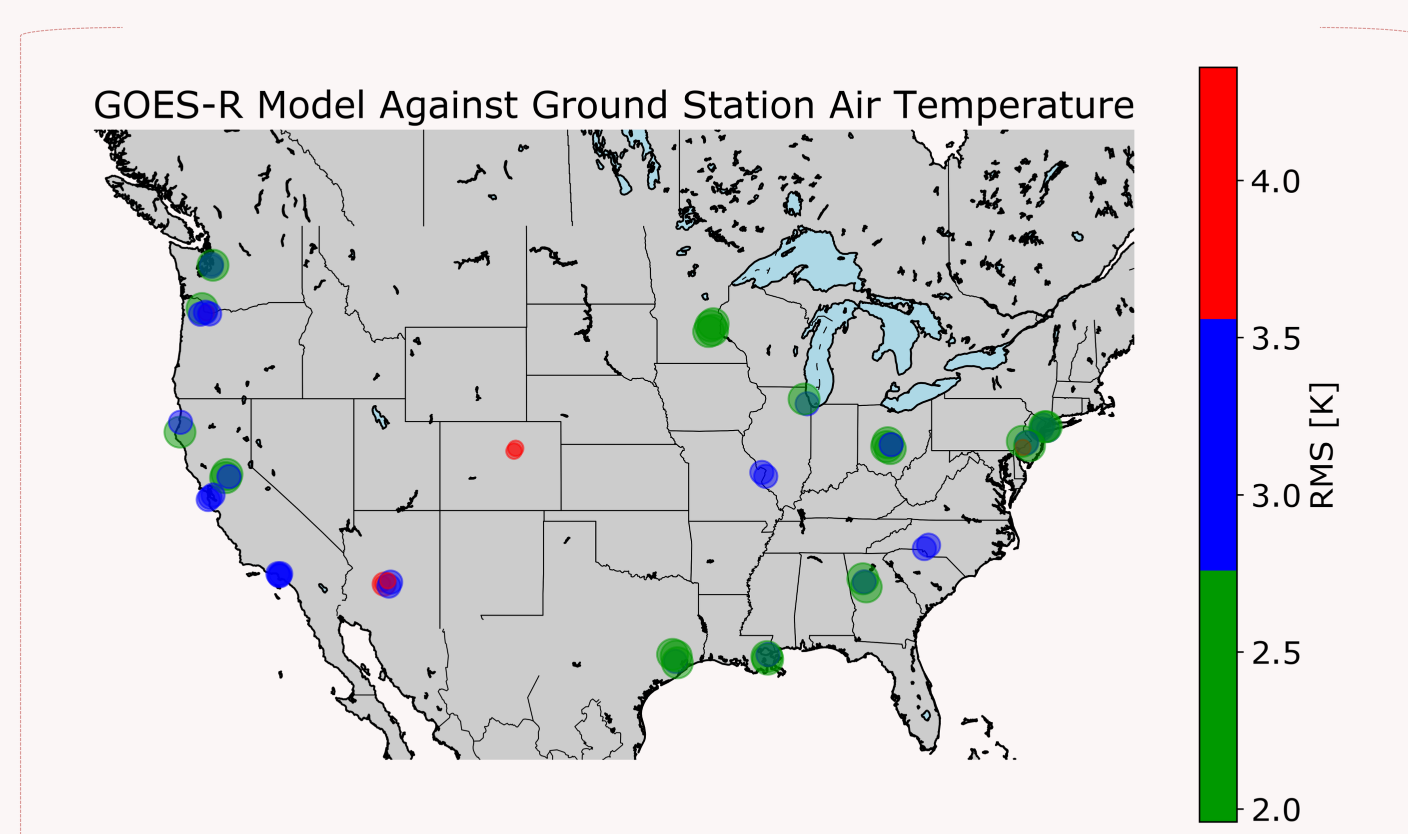

***Figure 3**: GOES-R air temperature average root-mean-square error against ground station 2-m air temperature measurements. The overall RMS was found to be 3.0 K for 20 cities across the U.S.*

-- Numerical Urban WRF Model Comparison --

Numerical simulations were performed with an urbanized-Weather Research and Forecasting (uWRF) Model, using three nested domains (9-km, 3-km, 1-km) initialized with the North American Mesoscale (NAM) forecast model (12-km). The numerical model was used to further justify the lightweight GOES-R air temperature model performance against the numerical model's computation-heavy 2-m air temperature. The WRF simulation provided 1-km air temperature data, which outperformed the GOES-R model by 1-2 K on average for multiple New York City locations.

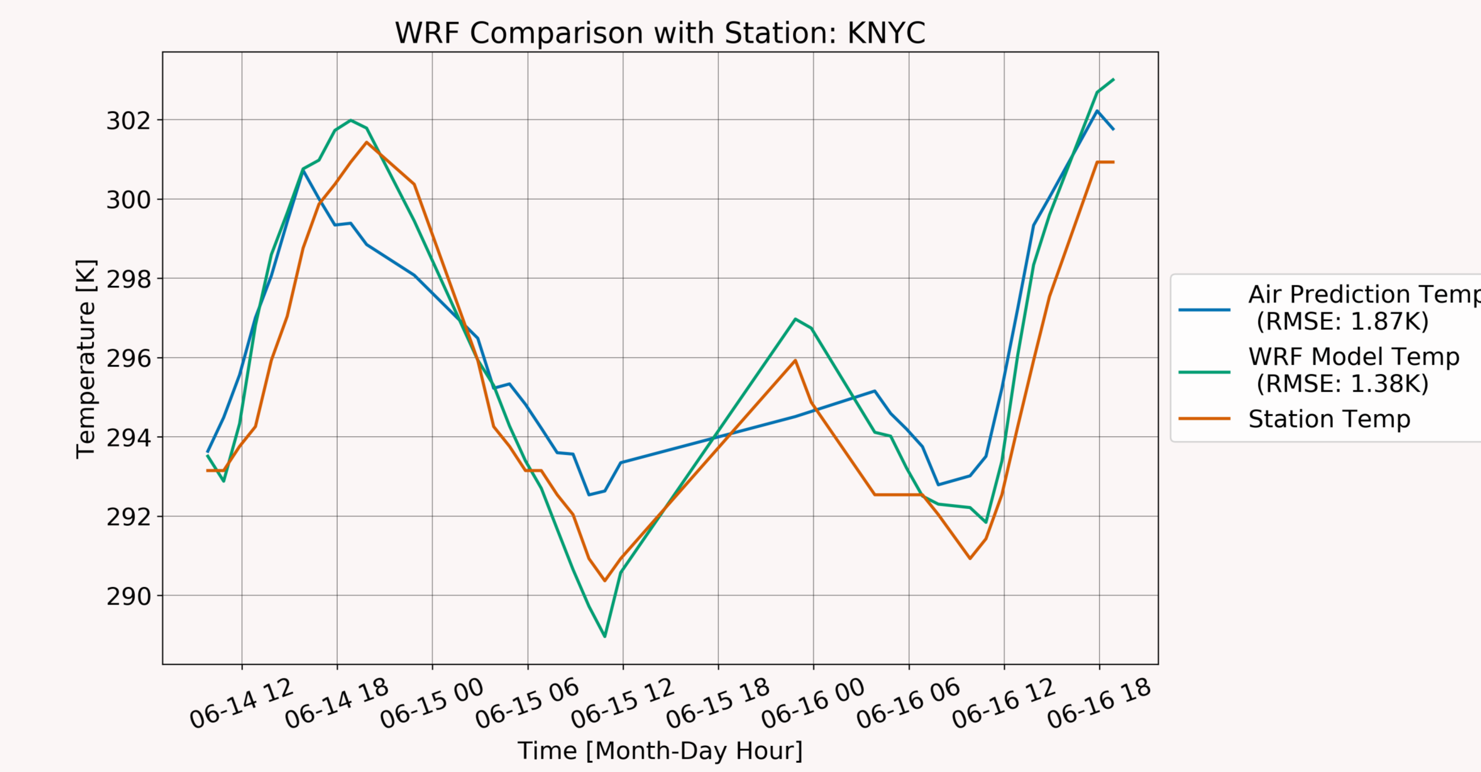

***Figure 4**: WRF air temperature simulation compared to the GOES-R air temperature prediction and ground station air temperature. The WRF model, on average, outperformed the GOES-R predicted air temperature by 1-2 K.*

Conclusions

This research combined GOES-R LST with landcover properties, geographic coordinates, elevation information, and time-of-day to create a robust Gaussian approximation of 2-m air temperature. The coefficients for each satellite pixel were derived using a regressive neural network and comparison against true air temperature at ground stations across the U.S. The performance of the GOES-R air temperature model was further validated by comparison with a numerical, high-resolution WRF model, indicating good agreement and performance between the satellite air temperature model and numerical 2-m air temperature.

Future Work

Work is currently being done to test the model against the WRF numerical simulation for multiple locations and months. The model will also include more cities and stations, along with more complex training. A similar model is also being applied to humidity, which will help with extreme heat prediction in urban areas.

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