Estimating Wet Bulb Globe Temperature From a Machine Learning Approach Using Readily Available Meteorological Data

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Background and Motivation

Wet Bulb Globe Temperature (WBGT) is a function of heat stress in direct sunlight, while also taking into account environmental factors including air temperature, dew point temperature, and cloud cover (American Meteorological Society, 2023). WBGT is used operationally by the military, government agencies, and private companies to assess heat stress and potential risk for heat-related casualties. Throughout the U.S. Navy and Marine Corps, WBGT is used to determine flag conditions which can limit strenuous outdoor exercise. At the U.S. Naval Academy (USNA), WBGT is manually measured by the U.S. Naval Health Clinic (NHC) Annapolis, which is across the Severn River from USNA and away from the immediate marine environment. To reduce inaccuracies, this study aims to develop a machine learning model to predict WBGT based on readily available meteorological data collected by the KNAK autonomous surface observing system (ASOS). These weather stations are standard meteorological equipment deployed at operational airfields worldwide.

The goal of this study is to develop a machine learning model that predicts the WBGT based on readily available meteorological data

Study Area

WBGT measurements during the Summer of 2020 and 2021 were made by the NHC-Annapolis, located at Naval Support Activity (NSA) Annapolis (**Fig. 1**). The ASOS KNAK weather station is located on U.S. Naval Academy (USNA) Hospital Point and approximately 1 km from both the USNA Hendrix Oceanography Lab and NHC-Annapolis.

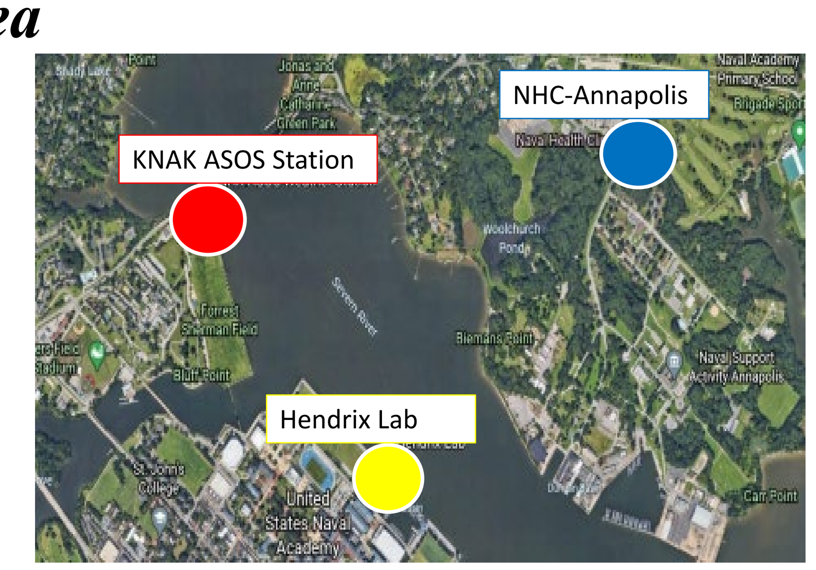

Figure 1: The study area depicts the locations of NHC-Annapolis where the WBGT values were manually recorded, the KNAK ASOS weather station where the environmental data was recorded, and Hendrix Oceanography Laboratory. NHC-Annapolis and the KNAK ASOS station are 1 kilometer apart (Google Earth, 2023).

Methods

Data Collection and Organization:
NHC-Annapolis WBGT data from June through September in 2021 and 2022 were digitally converted from written duty logs. In total, 417 total WBGT observations were recorded using QUESTempº 32-34-36 Area Heat Stress Monitors in 2020 and 474 observations for 2021. Meteorological data from the KNAK ASOS were downloaded from Iowa State University, and included air temperature (Temp, °F), dewpoint temperature (Dew Pt.,°F), relative humidity (%), wind speed (mph), wind direction (degrees), wind gust (mph), mean sea level pressure (MSLP, mb), precipitation (inches), visibility (statute miles), sky cloud layer altitude at three levels (feet), and sky cloud cover (SkyCov, %) at the same three levels. Sky cover at each level was determined by the percentage of sky cover based on the descriptive categories (Table 3, ASOS User's Guide, 1998; e.g. CLR, FEW, SCT, BKN, and OVC). WBGT readings were recorded inconsistently throughout the day while the KNAK ASOS data were recorded hourly. To create a coincident dataset, ASOS data collected within 20 minutes of a NHC-Annapolis WBGT measurements were used. This resulted in 352 coincident data observations for 2020, and 382 data observations for 2021. **Figure 2** shows the model development progression.

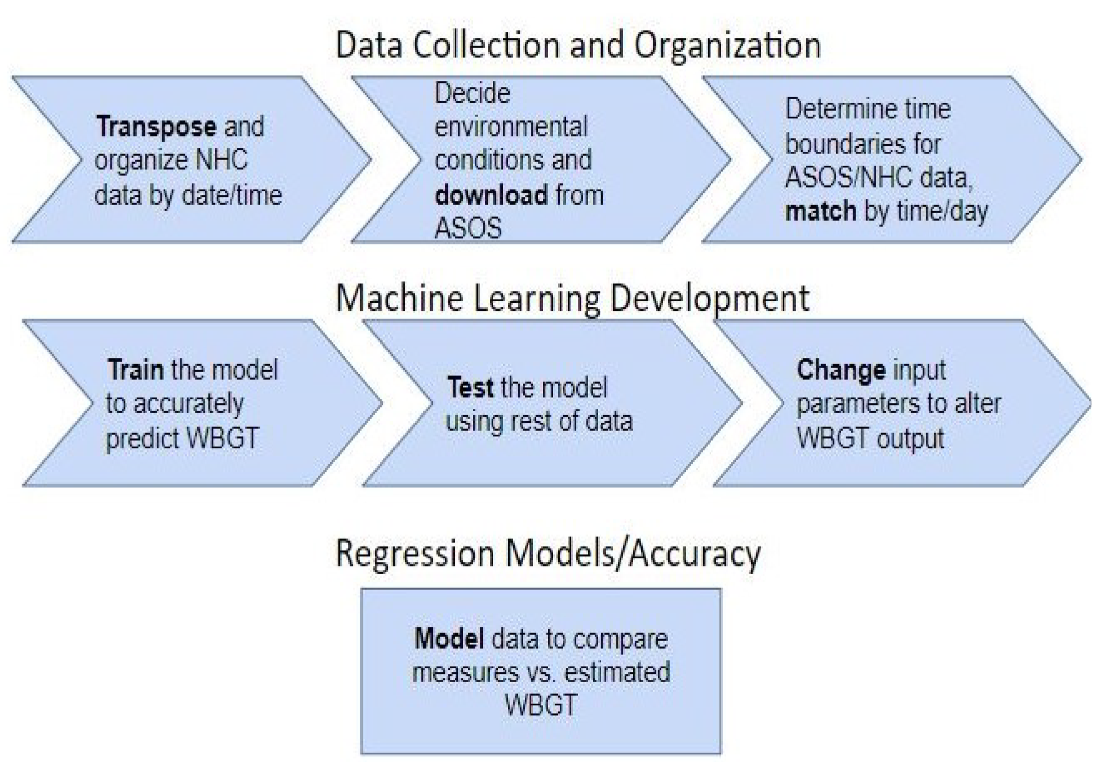

Figure 2: Flow chart depicting the methodology used in this study to estimate WBGT using a machine learning module with observed WBGT data and readily available meteorological data. The project was conducted in three phases focused on gathering the original data, organizing the data, and visualizing data from the developed model.

Machine Learning Development:
The yearly coincident data were combined and randomly split with 70% of the data used for training machine learning models and 30% used to test the models. In addition to the KNAKS ASOS data listed above, time of day and month were also used as predictor variables to train the machine learning models. First, all predictor variables were individually plotted against the NHC-Annapolis WBGT measurements (not shown) to determine if any apparent relationships existed; air temperature and dew point temperature showed a positive linear trend. The MATLAB Regression Toolbox was then used to train linear models for all combinations of predictor variables. The total number of predictor variables was 21, but 7 were determined to be the most important in predicting WBGT: temperature, dew point, sky cover at level 1, mean sea level pressure, windspeed, time of day, and month. This resulted in 127 possible predictor variable combinations. The model's predicted WBGTs were then plotted against the NHC-Annapolis WBGT measurements with the root mean square error (RMSE) used to determine which combination of variables created the most accurate model. The most accurate model was then statistically tested against 30% of the data.

Results and Discussion: Training The Machine Learning Model

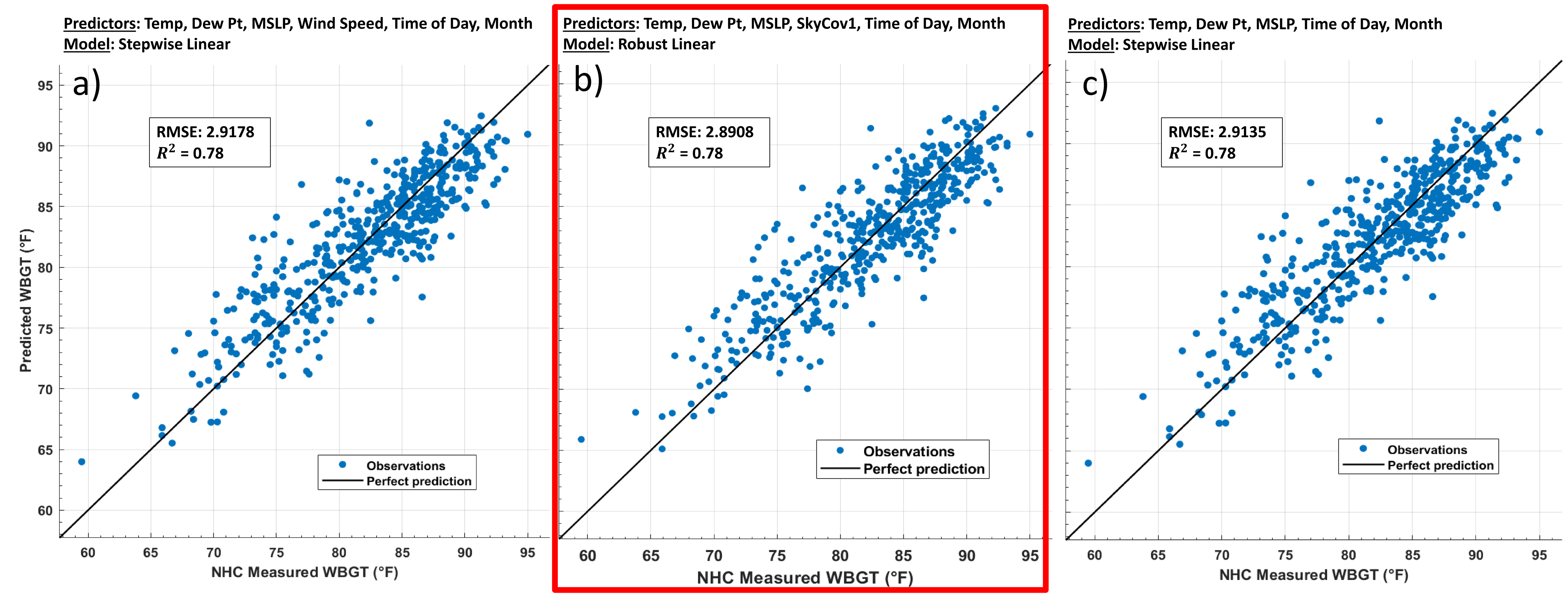

Figure 3 (a-c): Predicted WBGT values vs. measured WBGT values using the randomized training dataset (70% of data) and different predictor variable combinations. (b) Produced the model with lowest RMSE and similar correlation values to the other two best combinations.

The model with the strongest linear correlation based on its RMSE and R^2 value is shown in **Figure 3b** with the following six predictor variables: temperature, dew point, sky cover at level 1, mean sea level pressure, time of day, and month. While windspeed was thought to have a larger effect on enhancing the body's evaporation of sweat, therefore reducing WBGT, the models with windspeed (**Fig 3a,c** and other model results not shown) produced greater RMSE values. The models shown above are stepwise linear which finds the best subset of the explanatory variables by adding and removing predictors interactively, and robust linear which assign less weight to data outliers when building the model (Agostinelli, 2002).

Results and Discussion: Testing The Machine Learning Model

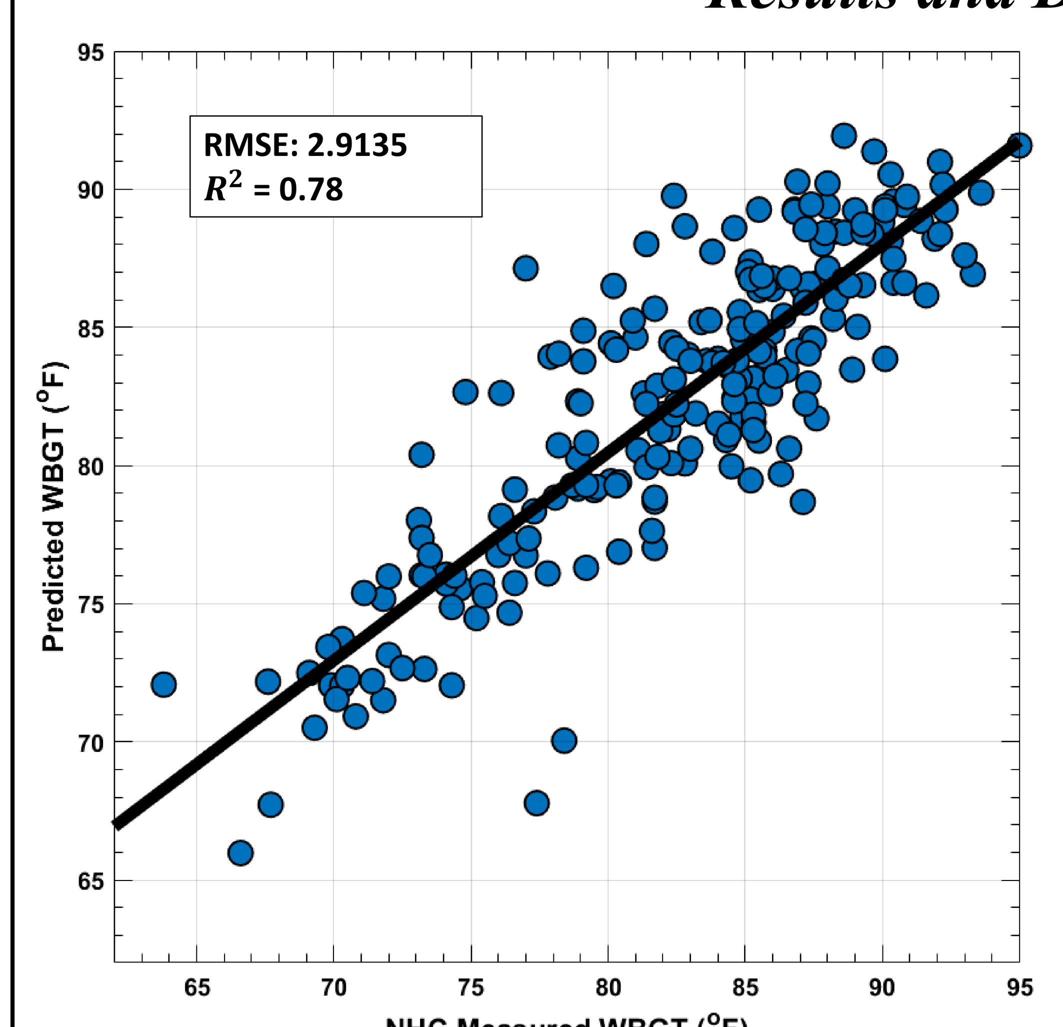

Figure 4: Predicted WBGT values compared to measured WBGT values using the testing day (randomized 30% of the overall data). Model used from **Fig. 3b**.

After identifying the model with the best RMSE (**Fig. 3b**), the KNAK ASOS testing data (randomized 30% of the data) was ran using the six input predictor variables. The testing model results (**Fig. 4**) have a similar RMSE as the training results (**Fig. 3b**), which indicates a high degree of confidence. However, WBGT values below 80 °F have no significance operationally on flag conditions. Therefore WBGT values above 80°F were only taken into account when training the model a second time. The model was then tested with the full range of WBGT values, which reduced the number of outliers and generated a RMSE of 1.88 (**Fig. 5**).

Spatial differences between the location of WBGT measurements and environmental observations must be taken into account. If the WBGT is measured in a location that is in a different physical environment, the values that are observed may differ from the values predicted. This is particularly true for variables more influenced by the marine environment like wind speed, dew point temperature, and air temperature. This suggests this methodology could be more robust in more homogenous locations. Additionally, the WBGT values are likely dependent on the surface material (grass v. pavement).

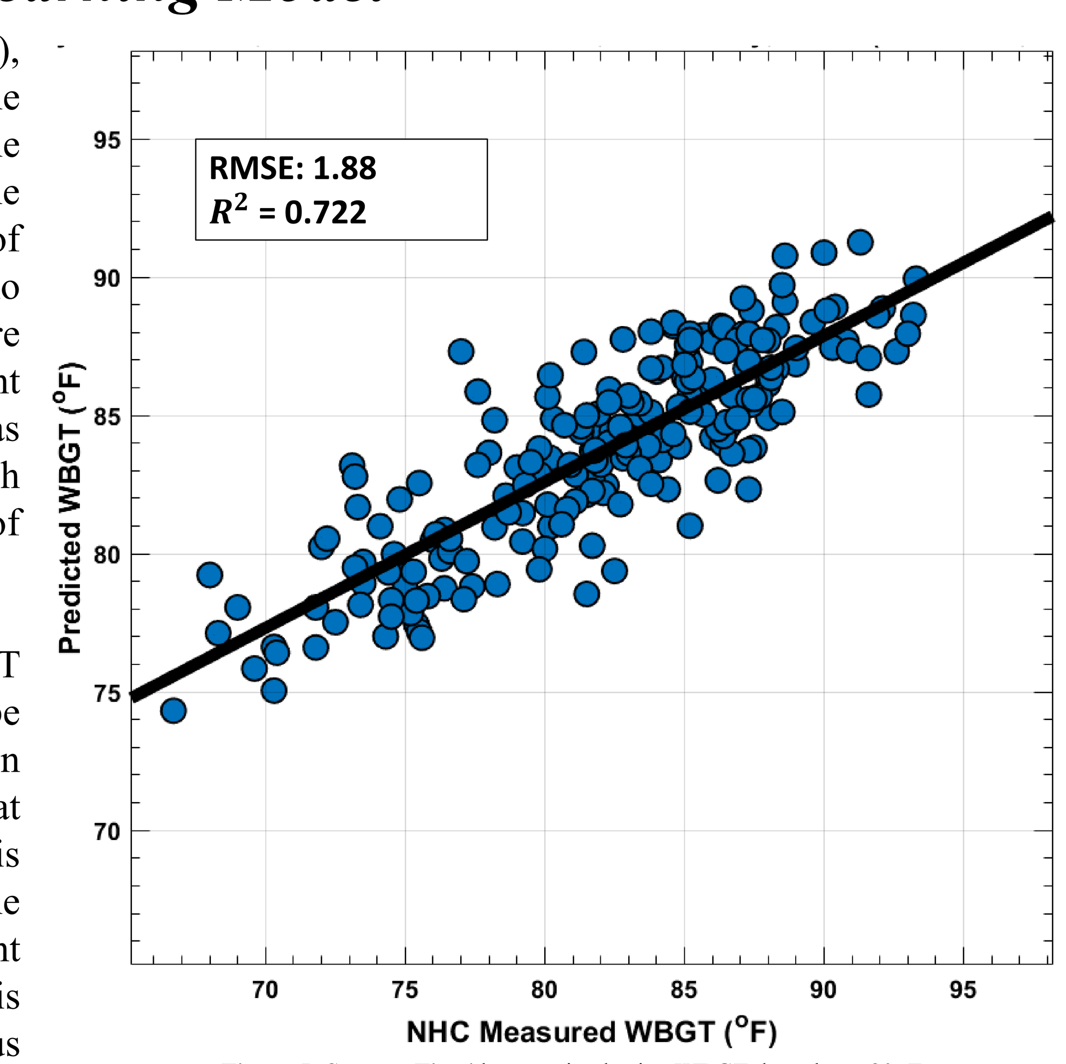

Figure 5: Same as **Fig. 4** but retrained using WBGT data above 80 °F.

Key Findings:

- **The environmental parameters that resulted in a model with the lowest RMSE were temperature, dew point, mean sea level pressure, sky cover at level 1, time of day, and month.**
- **Training the model in Fig. 3b using only WBGT data above 80°F produced the lowest overall RMSE (1.88) value when run against the testing dataset.**
- **Future efforts should include recording WBGT and meteorological data in the same local environment in order to reduce the error caused by spatial differences.**

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References:
Ref 1. American Meteorological Society, 2023
Ref 2. ASOS's User's Guide, 1998
Ref 3. Robust Stepwise Regression, Journal of Applied Statistics, 2002