

Decoding sub-seasonal predictors of extreme heat with interpretable machine
learning

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1 Abstract

2 As climate change accelerates, heat waves are becoming more frequent, intense, and
3 deadly. Enhancing forecasting capabilities through a better understanding of sub-seasonal
4 predictors of extreme heat is crucial for adaptation efforts. This study utilizes an interpretable
5 machine learning model, implementing Extreme Gradient Boosting (XGBoost) with SHapley
6 Additive exPlanations (SHAP), to evaluate the predictive strength of various climate factors—
7 including local weather, global climate indices, geopotential heights, soil moisture, and sea
8 surface temperatures—on extreme daily maximum temperatures. This model demonstrates
9 strong predictive performance for extreme heat in Austin, TX, USA, on the sub-seasonal time
10 scale, with soil moisture features emerging as more influential than atmospheric features.
11 Notably, our analysis uncovers previously underexplored teleconnections between distant soil
12 moisture anomalies and local extreme heat, warranting further investigation. It is also shown that
13 the Madden-Julian Oscillation (MJO) has predictive value for extreme heat in Austin,
14 underscoring its utility relative to other indices like ENSO and NAO. This method shows
15 promise for application to other cities and for integration with dynamical modeling approaches,
16 advancing sub-seasonal extreme heat forecasting more broadly.

17

18 Significance Statement

19 As heat waves intensify with climate change, there is an urgent need for more accurate sub-
20 seasonal forecasts. This research presents a novel machine learning-based method to improve
21 heat wave predictions, offering insights into key drivers of heat on the sub-seasonal scale and
22 enabling earlier, more precise public health interventions that can reduce heat-related illness and
23 mortality.

24

25 1. Introduction

26 Heat waves pose a significant and escalating threat to public health worldwide, with global
27 trends demonstrating increases in their intensity, duration, seasonal length, and frequency due to
28 anthropogenic climate change (Perkins-Kirkpatrick and Gibson 2017). The rate of heat wave
29 occurrences has accelerated, resulting in a notable rise in heat-related mortality (Howard et al.
30 2024). However, forecasting heat waves, especially on sub-seasonal timescales (two weeks to
31 two months) remains a challenge. While there are efforts using dynamical, statistical, machine-

32 learning, and hybrid models for sub-seasonal forecasting efforts, their performance varies, and
33 they are not currently operational for forecasting extreme heat events. Developing reliable
34 methods to forecast these events with extended lead times is critical for enacting timely public
35 health interventions.

36 This study introduces a novel machine-learning-based methodology to enhance sub-seasonal
37 heat wave prediction. By extending the lead time and improving reliability of heat wave
38 forecasts, this research aims to advance early warning systems and support public health
39 strategies to mitigate the adverse effects of extreme heat.

40 Furthermore, this approach enables quantification and examination of the predictors and
41 drivers of extreme heat on the sub-seasonal timescale, illuminating the specific interactions of
42 various meteorological, land-surface, atmospheric, and ocean processes. This information will
43 not only improve heat wave forecasting but also enhance broader understanding of sub-seasonal
44 weather patterns, facilitating improvements in future models.

45

46 2. Related Work

47 Over the past decade, operational dynamical sub-seasonal forecasts have advanced
48 significantly in skill, application, and utility (White et al. 2022), with the European Centre for
49 Medium-Range Weather Forecasting (ECMWF) extended-range (up to 46 days) ensemble
50 forecasts (Richardson et al. 2020) and the SubX Subseasonal Experiment (Pegion et al. 2019)
51 among the leading efforts. While these models have successfully forecasted some extreme events
52 (Vitart and Robertson 2018), other events have not been captured beyond three weeks lead time
53 (Lin et al. 2022). The body of research on sub-seasonal extreme heat forecasting is still limited,
54 restricting its operational use in emergency preparedness. Studies indicate that accurate sub-
55 seasonal climate forecasting is the missing link in developing an early-warning system for heat-
56 related mortality (Lowe et al. 2016), emphasizing that temperature-related illnesses are largely
57 preventable with timely interventions.

58 Purely statistical or machine learning-based models for sub-seasonal forecasting of extreme
59 heat have shown considerable skill, often matching or exceeding the performance of dynamical
60 models (Miller et al. 2021; Weirich-Benet et al. 2023). Studies have identified dry soil moisture
61 and persistent atmospheric blocking patterns as key factors for predicting extreme heat events
62 (Wehrli et al. 2019; Lee et al. 2016; Zhang et al. 2023). Recently, hybrid models that integrate

63 dynamical and machine-learning approaches, have demonstrated enhanced predictive skill
64 compared to dynamical models alone (He et al. 2022; Chung et al. 2024; Hwang et al. 2019).
65 However, further refinement in the selection of covariates and methodological approaches is
66 needed to optimize the performance of these hybrid models.

67 Heat wave characteristics and drivers of heat waves vary by region and individual event
68 (Wehrli et al. 2019; Jiang et al. 2023), underscoring the need for a thorough understanding of
69 region-specific drivers to improve forecast accuracy. Austin, Texas, USA, is particularly
70 vulnerable to the health effects of heat waves (Seong et al. 2023; Boumans et al. 2014), making it
71 an ideal test case for this novel machine learning-based methodology. With drying summer soil
72 moisture—a trend expected to persist (Nielsen-Gammon et al. 2020)—Austin’s climate is shaped
73 by complex land-atmosphere interactions, influences from the nearby Gulf of Mexico, and
74 broader climate patterns originating from the Pacific, Atlantic, and Indian Oceans. Additionally,
75 atmospheric blocking patterns contribute to the formation and persistence of heat waves in the
76 region.

77 This study aims to assess the influence of these drivers through a machine-learning approach
78 tailored to local heat wave prediction, leveraging a comprehensive range of variables. By
79 examining the impact of these drivers, we aim to advance sub-seasonal heat wave forecasting in
80 Austin and lay the groundwork for future regional hybrid models that integrate machine learning
81 and dynamical approaches.

82

83 3. Data

84 Data for this study span the heat-wave season (June 1st through September 30th) for the 11-
85 year period from 2013 through 2023. This period was chosen to ensure data availability for each
86 of the predictive variables. Limiting the study to this period helps mitigate the confounding
87 effects of vegetation change in Austin, TX and increased urbanization on heat wave prediction.
88 Variables that change monotonically over the study period and/or vary too slowly would have
89 insufficient training spaces for prediction and were therefore excluded from analysis, such as
90 longer-term climate oscillations (e.g. Pacific Decadal Oscillation).

91 Climatological data were sourced from the NOAA NCEI Global Historical Climatology
92 Network (GHCN) – Daily from the Austin Bergstrom International Airport (Station ID:
93 USW00013958) (Menne et al., 2012). The climatological data for daily maximum temperatures

94 were averaged for each day of the year over a 30-year period (1993 – 2022). Missing data (<1%
95 of days) were excluded when averaging and calculating standard deviation. The standard
96 deviation of daily maximum temperature was calculated for each day over the thirty-year period
97 and used to create the 85th percentile threshold for defining heat-days. Both the mean and
98 standard deviation were smoothed with a 2-week running average to reduce noise arising from
99 natural variability.

100 The same Austin station provided daily weather data. These data contained fewer than 11
101 missing values over the study period (<1% of days), which were imputed with values from the
102 nearest available date.

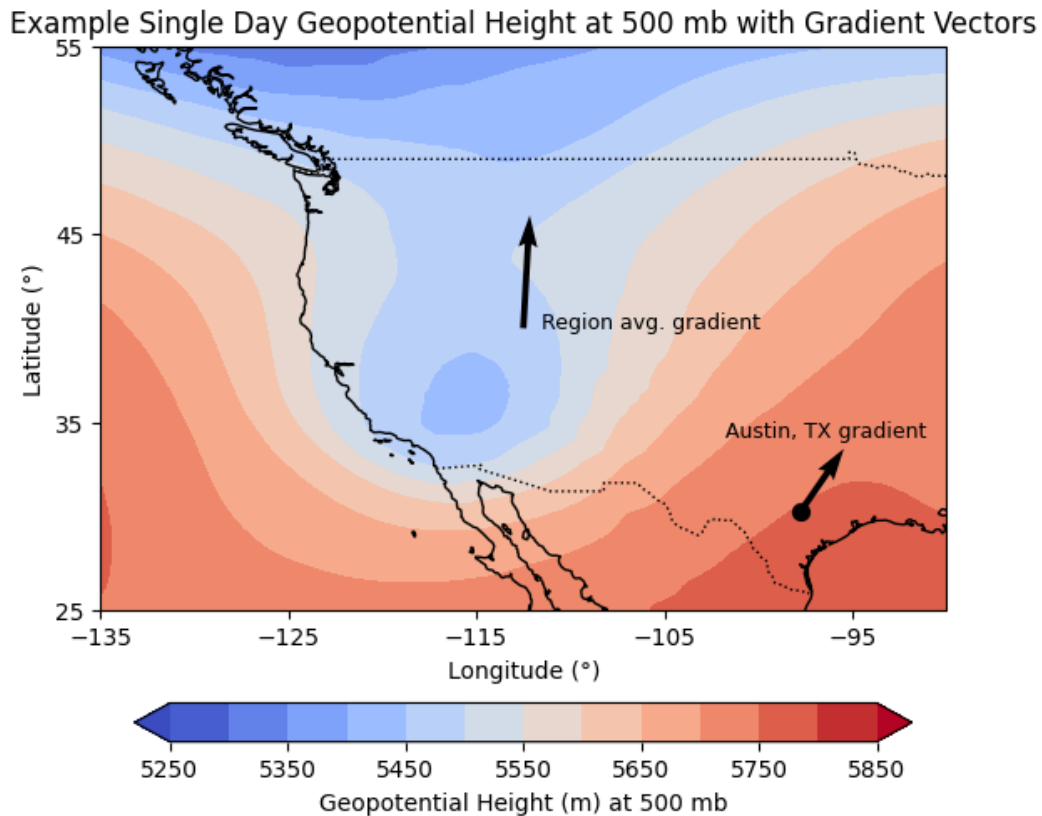
103 The Gulf of Mexico sea surface temperatures were obtained from the NOAA Optimum
104 Interpolation Sea Surface Temperature (OISST) v2.1 dataset (Huang et al. 2021)—This gridded
105 dataset incorporates buoy measurements, corrected by remotely sensed and ship data, and is
106 interpolated to a 0.25° x 0.25° grid. The Gulf of Mexico region was defined by the grid cells
107 within 20°N to 30°N latitude and 82°W to 95°W longitude. Daily sea surface temperatures
108 (SSTs) across this area were averaged to produce a single daily mean SST value representing the
109 Gulf of Mexico.

110 Global climate variability data were included to represent the state of the El Nino-Southern
111 Oscillation (ENSO), the Madden-Julian Oscillation (MJO), and the North Atlantic Oscillation
112 (NAO). First, the daily Southern Oscillation Index (SOI) from the Queensland Government’s
113 Long Paddock Centre was used, calculated as the pressure difference between Tahiti and Darwin
114 relative to a 1933 – 1922 baseline (Queensland Government Dept. of Environment and Science
115 2019). Second, the Real-time Multivariate MJO (RMM) index, which characterizes the MJO
116 through two values (RMM1 and RMM2), was used to represent the MJO’s phase and amplitude.
117 For clarity, the phase and amplitude values derived from this dataset were used instead of the
118 raw RMM1 and RMM2 values (Wheeler and Hendon 2004). Finally, the daily NAO index
119 sourced from NOAA/OAR/PSL (Boulder, Colorado, USA) and available from their website at
120 <https://psl.noaa.gov> was used (Kalnay et al. 1996). This index compares 500 mb geopotential
121 height anomalies to standard Northern Hemisphere loading patterns to produce a single NAO
122 index value.

123 Atmospheric data were obtained from the ECMWF Reanalysis v5 (ERA5) hourly dataset
124 (Hersbach et al. 2023), provided on a 31 km by 31 km grid and limited to the Western North

125 America region, spanning from 25°N to 55°N latitude and 90°W to 135°W longitude. Three
 126 pressure levels were analyzed, 850 mb (lower troposphere), 500 mb (mid-troposphere), and 250
 127 mb (upper troposphere). For each pressure level, five metrics were derived: the latitudinal and
 128 longitudinal gradients of geopotential height across the Western North America region, the
 129 latitudinal and longitudinal gradients of geopotential height specific to Austin, Texas, and the
 130 geopotential height at Austin (30.25°N, 97.75°W). Gradients were calculated by converting
 131 latitude and longitude points to meter-based distances and computing the partial derivative of
 132 geopotential height in the north-south and east-west directions. This resulted in a total of fifteen
 133 values overall, five for each pressure level. Figure 1 provides an example of the 500 mb
 134 geopotential gradient variables for a single-timestep example.

135



136

137 Figure 1. Example of 500 mb geopotential height on a single day, with vectors illustrating the
 138 average gradient across the Western North America region and the local gradient at Austin,
 139 Texas.

140

141 Finally, eighteen soil moisture values are included in the analysis, each representing one of
 142 the USGS-delineated hydrological regions across the United States (U.S. Geological Survey
 143 2024). These values were generated by averaging the daily gridded soil moisture data from the
 144 Climate Prediction Center (CPC), which represent the soil moisture quantities within the top 1.6
 145 meters of soil on an $0.25^\circ \times 0.25^\circ$ grid (van den Dool et al. 2003), The GeoPandas package
 146 v1.0.1 (Jordahl et al. 2020) in Python v3.12.6 (Python Software Foundation 2023) was used to
 147 map each CPC soil moisture grid cell to its respective hydrological region. All grid cells within
 148 or intersecting a hydrological region were averaged to yield daily mean soil moisture for each
 149 hydrological region.

150

151 *Prediction with multiple leads*

152 Variables were classified as either “fast-changing” or “slow-changing.” For fast-changing
 153 variables, three different leads were prescribed: the first representing the mean values of each
 154 daily variable from 21 to 23 days before the prediction, the second from 24 to 27 days, and the
 155 third from 28 to 34 days. For slow-changing variables, such as sea surface temperatures, certain
 156 global climate oscillations, and regional soil moisture, only one lead was used, representing the
 157 times from 21 to 34 days prior to the prediction. Only variables with leads were utilized for
 158 prediction, except for climatology, where values for the specific prediction day were provided. A
 159 full table of variables and their lead classification is shown below (Table 1).

160

Variable Name	Variable Type	Leads	Data Source
Max.Temp.	Meteorological	Fast-changing	NOAA NCEI GHCN (Menne et al., 2012)
Min. Temp.			
Relative Humidity			
Avg. Wind Speed			
Total Precip.			
Normal Max. Temp.	Climatology	None	
Normal Min. Temp.			
SO Index	Global Climate Variability	Slow-changing	Daily SOI (Queensland Government Dept. of

			Environment and Science 2019)
NAO Index		Fast-changing	Daily NAO Index (Kalnay et al. 1996)
MJO Index (Amplitude & Phase)			Real-time Multivariate MJO Index (Wheeler and Hendon 2004)
Gulf of Mexico SST	Ocean	Slow-changing	NOAA OISST (Huang et al. 2021)
Lon. Grad. of W.N.A. 850 mb Geo. Height	Atmosphere	Fast-changing	ERA5 hourly single pressure level data (Hersbach et al. 2023)
Lat. Grad. of W.N.A. 850 mb Geo. Height			
Lon. Grad. of W.N.A. 500 mb Geo. Height			
Lat. Grad. of W.N.A. 500 mb Geo. Height			
Lon. Grad. of W.N.A. 250 mb Geo. Height			
Lat. Grad. of W.N.A. 250 mb Geo. Height			
Austin, TX 850 mb Geo. Height			
Austin, TX 500 mb Geo. Height			
Austin, TX 250 mb Geo. Height			
USGS Hydro. Unit-Averaged SM	Land Surface	Slow-changing	CPC Daily Soil Moisture (U.S. Geological Survey 2024)

161 Table 1. Variable name, type, leads, and data source for all daily predictive variables.

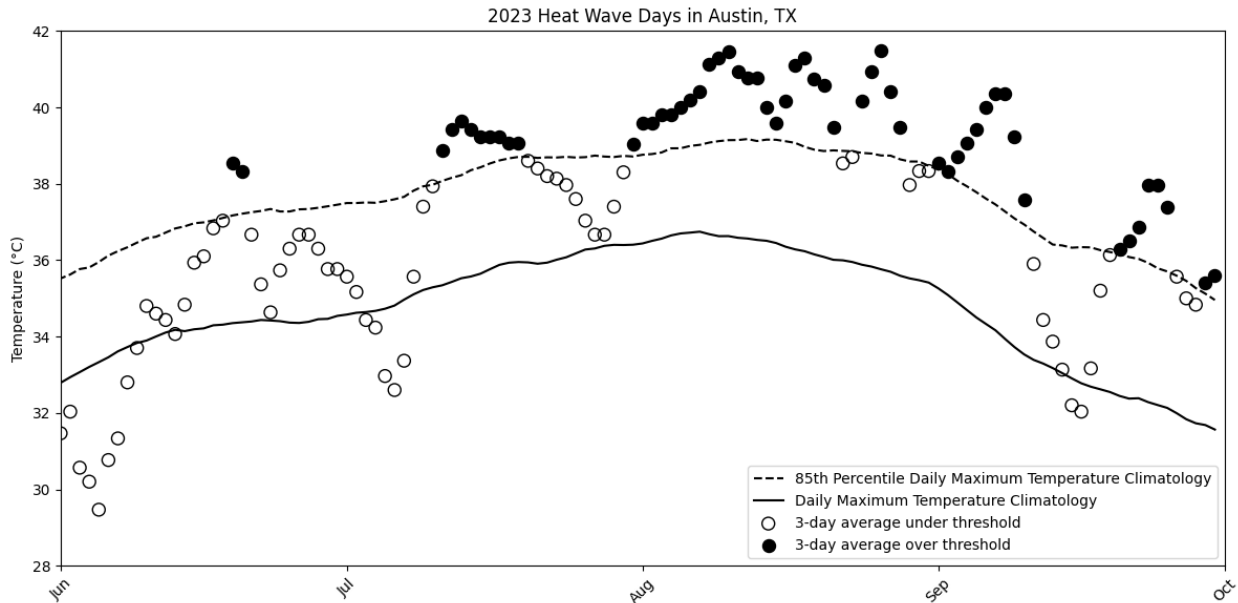
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163 *Heat wave identification*

164 Heat wave days were identified by comparing daily maximum temperatures to the 85th
165 percentile of the climatological maximum temperature. Specifically, a day was classified as a
166 heat wave day if the three-day running average of daily maximum temperatures, centered on the
167 current day, exceeded the 85th percentile of the smoothed climatology for that day. An example
168 heat wave day classification is shown below for the summer of 2023 (Figure 1), where days are
169 categorized as either heat wave days or non-heat wave days based on the climatological

170 threshold. This definition allows flexibility. For instance, a single day with a maximum
 171 temperature significantly higher than climatology or three consecutive days with temperatures
 172 just over the 85th percentile both qualify as heat wave days.

173



174

175 Figure 2. Heat wave identification in Austin, TX during 2023. Curves represent smoothed daily
 176 maximum temperature climatology using a two-week running average. Individual points
 177 represent 3-day average daily maximum temperatures.

178

	June	July	August	September	Total
2013	5	2	4	0	11
2017	0	3	0	0	3
2018	7	9	1	0	17
2019	0	0	0	8	8
2020	0	3	5	0	8
2021	0	0	0	1	1
2022	13	11	1	0	25
2023	2	10	26	18	56
Total	27	38	37	27	129

179

180 Table 2. Descriptive statistics of heat wave days in Austin, TX during the months of June
181 through September of 2013 through 2023.

182

183 A total of 129 days met the criteria for a heat wave day over the months of June through
184 September of 2013 through 2023. 37 of the days were in June, 38 were in July, 27 were in
185 August, and 37 were in September. More than 40% of the days were in the summer of 2023, with
186 11 in 2013, 3 in 2017, 17 in 2018, 8 in 2019, 8 in 2020, 1 in 2021, and 25 in 2022.

187

188 4. Prediction & Interpretation

189 Machine learning models for heat wave-day classification were developed using eXtreme
190 Gradient Boosting (XGBoost) (Chen and Guestrin 2016), chosen for its efficiency and high
191 performance in handling diverse input variables in classification tasks. XGBoost models were
192 run through Scikit-learn package v1.5.2 (Pedregosa et al. 2011) in Python v3.12.6. Each variable
193 listed in Table 1 was used to predict whether a day meets the heat-wave day criteria in a binary
194 classification task with logistic regression as the output function, evaluated by the log loss
195 metric.

196 To ensure robust model performance without overfitting, four-fold validation was used.
197 For this, the dataset was randomly divided into four subsets, each containing at least 25 heat
198 wave days to ensure balance across folds. In each iteration, the model was trained on three of the
199 four subsets and tested on the remaining subset. This process was repeated to create a single
200 ensemble model with predictive guidance based on the mean outcomes from the validation folds.
201 All models were created using common parameters. The learning rate, eta, was set to 0.1. The
202 maximum tree depth was set to 4. The fraction of rows sampled by each tree was set to 0.8. The
203 fraction of features sampled by each tree was also set to 0.8. The class imbalance weighting was
204 calculated to be 11.3 and set accordingly.

205 The complete four-fold validation process was repeated ten times, producing an ensemble
206 of models. Performance metrics, including accuracy, precision, recall, and F1 score were
207 aggregated across all ensemble members to derive mean performance values.

208 To interpret the contributions of each feature in the machine learning model, Shapley
209 Additive exPlanations (SHAP) values were utilized (Lundberg and Lee 2017). SHAP values
210 quantify each variable's impact on model output, providing a clear interpretation of feature

211 influence on heat-wave day classification. These values are derived by evaluating the average
212 marginal contribution of each feature to the model's predictions. By assigning an importance
213 score to each feature based on its contribution, the relative predictive strength of features
214 influencing heat-wave days at a sub-seasonal time scale can be quantified. SHAP values were
215 averaged across the ten models in the ensemble to produce mean absolute SHAP scores for each
216 feature, as well as ensemble-based partial dependence plots, which display SHAP values as a
217 function of feature value.

218 After creating an initial XGBoost model that included all features, correlation analysis was
219 conducted to ensure features were not highly collinear. Between variables with leads, there were
220 thirty-three pairwise correlations such that $|r| > 0.8$. In these cases, the variable which had the
221 higher SHAP score in the model inclusive of all variables was retained from each correlated pair
222 and the other was excluded. This continued until no variables had a correlation $|r| > 0.8$.
223 Ultimately, twenty features were excluded from the final refined model: four regional soil
224 moisture features (Rio Grande Region, Upper Colorado Region, California Region, Arkansas-
225 White-Red Region), two meteorological features (maximum temperature 21-day lead, maximum
226 temperature 28-day lead), and fourteen atmospheric features (500 mb NA mean y-gradient 21-,
227 24-, and 28-day leads, 250 mb NA mean x-gradient 24- and 28-day leads, 500 mb NA mean x-
228 gradient 28-day lead, 250 mb Austin geopotential height 21-, 24-, and 28-day leads, 500 mb
229 Austin geopotential height 28-day lead, 500 mb y-gradient 21- and 28-day leads, 250 mb y-
230 gradient 24- and 28-day leads). Full details on the SHAP scores of the initial model as well as the
231 covariance matrix are provided in Supplemental Table 1 and Supplemental Figure 1.

232 A final case study of the 2023 heat wave season was performed. Each feature was averaged
233 across 56 days during this season which met the heat wave day condition. The mean conditions
234 for each feature were then inputted into the ensemble XGBoost prediction model. The resulting
235 probability of a heat wave day for these conditions is then outputted by the model, and a SHAP
236 explainer plot is generated showing the relative contribution of each feature to this prediction.

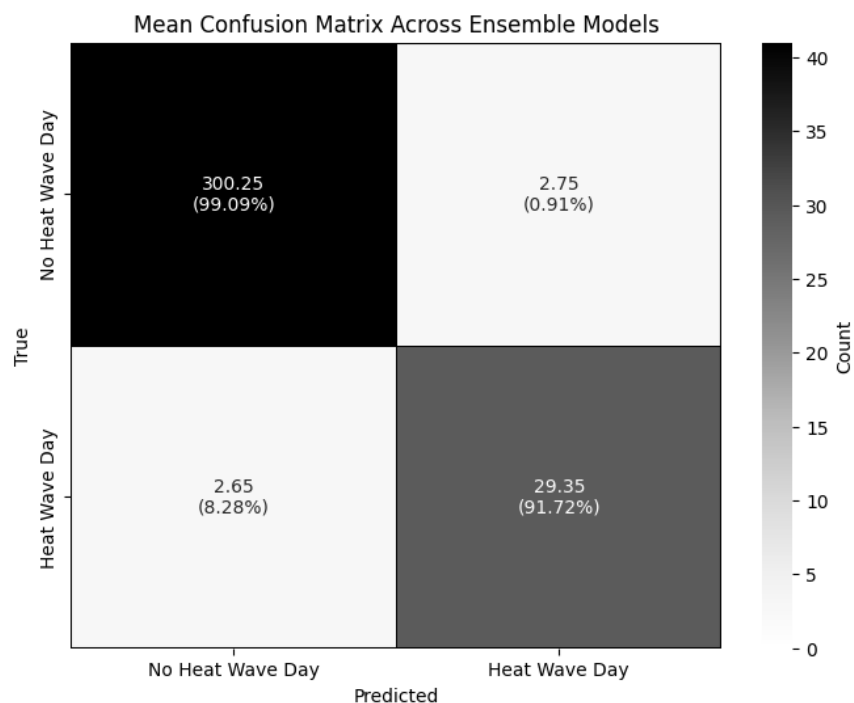
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238 5. Results

239 The refined XGBoost ensemble model demonstrated strong predictive performance across
240 several metrics. The mean accuracy across ensemble members was approximately 0.984, with
241 recall, precision, and F1 score all exceeding 0.915 (Figure 2, Table 2). This indicates that the

242 model was effective at identifying heat wave days while minimizing false positives and
 243 negatives.

244



245

246 Figure 3. Mean confusion matrix of XGBoost model ensemble with refined feature selection.

247

Metric	Mean	Standard Deviation	95% Confidence Interval
Accuracy	0.984	0.002	(0.980, 0.988)
Recall	0.917	0.011	(0.895, 0.940)
Precision	0.915	0.012	(0.892, 0.938)
F1 Score	0.916	0.012	(0.893, 0.939)

248 Table 3. Performance metrics for XGBoost ensemble models using refined feature selection.

249

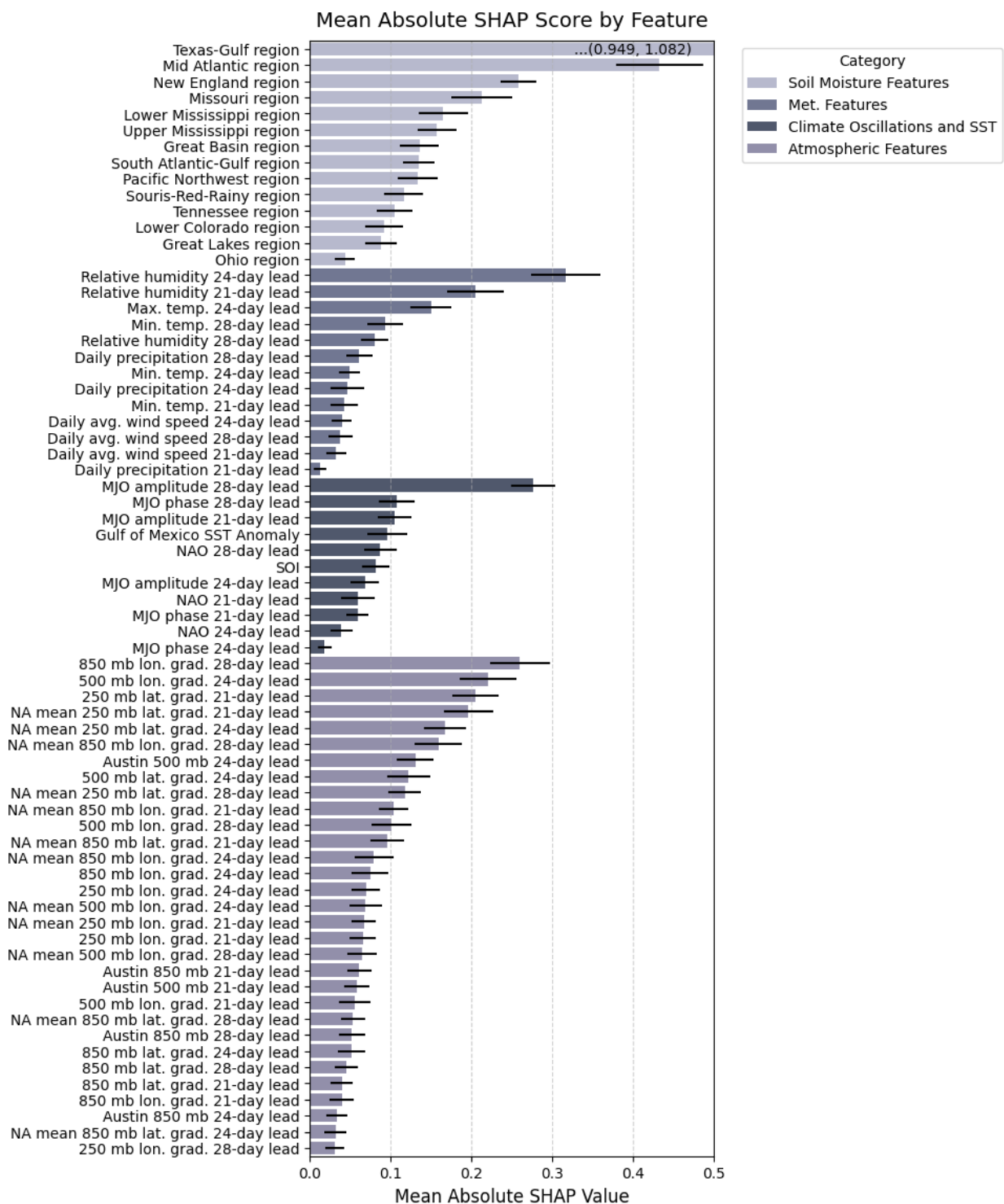
250 Among the predictors, the Texas-Gulf Region soil moisture stood out as the most
 251 influential feature (mean absolute SHAP value = 1.015), far exceeding the next strongest
 252 predictor, which had a mean absolute SHAP value of 0.432. Four of the top ten features were
 253 regional soil moisture values, including the Mid-Atlantic, New England, and Missouri regions.
 254 Relative humidity at 21- and 24-day leads were also strong predictors. Additionally, MJO

255 amplitude at 28-day lead emerged as the fourth strongest feature. Geopotential height gradients,
256 both longitudinal gradients at low to medium pressure levels (28- and 24-day leads, respectively)
257 and latitudinal gradients at high pressure levels (21-day lead), were also among the top
258 predictors.

259 As shown in Figure 3, predictors are divided into meteorological, atmospheric, and
260 climate features for comparison. Notably, MJO amplitude and phase at 28-day lead time was a
261 stronger predictor of heat wave days on the sub-seasonal time scale than the Gulf of Mexico
262 SST, NAO at any lead, and SOI.

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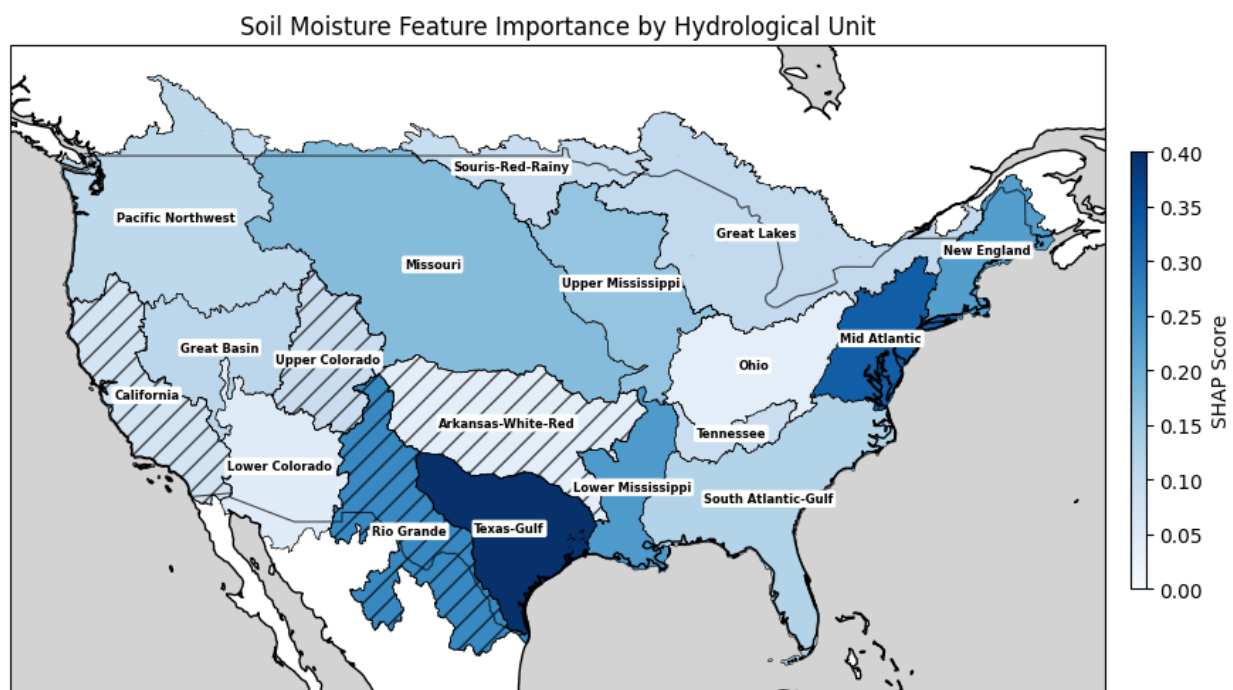
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267 Figure 4. Mean absolute SHAP scores for land surface soil moisture, meteorological,

268 atmospheric, and climate features.

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Many regional soil moisture features demonstrated relatively high predictive power, as illustrated in Figure 4. Soil moisture values in distant regions, including the Mid-Atlantic and New England, were among the top predictors. Some nearby regions such as the Arkansas-White-Red region (omitted from refined model) did not show predictive skill.



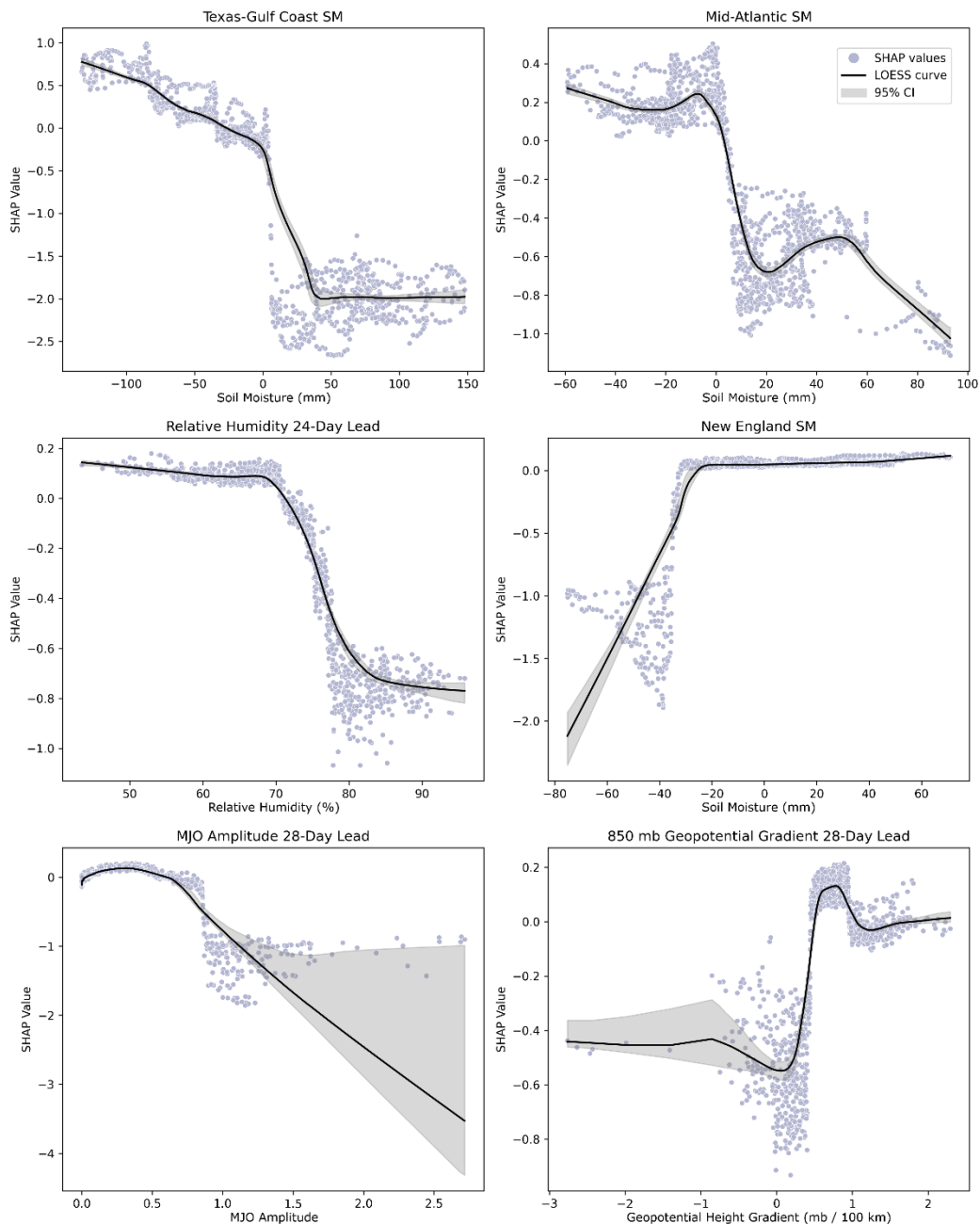
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Figure 5. Map of soil moisture feature importance by means absolute SHAP score in initial unrefined ensemble model. Hatched regions were excluded in the refined ensemble model to reduce collinearity effects.

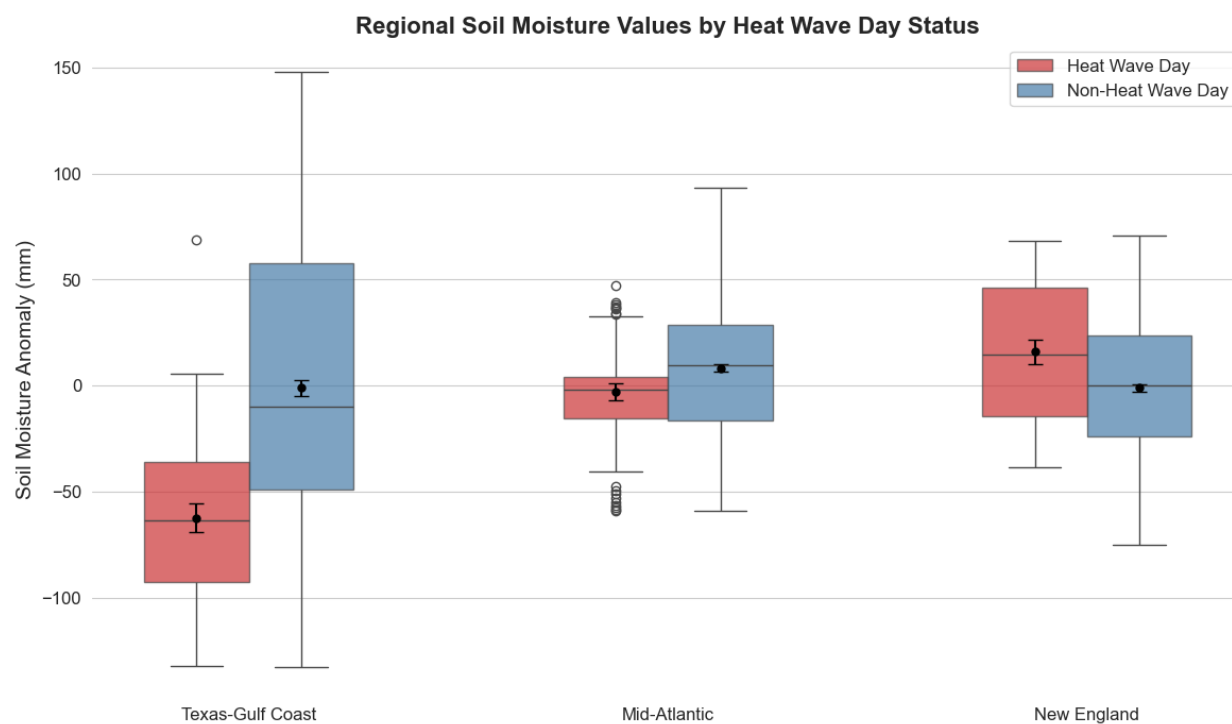
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Figure 5 presents the partial dependence plots for the top five predictors in the model. The Texas-Gulf Region soil moisture had the strongest influence on heat wave prediction, with positive anomalies significantly reducing the likelihood of heat wave days. Conversely, the likelihood of a heat wave day increased with decreasing negative soil moisture anomalies. The Mid-Atlantic soil moisture exhibited a more complex relationship, but similarly, positive anomalies were associated with a lower chance of heat waves in Austin. The opposite trend is seen between New England soil moisture and Austin heat wave days. Lower relative humidity at a 24-day lead (below 70%) was more strongly correlated with heat waves, while higher values

288 decreased this likelihood. High-amplitude MJO conditions (greater than 0.75) also reduced the
 289 probability of heat waves. Finally, stronger east-to-west 850 mb pressure gradients at a 28-day
 290 lead were linked to an increased likelihood of heat waves.
 291



292
 293 Figure 6. Partial dependence plots for the six features with the greatest mean absolute SHAP
 294 scores.
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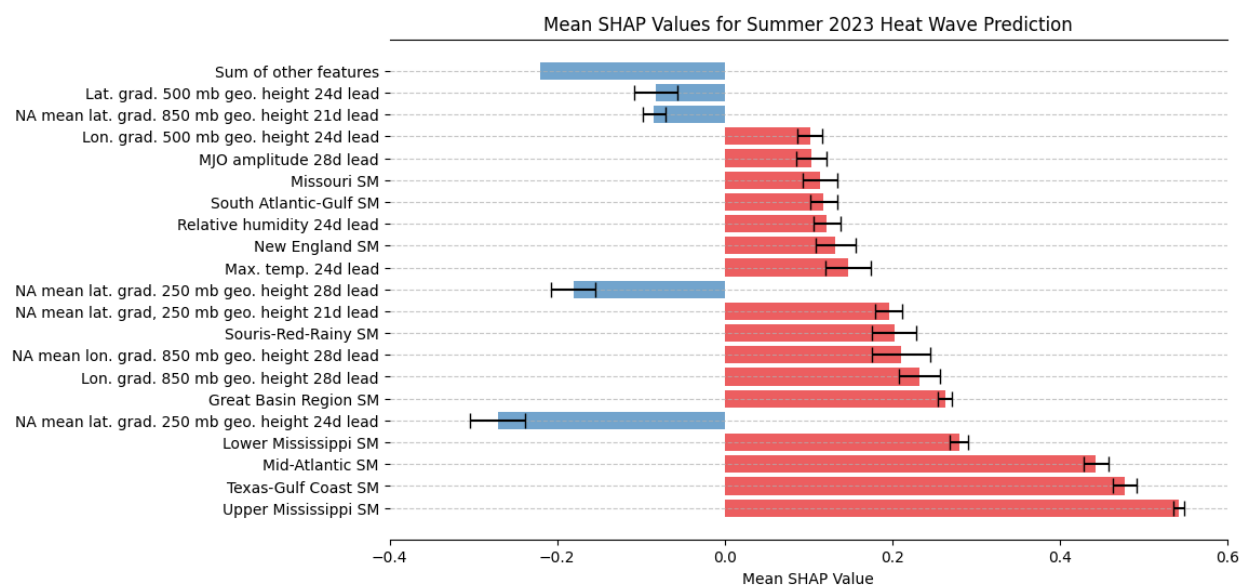


296
 297 Figure 7. Box plot of soil moisture anomalies for heat wave day and non-heat wave day
 298 conditions for three strongest regional soil moisture features. Innermost black points and error
 299 bounds represent 95% confidence interval for the true mean.

300
 301 Mean soil moisture anomalies were significantly lower on heat wave days compared to
 302 non-heat wave days in the Texas-Gulf Coast and Mid-Atlantic regions ($p < 0.05$) (Figure 7). In
 303 the Texas-Gulf Coast region, mean soil moisture anomalies were at least 50 mm lower during
 304 heat wave days than on non-heat wave days. Conversely, in the New England region, soil
 305 moisture anomalies were significantly higher on heat wave days than on non-heat wave days ($p <$
 306 0.05).

307 The mean conditions during the 2023 heat wave resulted in the ensemble model
 308 predicting a 97.2% chance of a heat wave day, with a 95% confidence interval for the mean
 309 predicted probability of the ensemble members ranging from 96.6% to 97.9%. Figure 8 shows
 310 that regional soil moisture features primarily drive this prediction, with soil moisture conditions
 311 in Texas and neighboring regions, as well as more distant areas, counteracting upper
 312 tropospheric latitudinal geopotential height gradients in predicting heat wave days in Austin. In
 313 this figure, positive SHAP values (red) indicate contributions toward predicting heat wave days,
 314 while negative SHAP values suggest a prediction trend toward non-heat wave days.

315



316

317 Figure 8. SHAP values derived from ensemble model predictions using mean 2023 heat wave
 318 day feature values. Error bars represent calculated 95% CI across the 10 ensemble model
 319 members.

320

321 Discussion

322 These results indicate that individual soil moisture features are the strongest predictors of
 323 sub-seasonal heat waves, with additional significant predictors spanning a variety of
 324 meteorological, atmospheric, and MJO indicators. Prior studies have similarly highlighted the
 325 influence of both atmospheric blocking patterns and land-surface characteristics on heat waves.
 326 However, this study finds that, at the sub-seasonal scale, local and teleconnected soil moisture
 327 features are generally more predictive of heat waves in Austin, Texas, than atmospheric factors
 328 alone (Wehrli et al. 2019). This finding aligns with other results which show soil moisture in
 329 Texas strongly correlating with temperature and heat waves specifically (Miralles et al. 2012).

330 The partial dependence plot for soil moisture in the Texas Gulf Coast region supports
 331 existing literature, showing that positive soil moisture anomalies are typically associated with a
 332 reduced likelihood of heat-wave days. Benson and Dirmeyer (2021) found a strong negative
 333 correlation ($r < -0.7$) between daily soil moisture and maximum temperature in the Texas-Gulf
 334 Coast region, though they note that the relationship is not linear and varies through different
 335 coupling regimes (weakly-coupled, sensitive, and hypersensitive). This study provides strong

336 evidence that, below the mean soil moisture threshold, heat extremes are more likely, marking
337 the transition between the sensitive and hypersensitive regimes in Austin, Texas. Dynamic
338 modeling studies have shown that soil moisture conditions are particularly critical in heat wave
339 modeling for regions situated between humid and arid climates (Seo et al. 2019), which supports
340 the importance of local soil moisture in predicting Texas heat waves.

341 The predictive relationship between soil moisture in distant regions and heat waves in Texas
342 has significant physical implications. This relationship, shown in this study by the strong mean
343 absolute SHAP scores in the general XGBoost model and strengthened by similarly strong
344 feature importances in the 2023 heat wave case study, shows that while some atmospheric
345 features predicted against the likelihood of a heat wave, teleconnected soil moisture features
346 countered these atmospheric features in accurately predicting a heat wave with the conditions
347 prescribed. Sub-seasonal planetary wave patterns, commonly associated with heat waves
348 (Barriopedro et al. 2023; Teng et al. 2013)—especially those with wavenumbers 5 through 8—
349 may drive or be driven by teleconnections between soil moisture anomalies and extreme heat
350 events across different areas. For instance, Li et al. (2024) suggest a mechanism for the 2021
351 Pacific Northwest Heat Dome, where decreased soil moisture induced a high-pressure ridge,
352 ultimately leading to quasi-resonant amplification of planetary waves and a stationary high-
353 pressure ridge. In such cases, soil moisture anomalies in one region may influence the ridge-
354 trough pattern of Rossby waves, affecting the likelihood of extreme temperatures in Texas. Other
355 studies have noted that heat waves often co-occur within spatially networked regions across
356 CONUS (Mondal and Mishra 2021) and other global regions (Miloshevich et al. 2023),
357 potentially linking these patterns to cross-regional soil moisture correlations. Future research
358 should investigate the co-occurrence of heat waves in the Mid-Atlantic, New England, and Texas
359 Gulf Coast regions, focusing on soil moisture effects using coupled Land Surface Models and
360 GCMs.

361 The MJO was found to be a stronger predictor of heat waves over Texas than ENSO or NAO
362 on the sub-seasonal time scale. Lower MJO amplitude at a longer lead time (28 to 34 days) was
363 more strongly associated with heat waves over Austin. Other studies have shown summertime
364 temperatures and heat waves over CONUS associated with MJO (Lee and Grotjahn 2019;
365 Krishnamurthy et al. 2021). While the relationship between phase and amplitude at various lead-

366 times on extreme heat is difficult to decode in this study, future work should investigate different
367 MJO definitions to maximize predictability on heat waves over Austin.

368 Atmospheric features, though shown in this study and others (Adams et al. 2021) to be
369 significant predictors of heat waves, are also complex to interpret. These results show that
370 stronger east-to-west low-level geopotential gradients at 28- to 34-day lead time are more likely
371 to result in heat wave formation in the US. However, combinations of different atmospheric
372 variables are not easily interpretable. Different methodologies for simplifying complex multi-
373 level atmospheric information into a series of interpretable variables should be investigated to
374 better understand the value of local and global atmospheric trends on heat-wave predictability.

375 Though this model shows strong skill with similar amounts of false positives and negatives,
376 for operational purposes, this method can intentionally be modified to minimize false negatives,
377 erring on the side of over-predicting heat waves rather than missing true heat waves in
378 prediction. However, it should be emphasized that the model will be tested in live-time and
379 likely amended with dynamical model data and other covariates before being recommended for
380 any operational use.

381

382 6. Conclusions

383 The ensemble model's strong performance in predicting heat wave days underscores its
384 potential as an effective tool for sub-seasonal heat wave forecasting in Austin. This study serves
385 as a significant foundation for regional hybrid models that leverage both machine-learning and
386 dynamical approaches, providing a promising pathway for localized heat-health impact systems.
387 With further refinement, this approach could offer critical advancements for public health
388 preparedness, particularly in urban settings facing increased heatwave risk. Future studies that
389 test regional differences will support a broader understanding of heat-wave formation on the sub-
390 seasonal time scale, providing information on how predictors vary in regions with different
391 climatic background conditions.

392 Future work will test these predictions in real-time and update the model with new
393 training sets. Heat-wave dynamics will likely change as the climate changes, changing the trends
394 and relative importance and of predictors. The model's flexible framework and high
395 interpretability make it a strong and usable option for developing early-warning heat-health

396 impact predictions, serving as a prototype for future guiding models on the health impacts of
397 extreme heat.

398

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405

406 Availability Statement

407 All data used for analyses in this study are publicly accessible through their original web
408 access point. Weather and climatological data are available at www.ncei.noaa.gov/access. Soil
409 moisture data are available at www.cpc.ncep.noaa.gov/products/Soilmst_Monitoring. SOI data
410 are available at www.data.qld.gov.au/dataset/the-southern-oscillation-index-daily. NAO data
411 are available at www.cpc.ncep.noaa.gov/products/precip/CWlink/pna/NAO.shtml. MJO data are
412 available at iridl.ldeo.columbia.edu/SOURCES/.BoM/.MJO/.RMM. Hydrological region data are
413 available at www.usgs.gov/national-hydrography/watershed-boundary-dataset. Atmospheric
414 reanalysis data are available at cds.climate.copernicus.eu/datasets. Sea surface temperatures data
415 are available at www.ncei.noaa.gov/products/optimum-interpolation-sst.

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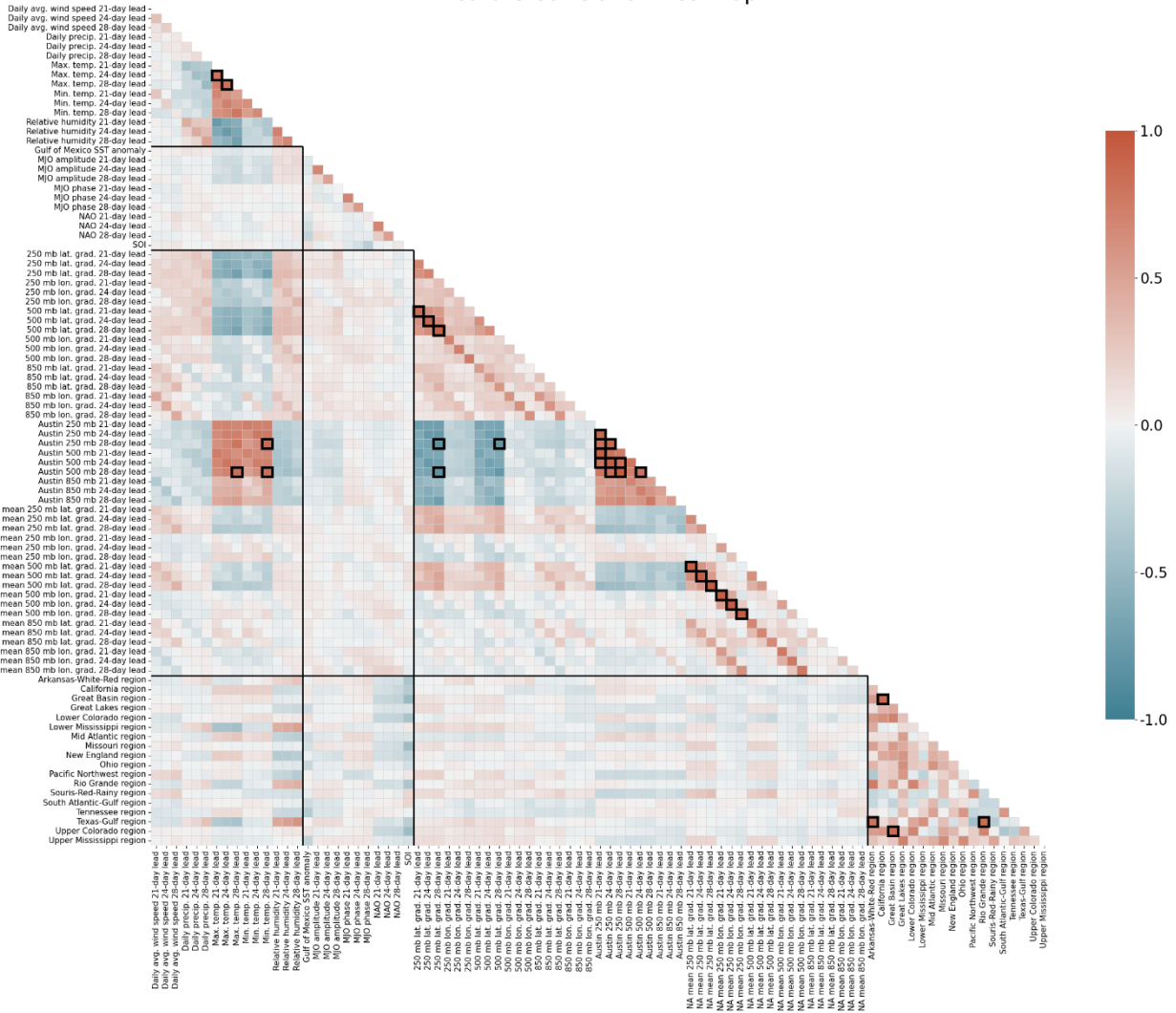
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Supplemental Materials

Feature Correlation Heatmap



Supplemental Figure 1. Linear correlation for all predictive variables with leads. Correlations with $|r| > 0.8$ are displayed with a dark black border.

Feature	Mean Absolute SHAP Value
Texas-Gulf region	0.792585
Mid-Atlantic region	0.328136
Relative humidity 24-day lead	0.296123
Rio Grande region	0.265358
MJO amplitude 28-day lead	0.250870

Lower Mississippi region	0.235458
New England region	0.228183
850 mb geo. height lon. grad. 28-day lead	0.221595
500 mb geo. height lon. grad. 24-day lead	0.210387
250 mb geo. height lat. grad. 21-day lead	0.176403
Missouri region	0.173935
Upper Mississippi region	0.159643
Relative humidity 21-day lead	0.151433
NA mean 250 mb geo. height lat. grad. 21-day lead	0.143922
250 mb geo. height lat. grad. 28-day lead	0.135279
Max. temp. 24-day lead	0.134719
NA mean 850 mb geo. height lon. grad. 28-day lead	0.129531
South Atlantic-Gulf region	0.123480
Great Basin region	0.113655
Austin 500 mb 24-day lead	0.111889
Pacific Northwest region	0.109545
NA mean 850 mb geo. height lon. grad. 21-day lead	0.105724
MJO amplitude 21-day lead	0.104921
Great Lakes region	0.103755
NA mean 250 mb geo. height lat. grad. 24-day lead	0.102857
Austin 250 mb 24-day lead	0.102441
MJO phase 28-day lead	0.095682
Souris-Red-Rainy region	0.093903
Upper Colorado region	0.092679
Max. temp. 21-day lead	0.091233
Tennessee region	0.090233
NA mean 850 mb geo. height lat. grad. 21-day lead	0.089210
Gulf of Mexico SST anomaly	0.081849
NA mean 500 mb geo. height lat. grad. 21-day lead	0.079515
Relative humidity 28-day lead	0.077347

500 mb geo. height lat. grad. 24-day lead	0.076134
NAO 28-day lead	0.075246
California region	0.072062
500 mb geo. height lon. grad. 28-day lead	0.071524
Min. temp. 28-day lead	0.068009
NA mean 850 mb geo. height lon. grad. 24-day lead	0.067713
850 mb geo. height lon. grad. 24-day lead	0.065769
250 mb geo. height lat. grad. 24-day lead	0.062603
250 mb geo. height lon. grad. 24-day lead	0.061901
250 mb geo. height lon. grad. 21-day lead	0.056795
SOI	0.055560
MJO phase 21-day lead	0.054662
Austin 850 mb 21-day lead	0.054332
Daily precip. 28-day lead	0.052217
500 mb geo. height lat. grad. 21-day lead	0.052208
MJO amplitude 24-day lead	0.051944
Min. temp. 24-day lead	0.051546
NA mean 500 mb geo. height lat. grad. 24-day lead	0.050523
NA mean 250 mb geo. height lat. grad. 28-day lead	0.049487
Lower Colorado region	0.048683
NAO 21-day lead	0.047635
Austin 250 mb 28-day lead	0.047609
NAO 24-day lead	0.047261
NA mean 250 mb geo. height lon. grad. 21-day lead	0.045935
850 mb geo. height lat. grad. 24-day lead	0.044530
Austin 500 mb 21-day lead	0.044491
NA mean 500 mb geo. height lon. grad. 28-day lead	0.044122
500 mb geo. height lon. grad. 21-day lead	0.043450
NA mean 500 mb geo. height lon. grad. 24-day lead	0.043334
Daily precip. 24-day lead	0.042774

NA mean 850 mb geo. height lat. grad. 28-day lead	0.042581
Ohio region	0.041911
Austin 500 mb 28-day lead	0.041396
Arkansas-White-Red region	0.040911
Austin 850 mb 24-day lead	0.039321
850 mb geo. height lat. grad. 21-day lead	0.038024
NA mean 500 mb geo. height lon. grad. 21-day lead	0.037193
850 mb geo. height lon. grad. 21-day lead	0.036836
Wind speed 24-day lead	0.035513
NA mean 500 mb geo. height lat. grad. 28-day lead	0.035395
NA mean 250 mb geo. height lon. grad. 24-day lead	0.035135
Min. temp. 21-day lead	0.032755
Austin 850 mb 28-day lead	0.032710
500 mb geo. height lat. grad. 28-day lead	0.032695
850 mb geo. height lat. grad. 28-day lead	0.030618
Wind speed 28-day lead	0.026686
Wind speed 21-day lead	0.026078
NA mean 250 mb geo. height lon. grad. 28-day lead	0.025838
250 mb geo. height lon. grad. 28-day lead	0.023873
Max. temp. 28-day lead	0.022848
NA mean 850 mb geo. height lat. grad. 24-day lead	0.021930
Austin 250 mb 21-day lead	0.019894
Smoothed 85th percentile max. temp. climatology	0.019654
MJO phase 24-day lead	0.014217
Daily precip. 21-day lead	0.011749

Supplemental Table 1. Full SHAP scores from initial model performance before variable exclusion.