The Indispensable Role of Weather Data in Consumer Spending Prediction: A Robust Machine Learning Assessment

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***Abstract*—Accurate forecasting of daily consumer spending is crucial for strategic decision-making in the retail sector, yet the dynamic influence of weather is often underestimated or insufficiently integrated into predictive models. This study presents a comprehensive evaluation of incorporating both historical and 7-day weather forecast data on predicting consumer spending amounts across three diverse sub-industries: Grocers, Home Improvement, and Casual Dining. We employed a robust methodology involving a comparative analysis of eight distinct machine learning (ML) models, from linear regression to ensemble methods, each trained both with and without weather data to isolate meteorological contributions independent of algorithmic choice. Our experimental framework encompasses 500k+ individual model training runs across all 50 US states, multiple sub-industries, and weather configurations, representing one of the most comprehensive evaluations of weather-informed consumer spending prediction to date. Our experiments demonstrate that incorporating weather data provides broad improvements across most model-sector combinations, with models utilizing weather data typically exhibiting substantial reductions in Root Mean Squared Error (RMSE) of predicted consumer spending amounts in some cases exceeding 60%. Post hoc analysis confirms that these improvements are statistically significant across nearly all configurations. Overall, these findings establish weather data as a broadly applicable enhancement for consumer spending forecasts regardless of the underlying ML approach, providing actionable insights for inventory optimization, resource allocation, and targeted marketing strategies in the retail sector.**

***Index Terms*—consumer spending prediction, weather data integration, ML, demand forecasting, retail analytics, time series forecasting**

I. Introduction

Accurately forecasting consumer demand is a persistent challenge, with weather conditions presenting a uniquely escalating source of uncertainty [1], [2]. The accelerating impacts of climate change are increasing the frequency and intensity of weather anomalies, such as extreme heatwaves and severe storms, which fundamentally alter consumer behavior [3]–[5]. This growing volatility creates a dual challenge: it not only undermines traditional forecasting models but also complicates the analysis of past performance. On one hand, methodologies that struggle to isolate weather from other factors [6]–[11] are becoming less effective for prediction. On the other hand, understanding weather's historical impact is equally valuable for explanation, allowing analysts to conduct accurate post-event evaluations—for instance, by attributing a low-revenue quarter to specific weather events rather than flawed strategy [12]. Consequently, the robust integration of dynamic weather data is no longer an enhancement but a critical necessity for both predictive accuracy and strategic insight.

A. Open Challenges in Consumer Spending Forecasting

A significant gap exists in the literature regarding methodological approaches that can effectively isolate weather impacts while maintaining robust forecasting performance. While various studies have explored weather effects on isolated industries or general economic behavior, there is a notable absence of comprehensive methodological frameworks that can systematically decompose and quantify weather impacts across different sectors and geographical areas [13]–[15]. This limitation is particularly evident in the context of ML applications, where the interaction between weather variables and other predictors often remains a "black box" [16]. Furthermore, there is a pressing need for robust comparative evaluation of forecasting methods in this domain. While numerous forecasting approaches exist, from traditional statistical methods to advanced ML techniques, their relative performance in handling weather effects across different contexts remains inadequately studied [17], [18].

These methodological limitations are compounded by significant scope and scale gaps in existing research. No comprehensive studies exist comparing weather impacts across different retail sectors such as grocers, home improvement, and casual dining within unified analytical frameworks. Most existing research focuses on single retailers, specific geographic regions, or limited product categories, preventing generalization across diverse consumer markets. Recent literature reviews have identified the absence of comprehensive weather variable integration in retail forecasting, with most studies utilizing only temperature data while missing precipitation patterns, humidity, atmospheric pressure, and extreme weather event impacts [19]. Additionally, advanced ML architectures remain underutilized in weather-informed consumer prediction, with ensemble methods demonstrating superior performance in individual retail contexts but lacking validation across diverse consumer spending categories. This underscores the importance of developing standardized evaluation frameworks that can assess both forecasting accuracy and the ability to isolate weather impacts effectively across multiple industries and geographic contexts.

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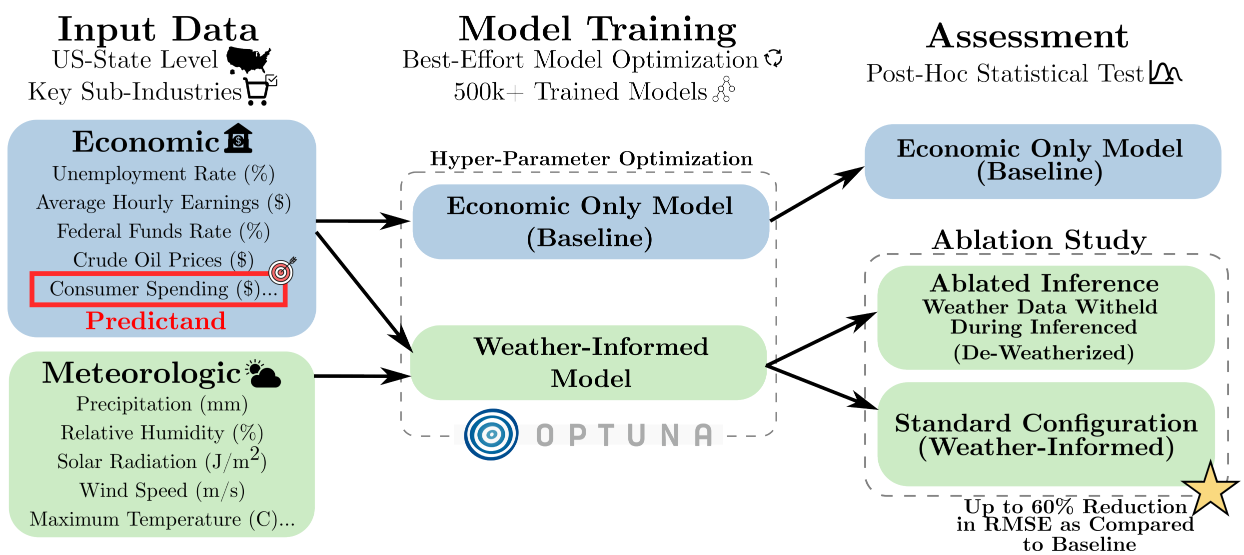


Fig. 1. Conceptual overview of the propose study demonstrating the value of weather data integration in consumer spending prediction. The Baseline forecasting approach relies exclusively on historical spending patterns, macroeconomic indicators, and labor market data, resulting in higher prediction errors. The Weather-Informed approach incorporates comprehensive meteorological features including historical and 7-day forecast data for temperature, precipitation, wind speed, humidity, and solar radiation. This integration achieves substantial improvements with up to 60% reduction in RMSE compared to baseline models without weather. The performance gains are consistently observed across eight diverse ML algorithms, three key retail sub-industries (Grocers, Home Improvement, Casual Dining), and all U.S. geographic regions, demonstrating the universal value and robust nature of weather data for enhanced demand forecasting accuracy.

B. Overview of Our Proposed Study

We present a comprehensive analysis of the impact of weather information on consumer spending prediction by systematically incorporating weather variables into several traditional and contemporary ML models, across three key industries, and across the entire geographic United States. Based on the theoretical understanding that weather conditions directly influence consumer behavior across multiple retail sectors, we hypothesize that **systematic integration of meteorological data will significantly improve consumer spending prediction accuracy compared to traditional forecasting approaches that rely solely on economic indicators and temporal patterns**.

This study addresses limitations in previous research through a comprehensive analysis of weather's impact on consumer spending forecasting. We examine multiple ML models with thorough hyperparameter optimization to ensure fair comparisons, evaluate performance across three distinct sub-industries to demonstrate weather's predictive value across various sectors, and assess results across all 50 states to validate geographic generalizability of Weather-Informed predictions. Our overall evaluation framework is depicted in Figure 1.

Our approach integrates weather datasets at the statewide level—adjusted for population distribution and preprocessed—with macroeconomic and consumer spending data to precisely measure meteorological influences on consumer behavior. We employ an iterative modeling strategy designed to isolate economic and weather influences within consumer spending patterns. We first develop Baseline models that forecast consumer spending without weather information, then retrain these models with weather variables included, creating what we term Weather-Informed models. Our comprehensive evaluation framework ensures fair model comparisons through three components. First, we train each model configuration multiple times using k-fold cross-validation and Optuna hyperparameter optimization to achieve optimal performance. Second, we evaluate all configurations across different model types, sub-industries, and US states to identify top-performing models and assess both industry-specific impacts and geographic performance trends. Third, we aggregate results from all model runs and conduct post hoc statistical testing to determine significance levels and validate the robustness of prediction improvements.

C. Contributions

This study advances weather-integrated demand forecasting research by addressing critical limitations in prior work. While earlier studies have explored weather integration in specific contexts—such as for weather-sensitive retail products [9], electricity demand [20], or ride-hailing services [21]—these efforts have been constrained by narrow scope and limited methodological validation. This paper makes three key contributions to establish the universal value of weather data in demand forecasting:

1) **Multi-Industry Benchmarking Framework:** We address a key gap in the literature by providing a systematic, comparative evaluation of weather's impact across three distinct consumer spending sectors (Grocers, Home Improvement, and Casual Dining). This approach provides a more holistic understanding than is possible with single-industry studies.
2) **Rigorous and Scalable Evaluation Methodology:** We implement a robust evaluation framework that combines k-fold cross-validation, large-scale hyperparameter optimization with Optuna [22], and post hoc statistical

testing. This addresses the methodological gaps of prior work [23], [24] and validates the performance of eight machine learning models, from off-the-shelf (OTS) algorithms to a domain-enriched model.

3) **Broad Generalizability of Weather Integration:** We demonstrate that the predictive benefits of weather data are mostly model-agnostic and geographically independent. Weather features delivered consistent performance gains (up to 60% RMSE reduction) across a wide array of algorithms—from linear regression to ensemble methods—and were validated in all 50 U.S. states, confirming weather is a universally valuable feature, not a region-specific or model-dependent phenomenon.

While more complex deep learning architectures like Long Short-Term Memory (LSTM) networks or Transformers have shown state-of-the-art performance in certain time-series domains [25], they were intentionally excluded from this analysis for three key reasons. First, their "black box" nature can complicate the primary goal of isolating and interpreting the impact of a specific feature set. Second, the massive scale of our experiment—encompassing over 500,000 individual model training runs—necessitated the use of computationally efficient yet powerful algorithms. Third, and most critically, the vast hyperparameter space and architectural complexity of deep learning models risk shifting the experimental focus from clear hypothesis testing to a large-scale engineering effort aimed at achieving absolute predictive accuracy. Our aim is to robustly demonstrate the role of weather, a task best served by a broad, methodologically sound comparison rather than a deep dive into optimizing a single, complex model.

Ultimately, large-scale forecasting competitions have repeatedly shown that meticulous methodology including feature engineering, robust cross-validation, and hyperparameter optimization is often more critical to success than the specific choice of a novel algorithm [18]. Our approach aligns with this principle. By focusing on a broad suite of established models and applying a rigorous evaluation framework, we provide a definitive and practically relevant conclusion on the indispensable role of weather data in demand forecasting.

II. Previous Work

The integration of weather data into consumer spending prediction represents a convergence of several research domains: the established impact of weather on consumer behavior, the evolution of machine learning in demand forecasting, and the methodologies for integrating heterogeneous data sources. This section reviews the literature from these domains to contextualize our study's contributions.

A. The Influence of Weather on Consumer Behavior and Retail Demand

The recognition that weather is a critical, yet often overlooked, variable in business forecasting is not new. Over two decades ago, Cawthorn [26] argued that as market dynamics shifted focus from the "supply chain" to the "demand chain", understanding the triggers of consumer behavior became paramount. He identified weather as a key factor that has a "profound influence" on consumer choice, store traffic, and demand for a wide array of products - from apparel and auto parts to food and beverages.

Building upon this foundational concept, a substantial body of modern empirical research has rigorously quantified the financial and operational impacts of meteorological conditions. For instance, a large-scale study of over 670 brick-and-mortar stores by Badorf, Hoberg, and Schamel [27] found that the impact of weather on daily sales can be as high as 23.1% based on store location and can soar to 40.7% for specific sales themes, confirming that weather is a variable of major financial significance. Their work also highlighted the complex, non-linear nature of these effects, noting that traditional models often incorrectly estimate the impact of extreme weather events. The influence of weather is not uniform; it varies significantly by season, product category, and geography. Rose et al. [10], in a comprehensive analysis of over 2,000 UK stores, found that weather's impact is greatest during the spring and summer months with product categories like health foods being particularly susceptible. Their study also revealed that out-of-town stores exhibit a more complex relationship with weather than traditional high-street locations, underscoring the need for geographically nuanced models. Similarly, studies focusing on specific product categories, such as non-alcoholic beverages [28] and seasonal garments [29], reinforce the finding that weather influences not just whether consumers buy, but precisely what and when they buy. Beyond direct purchasing, weather also affects the opportunity cost of other activities; Schmittmann and Prosad [30] found that retail investors tend to trade more actively on bad-weather days, suggesting a behavioral link between meteorological conditions and time allocation.

More recent methodological refinements have sought to isolate these weather effects with even greater precision. Dimitrov and de Mello [31] argue that it is critical to distinguish between weather (short-term atmospheric conditions) and climate (long-term regional norms). They demonstrate that failing to control for a region's climate can lead to the misclassification of a product's weather sensitivity, introducing a crucial layer of sophistication for building accurate predictive models. This progression from foundational observation to nuanced, quantitative analysis confirms that weather is an indispensable component in demand forecasting, requiring advanced modeling techniques to fully capture its complex influence.

B. ML for Enhanced Demand Forecasting

Traditional forecasting models, such as ARIMA, often rely on linear assumptions and struggle to capture the complex, non-linear dynamics introduced by external variables like weather, holidays, and promotions. The shift to ML has been driven by the need for models that can effectively learn from the high-dimensional, heterogeneous data characteristic of the modern retail environment. As noted by Makridakis et. al. [32], ML paradigms excel when sufficient data is available to uncover intricate patterns without assuming a fixed data-generating process.

For this study, we deliberately selected a diverse suite of well-established statistical ML models. This selection spans the spectrum from interpretable linear models (Linear Regression, ElasticNet) to powerful, non-linear ensembles (Random Forest, LightGBM, XGBoost). This selection was fundamental to the experimental design, which prioritized a robust assessment of the performance uplift from weather data across a representative range of common forecasting techniques over the pursuit of a single state-of-the-art model with the lowest possible error. By demonstrating consistent improvement across this varied set of algorithms, we can confidently conclude that the value of weather data is a generalizable phenomenon, not an artifact of one specific or highly- tuned model architecture.

III. Methodology

A. From Fragmented Evidence to Comprehensive Assessment

While the literature establishes the importance of weather and the power of ML, a significant methodological gap remains. Much of the existing research is constrained by a narrow scope focusing on a single retail sector, a limited geographic region, or a small subset of models. Consequently, the findings often lack the generalizability required for broad, industry-wide application. Furthermore, few studies have undertaken a large-scale, methodologically rigorous comparison that systematically isolates weather's impact across multiple industries, a wide range of geographies, and a diverse set of well-tuned algorithms simultaneously.

This is the precise gap our research addresses. By conducting a comprehensive assessment across three distinct retail sectors and all 50 U.S. states, and by employing a robust framework of model evaluation and hyperparameter optimization, our work moves beyond confirming that weather matters to definitively quantifying its universal value and establishing a new benchmark for weather-integrated demand forecasting.

B. Core Experimental Framework

Our methodology is designed for reproducibility and to rigorously test our central hypothesis. We first train two models: one without weather data (econ-only) and one where the weather predictors are included (econ + weather). Once these two models are trained, we conduct model predictions in three ways:

- **Baseline** results refer to predictions from the model that includes all predictors except the weather variables (i.e., econ-only).
- **Weather-Informed** results refer to predictions from the model that includes all predictors, including the weather variables (i.e., econ + weather).
- **De-Weatherized** results refer to predictions from the model that includes all predictors, including the weather variables (i.e., econ + weather), but with the weather variables artificially set to zero in z-score space after model training and before generating predictions. This set of results aims to answer the question: what would the outcome have been if the weather had simply reflected average conditions for that state?

The performance difference between the two trained models (econ-only vs. econ + weather) provides a direct measure of the value added by incorporating weather information. The difference in predictions between the **Weather-Informed** and **De-Weatherized** cases provides a direct estimate of the impact of weather on consumer spending behavior.

Our experimental design specifically tests whether weather's predictive value generalizes across diverse ML paradigms. Rather than comparing against external literature baselines, we train each of eight distinct algorithms (ranging from linear models to gradient boosting) independently with identical feature sets except for weather data inclusion. This approach isolates weather's contribution independent of algorithmic choice, testing whether meteorological features provide consistent value across diverse modeling paradigms.

C. Data Sources and Integration

Our analysis integrates data streams for all 50 U.S. states from January 2015 to January 2025. Missing values were linearly interpolated by state and sub-industry, and all numeric values were normalized by applying z-score normalization. Figure 2 depicts a sample of the predictors and the target variable over the entire dataset. Complete details of all features are provided in Appendix A. The final merged dataset was created from four key sources:

1) Consumer Spending Data: We utilize proprietary, anonymized credit card transaction data aggregated to the state and sub-industry level (Grocers, Home Improvement, Casual Dining) at a daily frequency. This serves as our target variable (predictand) for all forecasting models.

2) Macroeconomic Data: To account for general economic conditions, we incorporate daily-resampled macroeconomic indicators from federal sources including energy prices (crude oil, natural gas, electricity), financial market conditions (federal funds rate, treasury yields), production metrics (industrial production, capacity utilization), labor market indicators (employment, unemployment, wages), and consumer financial health measures (debt levels, delinquency rates).

3) Weather Data: We incorporate comprehensive weather data including temperature (daily minimum, maximum, and mean), precipitation, humidity, solar radiation, and wind speed. We applied population-weighted geographic aggregation to create state-level indicators that reflect the weather conditions experienced by the majority of each state's population.

4) Calendar Features: We included binary features to capture holiday-related spending patterns, specifically: (1) Thanksgiving week (Monday before through Friday after Thanksgiving), (2) Christmas week indicators (December 22-26), and (3) U.S. federal holiday flags, including indicators of the day prior and day subsequent. These features help account for systematic variations in consumer spending during major holiday periods. We also encoded day of week and month of year, as described in Section III.B.

An example correlation matrix for the Florida home improvement industry, illustrating typical variable relationships, is provided in Appendix C.

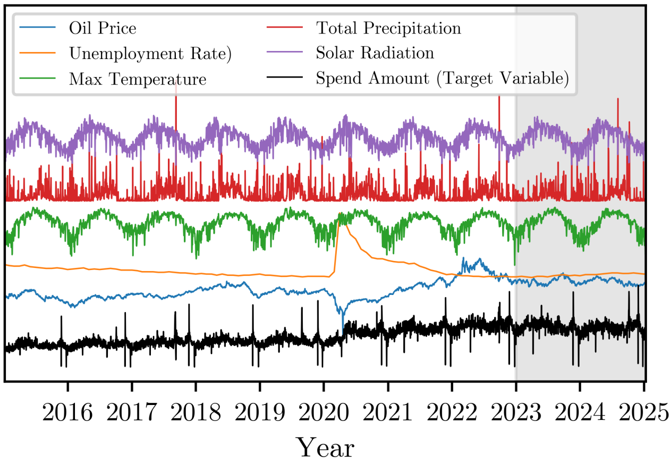


Fig. 2. Sample time series from our dataset including predictors and our predictand (Spending Amount). Values scaled and shifted for visualization clarity. The gray area represents our test period with the remaining date range used for training and validation.

D. Feature Engineering

Raw data were transformed to create a rich feature set. The ‘Baseline‘ models use only the non-weather features.

- **Temporal Features:** Day of week, month, and holidays were encoded to capture seasonality and regular sub-annual variability. Notably, some weather-related information will be indirectly included in the month variable, as month of year is correlated with weather conditions.
- **Economic Features:** Monthly-average macroeconomic indicators were linearly interpolated to daily then included directly.
- **Weather Features (Weather-Informed Only):** We engineered features from a window of 7 days prior to the target date up to a 6-day forecast, the time window within which weather forecasts retain considerable accuracy. Temperature variables were further processed to additionally capture local anomalies, seasonal aberrations, and weekly averages.
  - *Raw Values:* Temperature, precipitation, wind speed, humidity, and solar radiation, for the day of spending and the surrounding 13-day window.
  - *Local Anomalies:* Deviations from local patterns were captured using a 7-day centered rolling mean, calculated as:

$$\text{RollingMean}_t = \frac{1}{7}\sum_{i=t-3}^{t+3} x_i$$

    where x_i represents the weather variable value at time i.
  - *Seasonal Anomalies:* Long-term seasonal patterns were identified using a 30-day smoothing window on day-of-year averages derived from the period of record (2015-2024). Anomalies were then calculated as deviations from these smoothed seasonal patterns.

We used sine and cosine encodings for cyclical temporal features, including day of week and month of year. Simple integer encoding creates artificial distance between cyclically adjacent values—for example, January (1) and December (12) appear numerically distant despite being consecutive months. The sine-cosine transformation preserves the cyclical relationships by mapping temporally adjacent periods to nearby points in the feature space, enabling models to properly recognize patterns across period boundaries.

E. Evaluated ML Models

We conducted a comparative analysis of eight ML models to ensure our findings are robust and not specific to a single algorithm. For each sub-industry and state, every model was trained and evaluated for both the Baseline and Weather-Informed feature sets.

1) **Linear Regression [33]:** A linear model that assumes a linear relationship between features and target variables. Commonly used for baseline comparisons and interpretable predictions in economic forecasting due to its simplicity and clear coefficient interpretation.
2) **Elastic Net Regression [34]:** A linear regression model that combines both L1 (Lasso) and L2 (Ridge) regularization techniques. This hybrid approach balances feature selection capabilities of Lasso with the grouping effect of Ridge regression, making it particularly effective when dealing with correlated feature groups and when both feature selection and coefficient shrinkage are desired.
3) **Decision Tree Regressor [35]:** A tree-based model that creates interpretable decision rules by recursively splitting data based on feature values. Often used when feature interactions and non-linear relationships are important, and when model interpretability is valued over pure performance.
4) **LightGBM [36]:** A gradient boosting framework optimized for speed and memory efficiency using histogram-based algorithms. Popular for structured data competitions and production systems requiring fast training on large datasets with categorical features.
5) **Random Forest Regressor [37]:** An ensemble method combining multiple decision trees with bootstrap sampling and feature randomization. Widely used for its robustness to overfitting, ability to handle mixed data types, and natural feature importance ranking capabilities.
6) **Stochastic Gradient Descent (SGD) Regressor [38]:** A linear model optimized using stochastic gradient descent, making it suitable for large datasets. Commonly employed when computational efficiency is critical and when dealing with high-dimensional sparse data.
7) **XGBoost [39]:** An optimized gradient boosting algorithm known for its performance in structured data tasks. Widely adopted in ML competitions and industry applications for its superior predictive accuracy and built-in regularization techniques.
8) **Iterative XGBoost:** A domain-specific model inspired by [40] consisting of three-stages designed to systematically decompose consumer spending predictions by isolating different influence sources through residual modeling.

- *Stage 1:* An XGBoost model is trained on date features, economic indicators, and custom domain features to capture baseline spending patterns and economic trends.
- *Stage 2:* A second XGBoost model is trained exclusively on weather features to predict the residuals from Stage 1, explicitly isolating weather-driven spending variance.
- *Stage 3:* A third XGBoost model is trained on time-lagged target variables to predict the residuals from Stage 2, capturing temporal dependencies and autoregressive patterns in spending behavior that are not directly encoded in the predictors included in stages 1 and 2.
- The final prediction combines outputs from all three stages. This hierarchical approach enables explicit quantification of economic, meteorological, and temporal components of consumer spending, providing interpretable decomposition of prediction factors while maintaining high predictive accuracy.

F. Model Training and Evaluation

Our model training and evaluation framework employs a systematic approach to rigorously assess the impact of weather information on consumer spending prediction through comprehensive experimentation across multiple dimensions.

Data Partitioning: We implement a temporal split strategy with training/validation data spanning January 1, 2015 to December 31, 2023, and a hold-out test set covering January 1, 2023 to January 10, 2025 (see Figure 2 for depiction). This approach ensures proper temporal ordering and prevents data leakage while maintaining the time series structure essential for consumer spending forecasting.

Temporal Window Design: Our modeling framework incorporates carefully designed temporal features to capture both weather patterns and spending dynamics across multiple time horizons. For weather variables, we construct a comprehensive temporal window spanning 15 days using lags ranging from -7 to +6 days relative to the prediction target date. This design captures both historical weather conditions (lags -7 to -1) that may influence accumulated consumer behavior, contemporaneous weather (lag 0), and forecasted weather conditions (leads +1 to +6) that enable consumers to plan purchases in anticipation of upcoming conditions. The inclusion of weather forecasts is particularly valuable for situations and categories where consumers exhibit forward-looking behavior, such as stocking up before a hurricane, purchasing seasonal apparel, or buying outdoor equipment. Notably, all of the experiments presented in this paper assume perfect foresight in weather forecasts. The uncertainty in short-term weather forecasts, and its resulting impact on consumer spending predictions, is outside the scope of this paper, which is solely focused on quantifying the impact of weather.

For the target variable (spend_amount), we incorporate lagged features spanning the previous 4 to 7 days (lags -4 to -7) to capture recent spending patterns and seasonal trends while accounting for the inherent data availability constraints in our system. Our prediction objective targets a +1 day lead (next-day spending prediction), which aligns with practical business applications requiring short-term demand forecasting. The choice of a 4-day minimum lag for spending features reflects the operational reality of credit card transaction processing, where complete daily spending totals become available only after a settlement period. This temporal configuration ensures that our models operate under realistic data availability conditions that mirror actual deployment scenarios, where predictions must be made using only information that would be available at the time of prediction in a production environment.

Model Configuration Design: Our evaluation encompasses two parallel modeling universes: Baseline configurations (excluding weather data) and Weather-Informed configurations (incorporating weather features). This systematic comparison provides direct measurement of weather information value across different modeling approaches.

Hyperparameter Optimization Protocol: Each model undergoes extensive hyperparameter tuning using the Optuna framework (details in Appendix B) with 50 optimization trials per configuration. We employ 5-fold cross-validation using consecutive temporal chunks to preserve time series integrity, with the average MSE across folds serving as the optimization objective. This approach ensures robust hyperparameter selection that generalizes across different time periods.

Training Scale and Scope: We train models across 3 sub-industries × 50 US states × 2 weather configurations × 8 ML algorithms, yielding 2,700 unique model configurations. With 50 Optuna trials per configuration and 5-fold cross-validation per trial, our evaluation encompasses 600,000 individual model training runs, representing one of the most comprehensive assessments of weather-informed consumer spending prediction in the literature.

Training Objective Function: Mean Squared Error (MSE) serves as our objective function, chosen for its emphasis on penalizing large prediction errors that are typically most costly in business applications and is defined as

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{1}$$

where Y_i represents the actual consumer spending amount for day i, $\hat{Y}_i$ represents the predicted consumer spending amount for day i, and n is the total number of prediction instances in the evaluation period.

G. Evaluation Metrics

We employ two complementary metrics to comprehensively assess model performance in consumer spending forecasting: Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). This dual-metric approach provides both absolute and relative performance assessments, accommodating the diverse scales of consumer spending across different states and sub-industries.

Mean Absolute Percentage Error (MAPE): MAPE expresses prediction accuracy as a percentage of actual values, enabling direct comparison across states and sub-industries with vastly different spending scales:

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{Y_i - \hat{Y}_i}{Y_i} \right| \quad (2)$$

MAPE provides intuitive interpretation for stakeholders and enables meaningful aggregation of results across heterogeneous geographic and sector contexts. This scale-invariant property is essential given that daily consumer spending ranges from thousands of dollars in smaller states to millions in larger markets.

[41], [42] provides guidance for interpreting MAPE values in forecasting accuracy assessment. According to this framework, MAPE values below 10% indicate highly accurate forecasting performance, values between 10-20% represent good forecasting accuracy, values in the 20-50% range are considered reasonable, while values exceeding 50% are deemed inaccurate for practical forecasting applications.

Root Mean Square Error (RMSE): RMSE measures the standard deviation of prediction residuals, providing an absolute error metric in the same units as the target variable (dollars):

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2} \quad (3)$$

RMSE is particularly valuable for consumer spending applications as it heavily penalizes large prediction errors, which are typically most costly in business contexts such as inventory planning and marketing budget allocation. The metric's sensitivity to outliers aligns with the business reality that severely inaccurate spending predictions can lead to significant operational disruptions.

Statistical Significance Testing: To validate the robustness of our findings, we apply the Wilcoxon signed-rank test [43] to MSE values between actual and predicted spending amounts. This non-parametric approach compares error distributions between Baseline and Weather-Informed models, providing statistical confidence in our results while accommodating the non-normal error distributions characteristic of economic time series data.

IV. Results & Analysis

A. Overall Performance Results

Our comprehensive evaluation demonstrates that incorporating weather data substantially improves consumer spending prediction accuracy across diverse ML algorithms. Figure 3 presents the distribution of MAPE values for all eight evaluated models, comparing Baseline performance against Weather-Centric (i.e., Weather-Informed & De-Weatherized) configurations across all U.S. states and sub-industries. The results reveal a clear and consistent pattern: Weather-Informed models (shown in blue) generally outperform their Baseline counterparts (shown in red) across all tested algorithms. In addition, the violet distributions represent De-Weatherized models which, although trained with weather data, have their weather features set to their mean values during inference, illustrating counterfactual scenarios that estimate what consumer spending would have been in the absence of weather effects

Table I quantifies these improvements across sub-industries, revealing substantial performance gains that vary by both algorithm and sector. XGBoost emerges as the top-performing model across all sub-industries (MAPE of 15.4%), achieving a MAPE of 16.2% in Grocers sector and maintaining good results of 13.6% and 16.3% in Home Improvement and Casual Dining, respectively. Iterative XGBoost and LightGBM demonstrate the second-smallest overall MAPE at 18.2%. Notably, most algorithms across most sub-industries experienced improved MAPE scores when using weather data.

The sector-specific analysis reveals interesting patterns in weather sensitivity. The Grocers sub-industry shows the highest responsiveness to weather information, with most models achieving double-digit percentage improvements. Home Improvement demonstrates moderate but consistent gains across algorithms, while Casual Dining exhibits more variable results, with some models showing minimal or slightly negative improvements. This pattern suggests that weather influences on consumer behavior vary significantly by industry type, with essential goods purchases (groceries) being most sensitive to meteorological conditions.

B. Geographic Distribution of Improvement

The benefits of including weather data are not confined to a few "weather-sensitive" states but are geographically widespread. Figure 4 visualizes the percentage improvement achieved by the best-performing model (XGBoost) for each sub-industry. While states with more variable weather like Texas and Florida show large improvements, even states with more temperate climates like California and Oregon see gains of over 30%. This demonstrates the universal applicability and importance of incorporating local weather conditions into predictive models, regardless of region.

Additionally, Figure 5 displays the percentage improvement in prediction error (RMSE) across all 50 states when comparing Weather-Informed XGBoost models to Baseline models without weather data. We focus exclusively on XGBoost results since it demonstrated superior performance across all evaluated algorithms. Post hoc statistical significance testing between Weather-Informed and Baseline XGBoost models reveals that nearly all state-industry combinations show significant improvements in prediction accuracy when incorporating weather information.

C. Sample Time Series and Prediction Accuracy Analysis

Figure 6 presents a representative example of model performance using Texas Grocers data spanning the complete 10-year analysis period. Panel (a) demonstrates the full temporal scope of our analysis, with the training/validation period (2015-2023) shown in light blue for ground truth and blue for Weather-Informed predictions, followed by the test period (2023-2024) where ground truth appears in grey and Weather-Informed predictions in green. The visualization reveals how

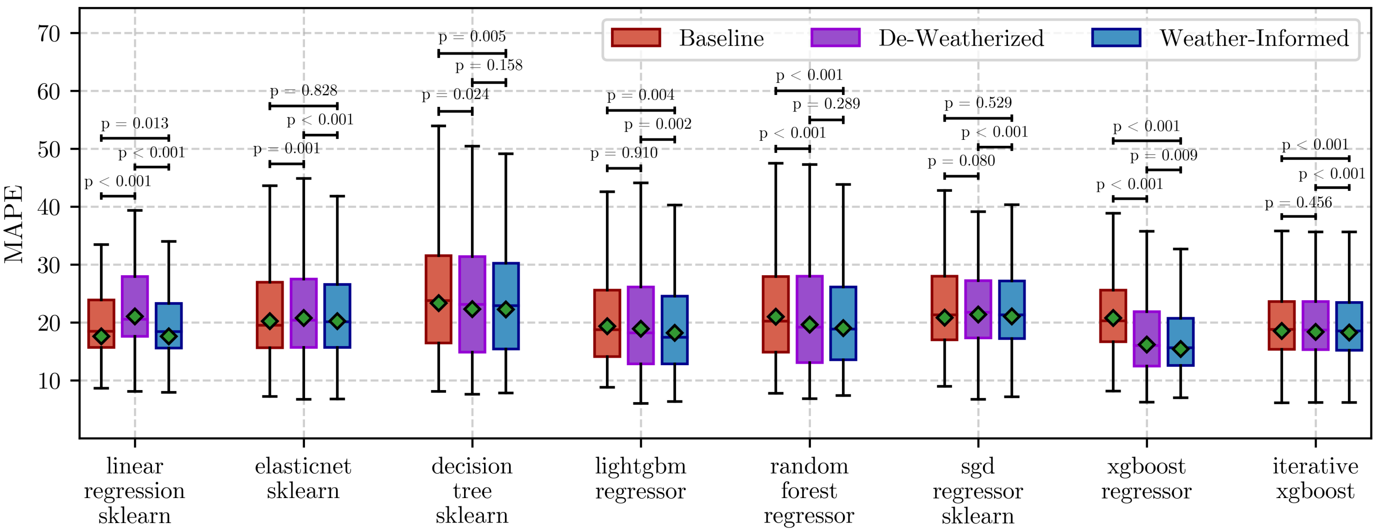


Fig. 3. Comparison of MAPE distributions for eight ML models with and without weather data. MAPE values were calculated separately for each state-sub-industry then averaged to treat each economic context as an equal experimental unit. Box plots show the distribution of MAPE values across all U.S. states and sub-industries. Weather-Informed models (blue) often demonstrate significantly lower prediction errors compared to Baseline models (red) and De-Weatherized models where weather is missing during test time (violet) across all tested algorithms. Horizontal bars indicate statistical significance determined by Wilcoxon signed-rank tests, with all comparisons showing $p < 0.001$, confirming the robust improvement gained by incorporating weather features. The boxes represent the interquartile range (25th to 75th percentiles), with the dark horizontal lines inside each box indicating the median. Whiskers extend to the most extreme data points within 1.5 times the interquartile range from the box edges. Green diamonds represent the mean MAPE values for each distribution. More detail available in Table I.

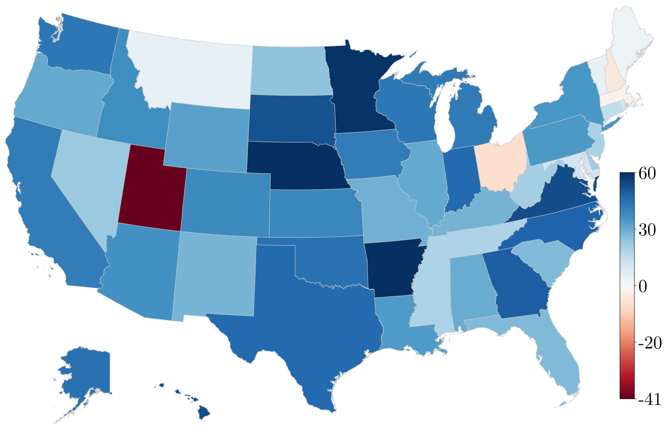
TABLE I

Model Performance (MAPE) With and Without Weather Data. Lower values indicate better performance. Best performance for each sub-industry shown in bold. WX-I: Weather-Informed model; DeWX: De-Weatherized model; Base: Baseline model; Impr: Percent improvement of Weather-Informed vs. Baseline. The Best Performance row shows the minimum MAPE achieved across all algorithms for each sub-industry.

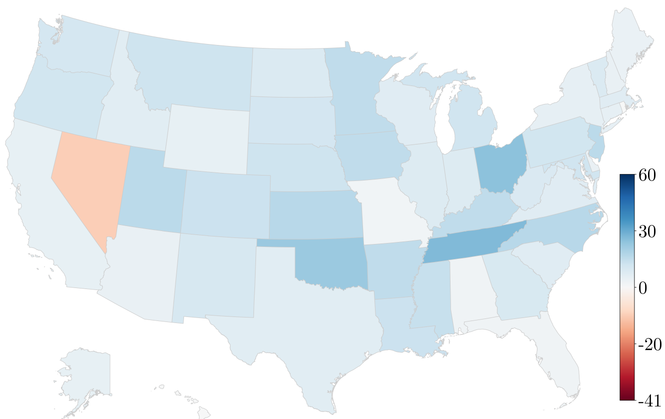
	Grocers				**Home Improvement**				**Casual Dining**				**Overall Mean**			
Model	**WX-I**	**DeWX**	**Base**	**Impr**	**WX-I**	**DeWX**	**Base**	**Impr**	**WX-I**	**DeWX**	**Base**	**Impr**	**WX-I**	**DeWX**	**Base**	**Impr**
linear regression sklearn	17.4	18.6	18.4	5.3%	16.4	21.8	15.6	-5.0%	18.9	22.6	18.8	-0.7%	17.6	21.0	17.6	0.1%
elasticnet sklearn	21.2	21.0	21.3	0.8%	21.3	23.1	21.7	1.8%	18.1	18.1	17.6	-3.0%	20.2	20.7	20.2	0.1%
decision tree sklearn	25.9	24.7	28.0	7.6%	24.3	25.8	24.8	2.0%	16.5	16.4	17.1	3.8%	22.2	22.3	23.3	4.7%
lightgbm regressor	19.2	18.7	19.9	3.6%	21.0	23.1	23.5	10.8%	**14.6**	14.3	15.7	7.4%	18.2	18.7	19.7	7.5%
random forest regressor	22.5	21.4	26.4	14.7%	19.7	22.9	20.5	4.0%	14.7	14.5	15.9	7.3%	19.0	19.6	20.9	9.3%
sgd regressor sklearn	21.7	21.5	22.0	1.6%	21.4	22.5	20.5	-4.3%	20.0	20.0	19.9	-0.5%	21.0	21.3	20.8	-1.0%
xgboost regressor	**16.2**	15.3	26.5	38.7%	**13.6**	16.7	14.8	7.6%	16.3	16.3	21.0	22.2%	**15.4**	16.1	20.7	25.7%
iterative xgboost	17.7	17.6	17.7	0.3%	16.8	16.8	17.3	3.0%	20.3	20.5	20.4	0.7%	18.2	18.3	18.5	1.3%
Best Performance	**16.2**	**15.3**	**17.7**	**8.5%**	**13.6**	**16.7**	**14.8**	**7.6%**	**14.6**	**14.3**	**15.7**	**7.4%**	**15.4**	**16.1**	**17.6**	**12.4%**

our models handle the transition from training to out-of-sample prediction. Panel (b) provides detailed examination of test period performance, directly comparing three modeling scenarios: Weather-Informed predictions (green), Baseline predictions excluding weather data (red), and De-Weatherized models with weather effects removed during inference (violet). The Weather-Informed model demonstrates improved accuracy compared to the Baseline model, as evidenced by the closer alignment between the green line and actual spending patterns. The violet line represents a counterfactual scenario showing what spending patterns might look like in an alternate reality where weather variability does not influence consumer behavior, rather than serving as a direct performance comparison. This weather-neutralized prediction illustrates the model's ability to isolate and quantify weather-driven spending variations, confirming that weather information contributes meaningfully to observed spending patterns.

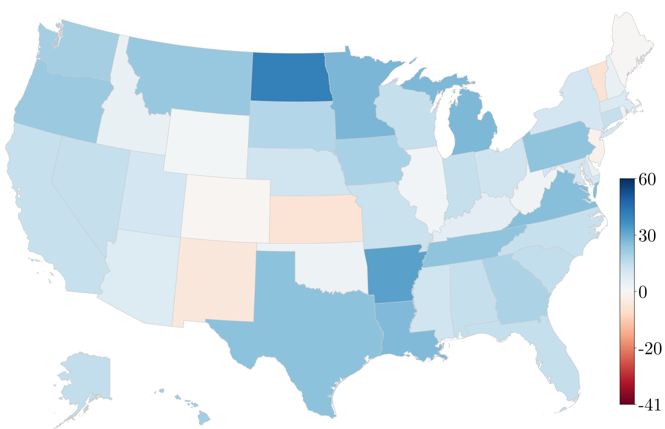
Figure 7 provides a comprehensive scatter plot analysis comparing predicted versus actual spending amounts across all three modeling configurations. The diagonal dashed line represents perfect prediction ($y = x$), where points closer to this line indicate more accurate predictions. The Weather-Informed model (green points) demonstrates the tightest clustering around the perfect prediction line, particularly in the central spending range, indicating superior prediction accuracy. The Baseline model (red points) shows greater scatter and systematic deviations from the perfect prediction line. This scatter plot analysis reinforces the temporal findings, demonstrating that weather information consistently improves prediction accuracy across the full range of consumer spending values. The visualization illustrates how weather data reduces both systematic bias and random prediction errors, providing



(a) Grocers



(b) Home Improvement



(c) Casual Dining

Fig. 4. Percentage improvement in RMSE for consumer spending prediction across three retail sub-industries and all U.S. states when incorporating weather data. The heatmap shows the performance gain of Weather-Informed models compared to Baseline models using the best-performing algorithm for each state-industry combination. Weather data consistently improves prediction accuracy across diverse geographic regions and retail sectors, with average improvements of 17% and even exceeding 60%, demonstrating the universal value of meteorological features in demand forecasting.

evidence for the practical value of meteorological features in consumer spending forecasting applications.

D. Case Study: Winter Storm Olive Impact on South Dakota Casual Dining

To illustrate the practical application of Weather-Informed forecasting during extreme weather events, we present a detailed analysis of casual dining spending patterns in South Dakota during Winter Storm Olive in February 2023 (Note that the storm occurs within the test set). This case study demonstrates how weather data integration provides substantial improvements in forecasting accuracy during severe weather conditions.

Storm Context: Winter Storm Olive, officially designated by The Weather Channel, occurred February 21-23, 2023, delivering severe meteorological impacts across 24 states from the Pacific Northwest to New England, with South Dakota experiencing 10-16 inches of snowfall and blizzard conditions in eastern regions [44], [45]. The storm generated widespread infrastructure failures including over 900,000 power outages across six states, 1,600+ flight cancellations nationwide, and up to 0.75 inches of ice accumulation in southeastern Michigan—levels described as unprecedented in nearly 50 years [45]. Emergency responses included Governor Tim Walz's peacetime emergency declaration activating the Minnesota National Guard, Governor Kristi Noem's closure of state offices in 36 South Dakota counties, and Governor Tony Evers' statewide energy emergency declaration in Wisconsin [46], [47]. The restaurant industry experienced severe economic disruption, with Minneapolis St. Paul Magazine extending Winter Restaurant Week due to storm impacts and individual establishments reporting 78-90% decreases in business volume during the storm period [48].

Spending Pattern Analysis: Figure 8 presents South Dakota casual dining spending data during the Winter Storm Olive period, spanning from January 23 to March 24, 2023, with the storm period highlighted in red (February 20-24). The visualization reveals clear patterns that demonstrate the value of weather data in casual dining demand forecasting:

1) **Storm Impact Period (February 20-24):** During the peak storm days (highlighted in the shaded region), casual dining spending drops dramatically to its lowest point in the observation period. The Weather-Informed model accurately captures this substantial decline, closely following the ground truth spending reduction. The Baseline model also captures the general downward trend but fails to track the full depth and timing of the weather-driven spending disruptions as precisely as the Weather-Informed model.
2) **Overall Tracking Performance:** Throughout the entire observation period, the Weather-Informed model demonstrates consistently better alignment with ground truth spending patterns. Quantitatively, one week before the storm, the Baseline model shows a MAPE of 23.52% compared to 19.79% for the Weather-Informed model. The performance gap becomes even more pronounced one week after the storm, with the Baseline model exhibiting a MAPE of 10.05% versus just 4.46% for the Weather-Informed model, representing a 56% improvement in accuracy.

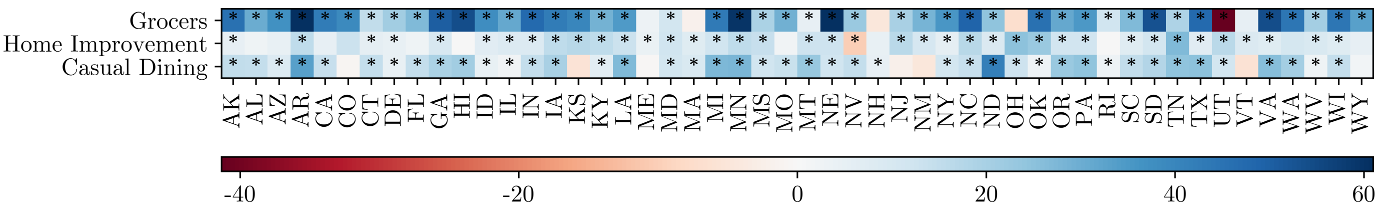
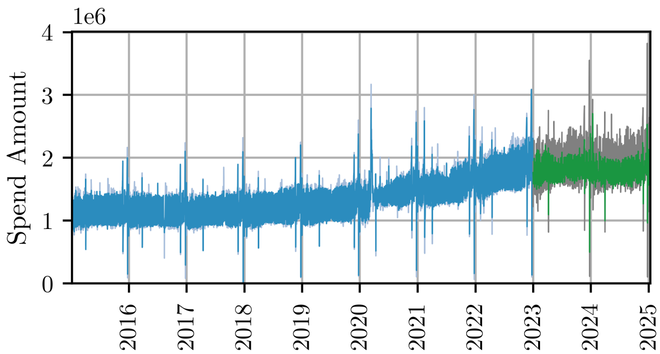
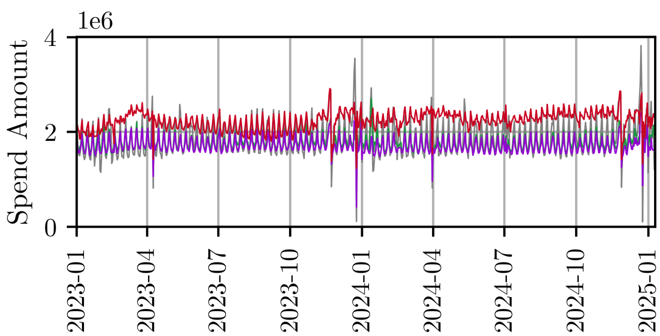


Fig. 5. Percentage improvement RMSE for consumer spending prediction across three retail sub-industries across the U.S. using XGBoost model (the best performing model). The heatmap compares Weather-Informed models against Baseline models that exclude meteorological data. Asterisks (*) indicate statistically significant differnces ($p < 0.01$) determined by Wilcoxon signed-rank tests. Weather data integration demonstrates widespread benefits across diverse geographic regions and retail sectors, with most state-industry combinations showing significant prediction accuracy gains, confirming the robust value of incorporating meteorological features into demand forecasting models.



(a) Complete Time Series: Texas Grocers (2015-2025)



(b) Test Period Detail: Weather-Informed vs. Baseline (MAPE: Baseline=28.03%, De-Weatherized=11.25%, Weather-Informed=11.13%)

Fig. 6. Sample time series demonstrating model performance on consumer spending prediction for Texas Grocers over 10 years of data. (a) Complete time series showing training/validation period (2015-2023) with ground truth (light blue) and Weather-Informed model predictions (blue), followed by test period (2023-2024) with ground truth (grey) and Weather-Informed predictions (green). (b) Detailed view of the test period comparing Weather-Informed model predictions (green) against Baseline model predictions (red) that exclude weather data and De-Weatherized models tested without weather data (violet). The Weather-Informed model demonstrates improved accuracy in capturing spending patterns.

3) **Recovery Pattern:** Following the storm period, both models show improved performance overall, but the Weather-Informed model maintains its superior accuracy in capturing the specific timing and magnitude of spending recovery. The Weather-Informed model continues to track closer to ground truth during the post-storm recovery phase through early March.

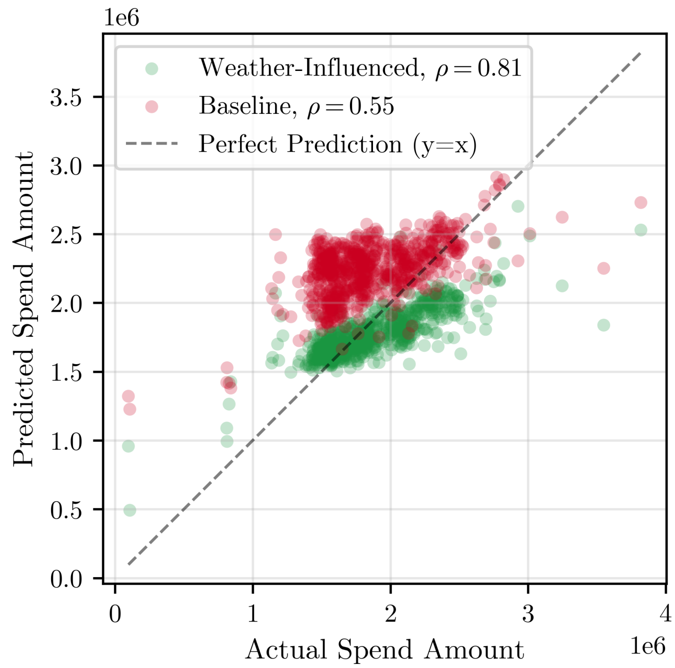


Fig. 7. Scatter plot comparing predicted versus actual spending on the test set. Each point represents a prediction, and the diagonal dashed line indicates a perfect forecast (y=x). The Weather-Informed model (green) clusters more tightly around the prediction line than the Baseline model (red), demonstrating improved forecasting performance. The Pearson correlation coefficient (ρ) quantifies this relationship for the Weather-Informed (ρ = 0.81) and Baseline (ρ = 0.55) models

E. XGBoost Feature Importance Analysis

Figure 9 displays the mean feature importance for the top 30 features comparing (a) Baseline models with (b) Weather-Informed models. Both models demonstrate that economic indicators play a crucial role in prediction accuracy, including Total Public Debt, unemployment rate, and temporal features such as day of the week. Holiday effects, particularly Christmas and Thanksgiving, also rank among the most important predictive features in both configurations.

The Weather-Informed model maintains similar rankings for these core economic and temporal features, though with reduced relative importance as the feature space expands to include meteorological variables. Notably, the Weather-Informed model assigns significant importance to specific weather features, particularly air temperature measured 2 meters above ground level and peak Surface Solar Radiation

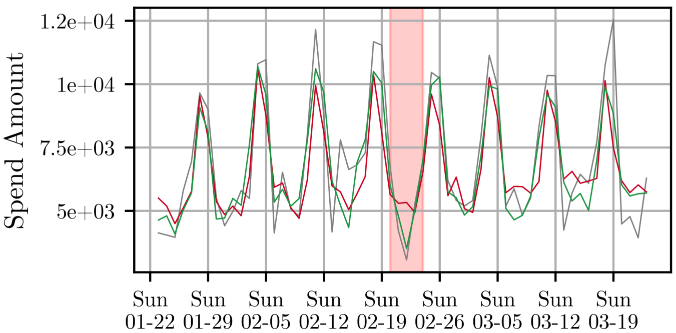
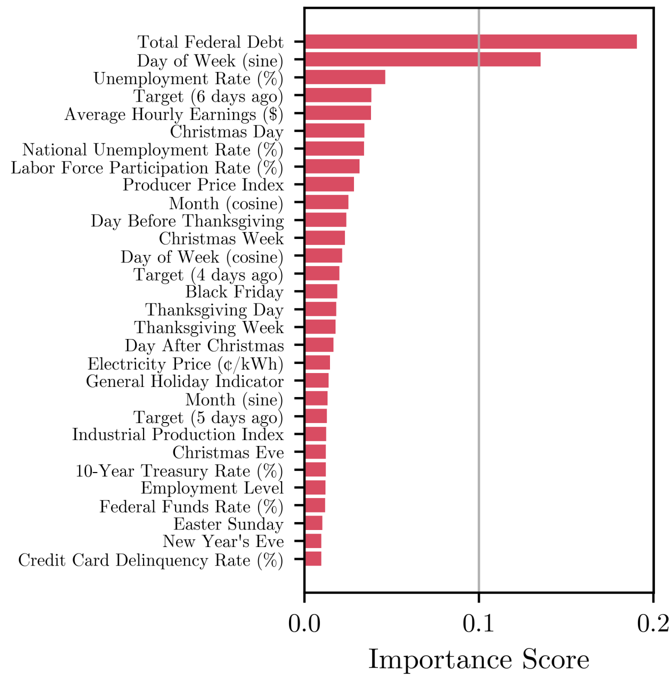
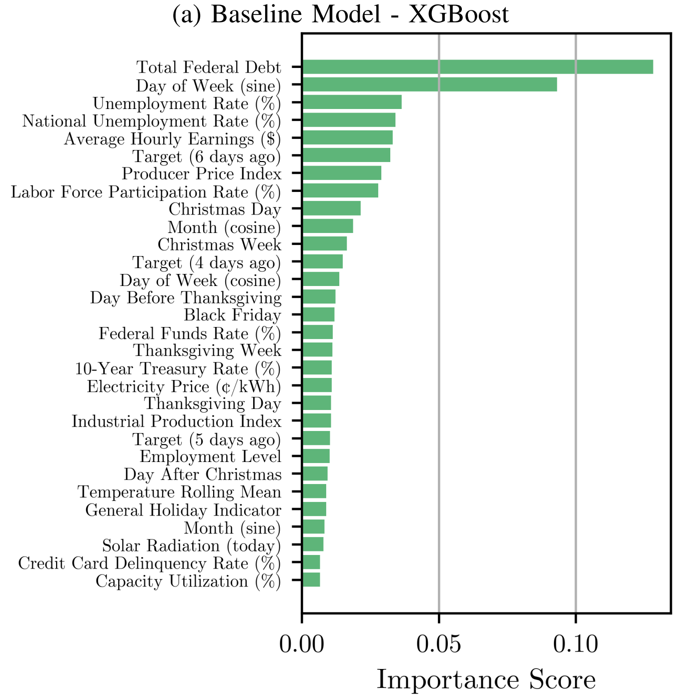


Fig. 8. South Dakota casual dining spending patterns during Winter Storm Olive (February 21-23, 2023) using XGBoost predictions. The storm period is highlighted in red, showing dramatic spending disruptions during the extreme weather event. The Weather-Informed model (green) demonstrates substantially improved tracking against the ground truth (gray) compared to the Baseline model (red), achieving 19.7% better MAPE (20.6% vs 16.7%). Scaled ground truth spending amounts are shown in grey.



(a) Baseline Model - XGBoost



(b) Weather-Informed Model - XGBoost

Fig. 9. Feature importance rankings from XGBoost models displaying top predictors and their associated importance scores for the target variable. The Weather-Informed model identifies temperature rolling mean and solar radiation among the highest-ranked features, indicating their significant contribution to predictive performance.

Downwards (SSRD). This shift in feature importance distribution illustrates how weather information complements rather than replaces traditional economic predictors, creating a more comprehensive feature set that captures both macroeconomic conditions and environmental factors influencing consumer spending behavior.

The comparison reveals that while foundational economic indicators remain critical for consumer spending prediction, the addition of weather features provides valuable complementary information that enhances overall model performance without diminishing the relevance of established economic drivers.

F. XGBoost Hyperparameter Optimization Convergence

Figure 10 illustrates the convergence behavior of Optuna's hyperparameter optimization process for XGBoost across 50 trials for a representative model configuration. The blue points represent individual trial objective values (i.e., MSE), while the green line tracks the best objective value observed throughout the optimization process. The visualization demonstrates the effectiveness of Optuna's Tree-structured Parzen Estimator (TPE) sampling approach in efficiently exploring the XGBoost hyperparameter space.

The optimization exhibits rapid initial improvement, with the best objective value decreasing from approximately 0.325 to 0.200 over the course of 50 trials. The algorithm demonstrates characteristic Bayesian optimization behavior, with early trials exploring diverse regions of the XGBoost hyperparameter space (shown by the wide distribution of objective values) before converging toward more promising parameter combinations in later trials. The green curve shows consistent improvement with diminishing returns, indicating that the optimization process successfully identifies near-optimal XGBoost configurations.

This convergence pattern validates our choice of 50 trials per model configuration, as the best objective value stabilizes in the latter portion of the optimization run. The final convergence to an objective value near 0.200 represents a substantial improvement from initial random trials, demonstrating the value of systematic hyperparameter tuning for XGBoost in achieving optimal model performance across our comprehensive experimental framework.

V. Conclusions & Future Work

This study supports our central hypothesis that systematic integration of meteorological data significantly improves con-

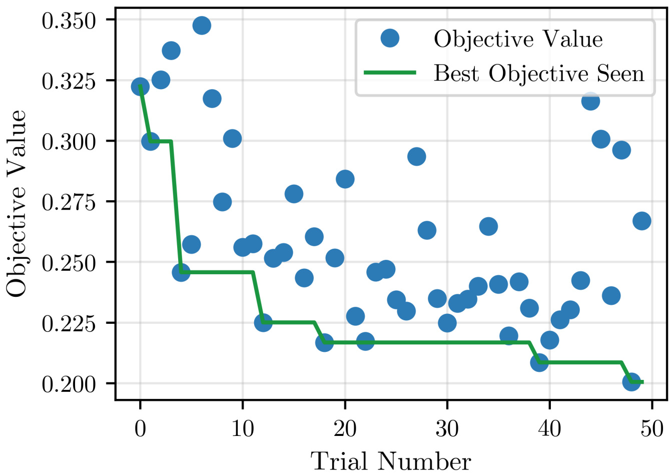


Fig. 10. Optuna hyperparameter optimization progress showing trial objective values and the best objective seen curve. The optimization converges as trials progress, demonstrating the effectiveness of the Bayesian optimization approach [49].

sumer spending prediction accuracy compared to traditional forecasting approaches relying solely on economic indicators and temporal patterns. Through rigorous experimentation across 500,000+ model training runs, we transform raw performance data into actionable knowledge: weather information provides consistent improvements averaging 17% and reaching 60% across diverse algorithms, sectors, and geographies, establishing it as a critical component of accurate demand forecasting.

These findings redefine adequate data requirements for consumer spending prediction. The universal nature of weather's predictive value—demonstrated across volatile and temperate climates, simple and complex algorithms, and essential versus discretionary purchases—reveals that meteorological conditions capture consumer behavioral patterns that economic indicators alone miss. Weather shifts from an external consideration to a core forecasting requirement.

Several promising avenues emerge from this work, each offering distinct strategic advantages. First, investigating the integration of extreme weather event forecasting and climate change projections could extend prediction horizons and enhance long-term strategic planning capabilities, enabling retailers to anticipate and prepare for climate-driven demand shifts years in advance. Second, exploring deep learning architectures specifically designed for weather-demand modeling could potentially achieve even greater performance gains beyond the 60% improvements demonstrated here, as these models excel at capturing complex non-linear interactions between meteorological variables and consumer behavior. Third, expanding the analysis to explicitly include seasonal and holiday interactions with weather patterns could provide more nuanced understanding of consumer behavior, revealing how unseasonably warm Christmas seasons affect winter apparel sales, how early spring weather impacts Easter purchasing, or how temperature anomalies during back-to-school periods influence timing and category preferences—insights that could revolutionize inventory planning and promotional strategies. Finally, developing real-time adaptive models that can adjust to sudden weather changes could enhance operational responsiveness in dynamic market conditions, allowing retailers to automatically rebalance inventory, adjust staffing, and modify marketing campaigns within hours of updated weather forecasts rather than relying on static seasonal plans.

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APPENDIX A
FEATURE DESCRIPTIONS

This appendix provides detailed descriptions of all features used in the consumer credit card spending prediction model. The target variable is **spend amount**, representing daily consumer credit card spending amounts.

A. Basic Features

- **Date**: Timestamp for each observation in the dataset given at a daily frequency.
- **Spend Amount**: Target variable (predictand) representing daily consumer credit card spending amounts (in USD), derived from a longitudinally consistent sample of credit and debit cards.

B. Economic Indicators

- **WTI Crude Oil Price ($/barrel)**: West Texas Intermediate crude oil spot price, a key benchmark for oil pricing and economic activity.
- **Natural Gas Price ($/MMBtu)**: Henry Hub natural gas spot price, reflecting energy costs and seasonal demand patterns.
- **Electricity Price (¢/kWh)**: Average retail electricity price across the United States, indicating energy costs for consumers.
- **Federal Funds Rate (%)**: The interest rate at which banks lend to each other overnight, set by the Federal Reserve as a monetary policy tool.
- **10-Year Treasury Rate (%)**: Yield on 10-year U.S. Treasury securities, reflecting long-term interest rates and economic expectations.
- **Industrial Production Index**: Measure of real output for manufacturing, mining, and electric and gas utilities sectors.
- **Capacity Utilization (%)**: Percentage of resources used by corporations and factories in production, indicating economic slack.
- **Producer Price Index**: Measure of average change in selling prices received by domestic producers for their output.
- **Unemployment Rate (%)**: Percentage of labor force that is unemployed and actively seeking employment.
- **Total Federal Debt**: Outstanding debt obligations of the U.S. federal government.
- **Household Debt Service (%)**: Required household debt payments as a percentage of disposable personal income.
- **Credit Card Delinquency Rate (%)**: Percentage of credit card loans that are past due at commercial banks.
- **Employment Level**: Total number of employed persons in the civilian labor force.
- **National Unemployment Rate (%)**: National-level unemployment rate, potentially differing from other unemployment measures.
- **Labor Force Participation Rate (%)**: Percentage of working-age population that is either employed or actively seeking work.
- **Average Weekly Hours**: Average number of hours worked per week by production and nonsupervisory employees.
- **Average Hourly Earnings ($)**: Average hourly earnings of production and nonsupervisory employees on private nonfarm payrolls.

C. Temporal Features

- **Day of Week (sine)**: Sine encoding of day of week to capture cyclical weekly patterns.
- **Day of Week (cosine)**: Cosine encoding of day of week to capture cyclical weekly patterns.
- **Month (sine)**: Sine encoding of month to capture cyclical seasonal patterns.
- **Month (cosine)**: Cosine encoding of month to capture cyclical seasonal patterns.
- **Thanksgiving Week**: Binary indicator for the week containing Thanksgiving holiday.
- **Christmas Week**: Binary indicator for the week containing Christmas holiday.

D. Historical Target Variables

- **Target (4 days ago)**: Credit card spending amount from 4 days prior to current observation.
- **Target (5 days ago)**: Credit card spending amount from 5 days prior to current observation.
- **Target (6 days ago)**: Credit card spending amount from 6 days prior to current observation.

E. Weather Features

Weather data includes multiple meteorological variables with temporal lags ranging from 7 days prior to 6 days ahead, enabling the model to capture both historical weather impacts and weather forecast influences on spending behavior.

1) Maximum Temperature: Features representing daily maximum temperature (°C) with lags from -7 to +6 days.

2) Minimum Temperature: Features representing daily minimum temperature (°C) with lags from -7 to +6 days.

3) Precipitation: Features representing total daily precipitation (mm) with lags from -7 to +6 days.

4) Wind Speed: Features representing daily wind speed (kph) with lags from -7 to +6 days.

5) Relative Humidity: Features representing daily relative humidity (%) with lags from -7 to +6 days.

6) Solar Radiation: Features representing surface solar radiation downwards (W/m²) with lags from -7 to +6 days.

F. Derived Temperature Features

- **Temperature Difference (raw)**: Raw difference in temperature from baseline or reference period.
- **Temperature Rolling Mean**: Moving average of temperature over a specified window period.
- **Temperature Difference (smoothed)**: Smoothed version of temperature differences to reduce noise.
- **Temperature Seasonal Anomaly**: Deviation of current temperature from long-term seasonal average.

G. Holiday Features

The dataset includes comprehensive holiday indicators capturing major U.S. federal holidays and their immediate surrounding days, recognizing that consumer spending patterns are significantly influenced by holiday periods.

1) Major Holidays:

- **General Holiday Indicator**: Binary flag indicating any federal holiday.
- **New Year's Day/Eve**: Indicators for January 1st and December 31st, capturing year-end spending patterns.
- **Christmas Day/Eve**: Indicators for December 25th and 24th, representing peak holiday shopping periods.
- **Thanksgiving Day**: November holiday marking the beginning of the holiday shopping season.
- **Black Friday**: Day after Thanksgiving, traditionally the busiest shopping day of the year.
- **Independence Day**: July 4th federal holiday affecting summer spending patterns.

2) Federal Holidays:

- **Martin Luther King Jr. Day**: Third Monday in January federal holiday.
- **Presidents' Day**: Third Monday in February (Washington's Birthday observance).
- **Memorial Day**: Last Monday in May, marking unofficial start of summer.
- **Juneteenth**: June 19th federal holiday established in 2021.
- **Labor Day**: First Monday in September, marking unofficial end of summer.
- **Columbus Day**: Second Monday in October federal holiday.
- **Veterans Day**: November 11th federal holiday.

3) Religious Holidays:

- **Easter Sunday**: Moveable Christian holiday affecting spring spending.
- **Easter Monday/Saturday**: Days surrounding Easter Sunday.

4) Holiday Proximity Effects: Each major holiday includes indicators for the day before and day after, capturing:

- Pre-holiday shopping and preparation behaviors
- Post-holiday returns, exchanges, and continued shopping
- Extended weekend effects for holidays falling on weekdays
- Travel and tourism spending patterns around holiday periods

These proximity indicators recognize that consumer spending behavior extends beyond the specific holiday date, with significant economic activity occurring in the days immediately surrounding major holidays.

Appendix B
Hyperparameter Search Distributions

This appendix details the hyperparameter search spaces used for Optuna optimization across all evaluated ML models. Each parameter distribution was selected based on best practices from the literature and preliminary experimentation to ensure comprehensive exploration of the hyperparameter space.

A. Decision Tree Regressor

- **max_depth:** Integer range $\{3, 20\}$
- **min_samples_split:** Integer range $\{2, 20\}$
- **min_samples_leaf:** Integer range $\{1, 20\}$

B. Elastic Net

- **alpha:** Log-uniform float range $\{1 \times 10^{-2}, 1 \times 10^{1}\}$
- **l1_ratio:** Uniform float range $\{0.0, 1.0\}$
- **fit_intercept:** Categorical choices {"True", "False"}
- **selection:** Categorical choices {"cyclic", "random"}

C. Linear Regression

- **fit_intercept:** Categorical choices {True, False}
- **positive:** Categorical choices {False, True}

D. Random Forest Regressor

- **n_estimators:** Log-uniform integer range $\{50, 1000\}$
- **max_depth:** Integer range $\{3, 20\}$
- **min_samples_split:** Integer range $\{2, 20\}$
- **min_samples_leaf:** Integer range $\{1, 20\}$
- **max_features:** Categorical choices {"sqrt", "log2", None}

E. Stochastic Gradient Descent (SGD) Regressor

- **loss:** Categorical choices {"squared_error", "huber", "epsilon_insensitive", "squared_epsilon_insensitive"}
- **penalty:** Categorical choices {"l2", "l1", "elasticnet"}
- **alpha:** Log-uniform float range $\{1 \times 10^{-4}, 1 \times 10^{-1}\}$
- **l1_ratio:** Uniform float range $\{0.0, 1.0\}$

F. LightGBM

- **n_estimators:** Integer range $\{100, 3000\}$
- **num_leaves:** Integer range $\{10, 300\}$
- **learning_rate:** Log-uniform float range $\{0.001, 0.3\}$
- **feature_fraction:** Uniform float range $\{0.4, 1.0\}$
- **bagging_fraction:** Uniform float range $\{0.4, 1.0\}$
- **bagging_freq:** Integer range $\{1, 7\}$
- **min_child_samples:** Integer range $\{5, 100\}$
- **max_depth:** Integer range $\{3, 15\}$
- **reg_alpha:** Uniform float range $\{0.0, 10.0\}$
- **reg_lambda:** Uniform float range $\{0.0, 10.0\}$

G. XGBoost

- **n_estimators:** Integer range $\{100, 3000\}$
- **learning_rate:** Log-uniform float range $\{0.001, 0.3\}$
- **max_depth:** Integer range $\{3, 15\}$
- **min_child_weight:** Integer range $\{1, 10\}$
- **gamma:** Uniform float range $\{0.0, 0.5\}$
- **subsample:** Uniform float range $\{0.6, 1.0\}$
- **colsample_bytree:** Uniform float range $\{0.6, 1.0\}$

H. Iterative XGBoost

The Iterative XGBoost model uses fixed hand-tuned hyperparameters for each of its three constituent models rather than Optuna hyperparameter optimization. All three stages share the same base parameter configurations:

- **n_estimators:** 500
- **max_depth:** 4
- **learning_rate:** 0.03
- **gamma:** 0.5
- **subsample:** 0.65
- **colsample_bytree:** 0.65
- **reg_lambda:** 4
- **min_child_weight:** 3

The key difference between stages is the evaluation metric:

- **Stage 1 (Economic Features):** Uses MAE evaluation metric (eval_metric = "mae")
- **Stage 2 (Weather Features):** Uses default MSE evaluation metric
- **Stage 3 (Lagged Features):** Uses default MSE evaluation metric

Each stage applies these parameters sequentially within the three-stage architecture, with the evaluation metric difference allowing for stage-specific optimization behavior.

I. Optimization Settings

For all models (with the exception of Iterative XGBoost), the following Optuna configuration was used:

- **Number of trials:** 50 per model configuration
- **Sampling algorithm:** TPESampler (Tree-structured Parzen Estimator)
- **Cross-validation:** 5-fold consecutive temporal splits
- **Objective:** Minimize average MSE across cross-validation folds

The hyperparameter ranges were selected based on established best practices and preliminary grid search experiments to ensure adequate coverage of the parameter space while maintaining computational feasibility across our large-scale experimental design.

Appendix C
Example Correlation Matrix: Home Improvement Sub-industry of Florida

This appendix presents the correlation matrix for the Florida home improvement sub-industry as a representative example of the relationships between economic indicators, weather variables, and consumer spending. The matrix displays pairwise Pearson correlation coefficients for this specific state-industry combination across the study period. Recall that "spend_amount" is the target variable in our study.

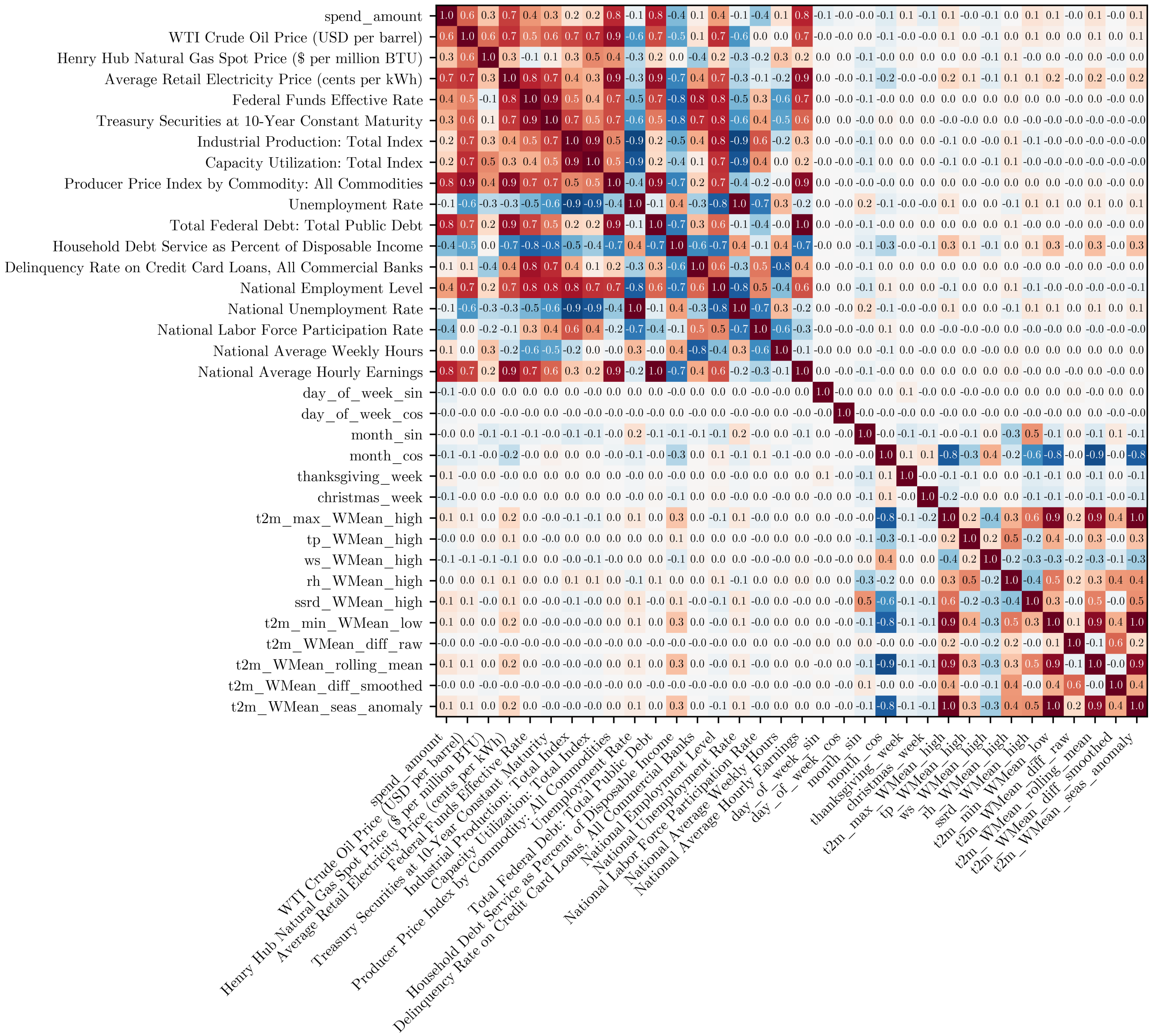

Fig. 11. Correlation matrix for Florida home improvement industry showing pairwise correlations between economic indicators, weather variables, and consumer spending. The color scale ranges from -1 (perfect negative correlation, dark blue) to +1 (perfect positive correlation, dark red), with white indicating no correlation. This representative example illustrates the typical relationship patterns observed across state-industry combinations in the dataset.