The Substantial 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 remains underutilized in predictive models. Grounded in the Stimulus-Organism-Response framework and demand theory, this study examines how weather acts as an environmental stimulus triggering behavioral responses that differentially affect spending across sectors of varying demand elasticity. We present a comprehensive evaluation of weather data integration for consumer spending prediction across three retail sectors: grocers, home improvement, casual dining. We employ a robust methodology involving eight distinct machine learning models, from linear regression to ensemble methods. Each is trained with and without weather features to isolate meteorological contributions independent of algorithmic choice. Our experimental framework encompasses 1.2 million individual model training runs across all 50 US states over 10 years, evaluating multiple scenarios ranging from operational forecasting to theoretical performance bounds. Models incorporating weather data achieve a mean symmetric Mean Absolute Percentage Error (sMAPE) improvement of 11.5% compared to baselines using only economic features, with some methods exhibiting statistically significant gains in 74% of combinations across states and industries. Performance gains vary systematically by sector, with grocers achieving 20.2% improvement, casual dining 12.2%, and home improvement 3.3%, reflecting differential weather sensitivity across necessity versus discretionary goods, consistent with demand theory predictions. These findings demonstrate weather data's substantial predictive value for consumer spending forecasting across diverse machine learning approaches and geographic contexts, with sector-specific performance differences reflecting underlying demand elasticity and weather-driven behavioral mechanisms predicted by economic theory.**

***Index Terms*—Consumer spending prediction; weather data integration; machine learning; 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, or adjusting performance-based compensation to account for weather-driven variance beyond managers' control [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]–[19].

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 [20]. 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

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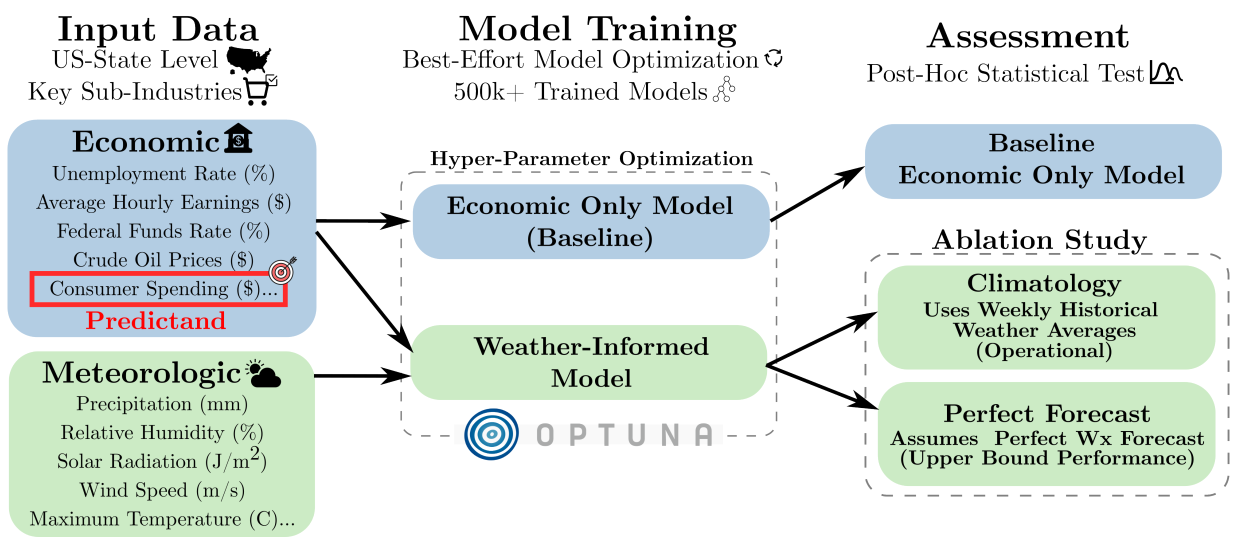


Fig. 1. Conceptual overview of the proposed study demonstrating the value of weather data integration in consumer spending prediction. The Baseline forecasting approach relies exclusively on historical spending patterns, macroeconomic indicators, and labor market data, resulting in higher prediction errors. The Weather-Informed models are trained incorporating comprehensive meteorological features including historical and 7-day forecast data for temperature, precipitation, wind speed, humidity, and solar radiation in addition to economic features. Models trained with weather data are evaluated in two scenarios to elucidate weather's role: Climatology uses weekly historical weather averages (operationally deployable using only past data available at prediction time), while Perfect Forecast uses actual observed weather (upper bound performance). Weather-informed models substantially outperform Baseline, with Climatology and Perfect Forecast achieving mean sMAPE improvement of 11.5% (Table II) and RMSE improvement up to 60% (Figure 4). Performance gains are generally realized across eight ML algorithms and U.S. geographic regions, with weather-sensitive sectors (grocers, casual dining) achieving substantial improvements (12-20%) while project-based categories show more limited gains, demonstrating weather data's value varies systematically by industry characteristics.

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.

Grounded in the Stimulus-Organism-Response (S-O-R) model and demand theory [21], we hypothesize that weather acts as an environmental stimulus evoking psychological responses (e.g., risk perception, mood alterations, and anticipatory behaviors) that differentially affect spending across sectors of varying demand elasticity: necessity goods see increases during threats (e.g., grocers: stockpiling essentials), while discretionary goods experience decreases or shifts (e.g., home improvement: deferred projects but preparatory actions like boarding up windows, followed by post-event repairs; casual dining: reduced mobility but potential recovery surges). Consequently, 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.**

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.

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 industries to demonstrate weather's predictive value across various sectors, and assess results across 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, industries, and US states to identify top-performing models and assess both subindustry-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 [22], or ride-hailing services [23]-these efforts have been constrained by narrow scope and limited methodological validation. This paper makes three key contributions to establish the substantial value of weather data in demand forecasting:

1) **Multi-Subindustry 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, casual dining.). This approach provides a more holistic understanding than is possible with single-subindustry 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 [24], and post hoc statistical testing. This addresses the methodological gaps of prior work [25], [26] and validates the performance of eight machine learning models, from off-the-shelf (OTS) algorithms to a domain-enriched model.
3) **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, see Figure 4) 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 substantially valuable feature, not a region-specific or model-dependent phenomenon.

While deep learning architectures like Long Short-Term Memory (LSTM) networks and Transformers have shown state-of-the-art performance in certain time-series domains [27], we intentionally excluded them from this analysis. Although these models can capture complex temporal dependencies and non-linear patterns that *shallow* methods may miss, several critical trade-offs informed our decision.

First, deep learning architectures require substantially larger datasets per model configuration to garner good results, which is problematic given our state-level granularity yields relatively modest sample sizes per geographic unit. Second, computational costs scale dramatically: a single LSTM hyperparameter search across our experimental scope (50 states × 3 industries) would require 10-100x more GPU hours than our current framework, potentially necessitating months of continuous training. Given our 1.2M individual model training runs, computational efficiency was essential.

Most critically, the vast architectural search space (layer depth, hidden units, dropout rates, attention mechanisms) and "black box" nature risk transforming our study from hypothesis testing about weather's value into an engineering optimization exercise. Our goal is to isolate and interpret weather's contribution to demand forecasting, not to achieve absolute predictive accuracy through architectural complexity. The chosen models provide sufficient sophistication to capture weather effects while maintaining interpretability and computational feasibility.

This approach aligns with findings from large-scale forecasting competitions, which 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 novel algorithms [18]. By focusing on a broad suite of established models with rigorous evaluation, we provide practically relevant conclusions about weather data's role in demand forecasting.

D. Subindustry-Specific Weather Sensitivity Mechanisms

Weather influences each retail category through distinct economic mechanisms that generate predictable differential effects [28]:

Grocery spending follows necessity good patterns with intertemporal substitution behavior. Adverse weather conditions trigger advance purchasing (stockpiling) as consumers anticipate mobility constraints and supply disruptions [29]. Since food represents non-deferrable consumption, weather primarily shifts purchase timing rather than total demand, creating predictable spikes before adverse conditions and temporary declines during severe weather. This behavior reflects standard demand theory for necessity goods with low price and income elasticity [30].

casual dining operates as discretionary, mobility-dependent consumption. Weather directly affects the transaction costs of restaurant visits through driving conditions, parking availability, and pedestrian comfort [31]. Unlike groceries, restaurant meals can be easily substituted with home cooking, making this category highly weather-elastic. Severe weather creates sharp demand collapses rather than temporal shifts.

Home improvement represents planned, seasonally-sensitive purchases where weather affects both feasibility and consumer motivation. Projects requiring outdoor work face direct weather constraints, while indoor projects may increase during confined periods. This category exhibits seasonal patterns as consumers time purchases around weather-suitable implementation periods.

These mechanism-based differences predict that casual dining will show the highest weather volatility, groceries will exhibit temporal substitution patterns, and home improvement will demonstrate seasonal optimization behaviors. Section II-C provides the full theoretical grounding for these mechanisms within the S-O-R framework and demand theory.

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 [32] 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 [28] found that the impact of weather on daily sales can be as high as 23.1% by location, rising to 40.7% for certain 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 [33] and seasonal garments [34], 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 [35] 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 [36] 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 substantial 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. [19], 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.

C. Theoretical Framework for Weather's Influence on Consumer Spending

While empirical studies have demonstrated weather's impact on consumer behavior, a robust theoretical lens is essential to explain the underlying mechanisms. This study draws on the Stimulus-Organism-Response (S-O-R) model, originally proposed by Mehrabian and Russell [21], to conceptualize how meteorological conditions drive spending patterns. In the S-O-R framework, environmental stimuli (S) evoke internal organism states (O), such as emotional or cognitive responses, which in turn elicit behavioral responses (R) like purchase decisions. Applied to retail forecasting, weather serves as a dynamic stimulus that influences consumers' psychological states, ultimately affecting their spending across sectors.

Adverse weather, such as extreme temperatures, precipitation, or high humidity, acts as a stimulus by altering perceived comfort and risk. For instance, heatwaves or storms may induce negative affective states (e.g., discomfort or anxiety), leading to risk-averse behaviors like reduced mobility or delayed purchases. During extreme weather events like hurricanes or snowstorms, consumers often stock up on essential supplies in preparation, reflecting anticipatory responses to potential disruptions [29]. Conversely, favorable conditions (e.g., mild sunshine) can enhance positive moods [37], [38], boosting impulsive or experiential spending. These organism responses align with psychological mechanisms, including mood congruence theory [39], [40] (where sunny weather elevates optimism and spending willingness and risk perception [41]), where severe weather heightens caution, redirecting budgets toward essentials.

The selection of grocers, home improvement, and casual dining as focal industries provides a compelling framework for evaluating the incremental predictive power of weather forecasts in short-term consumer spending models. Grocers exemplify essential retail, where weather events like impending storms or extreme temperatures can trigger immediate shifts in purchasing behavior, such as stockpiling perishables or adjusting to supply chain disruptions, thereby illustrating weather's role in forecasting staple goods demand. In contrast, the home improvement sector represents durable goods and project-based consumption, often influenced by seasonal or favorable conditions for outdoor activities like landscaping or renovations, allowing for an analysis of how forecasts mitigate uncertainties in discretionary yet weather-dependent spending. Casual dining, as a hospitality subcategory, captures leisure-oriented expenditures sensitive to daily weather variations, such as rain deterring outdoor seating or heatwaves boosting iced beverage sales, underscoring the impact on impulsive, experience-driven choices. Together, these diverse categories—spanning necessities, home maintenance, and dining out—demonstrate the robustness of weather-integrated models by showcasing improvements across heterogeneous economic segments, reducing potential biases from subindustry-specific idiosyncrasies and strengthening the generalizability of the findings.

Integrating demand theory [30] differentiates weather's effects across retail industries, which is why we selected grocers, home improvement, and casual dining for this study. These sectors represent a spectrum of demand elasticity and weather sensitivity: grocers exemplify inelastic necessities prone to stockpiling; home improvement involves semi-discretionary items tied to outdoor conditions and post-event repairs; and casual dining captures highly elastic, mobility-dependent experiences. Necessity goods, such as groceries, exhibit inelastic demand; consumers may increase spending during inclement weather due to stockpiling (e.g., buying perishables before a storm), reflecting survival-oriented responses in the S-O-R chain. In contrast, discretionary goods like home improvement items (e.g., outdoor tools or materials for boarding up windows) or casual dining experiences are more elastic and weather-sensitive; adverse conditions deter non-essential activities, as consumers defer purchases to avoid discomfort or opportunity costs (e.g., staying indoors during rain reduces dining outings). For instance, snowstorms often cause a dip in restaurant traffic, as people are unable or unwilling to venture out due to hazardous conditions [31] Some establishments, however, demonstrate resilience; the "Waffle House Index" [42] gauges disaster severity based on the chain's operational status, highlighting how certain restaurants reopen quickly post-disaster to serve communities [43]. After a storm, spending effects persist due to factors like economic recovery efforts (e.g., insurance payouts fueling rebuilding and repairs), supply chain disruptions delaying restocking, lost income from layoffs reducing overall consumption, psychological trauma altering priorities toward essentials or impulsive buys, and shifts in government aid or income transfers temporarily boosting disposable income in affected areas [44], [45]. This aligns with Maslow's hierarchy [46], where basic needs (necessities) take precedence during environmental threats, while higher-order desires (discretionary) are suppressed.

By anchoring our analysis in S-O-R and demand theory, this study moves beyond descriptive patterns to a mechanistic understanding of weather's role. For example, in grocers, weather stimuli trigger proactive responses like bulk buying; in home improvement, they may halt project initiation but spur post-event repairs; and in casual dining, they influence social mobility and recovery dining. This framework not only justifies our multi-subindustry scope but also highlights the need for weather-integrated models to capture these nuanced dynamics, addressing gaps in past research.

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, subindustry-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 quantifying its substantial value and establishing a new benchmark for weather-integrated demand forecasting.

We selected these three categories because they represent distinct theoretical archetypes of weather sensitivity: (1) Groceries exemplify necessity goods with stockpiling potential and low substitutability; (2) Casual dining represents discretionary services with high mobility dependence and easy substitutability; (3) Home improvement reflects planned purchases with seasonal timing flexibility. This selection enables systematic evaluation of how fundamental economic mechanisms translate to weather forecasting improvements across distinct consumer behavior patterns.

B. Core Experimental Framework

Our forecasting objective is to predict next-day consumer spending amounts $(t + 1)$ using only information available through day t, reflecting realistic operational constraints where predictions must be made before the target day begins. Our experimental design trains two model types and evaluates three prediction scenarios

We train an **economic-only model** (Baseline) and an **economic + weather model** (used for both Climatology and Perfect Forecast scenarios). The three prediction scenarios are:

- **Baseline**: Uses the economic-only model with no weather variables.
- **Climatology**: Uses the economic + weather model, but replaces all weather-derived features (both raw values and engineered features like rolling means and anomalies) with their corresponding long-term weekly averages computed from historical data (2015-2022). This substitution occurs during prediction time, representing operational forecasting using only climatological patterns without day-specific weather information. Represents operationally realistic forecasting without weather forecast models.

- **Perfect Forecast**: Uses the economic + weather model with actual observed weather during prediction. Represents an upper bound assuming perfect weather forecast accuracy.

The Baseline and Climatology configurations use no future information and are operationally deployable, while Perfect Forecast establishes the theoretical maximum value of weather information under perfect foresight. Comparing Baseline vs. Climatology quantifies the value of incorporating climatological patterns, while comparing Climatology vs. Perfect Forecast quantifies the additional value of accurate day-to-day weather forecasts.

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. A total of three missing values were imputed using linear interpolation, reflecting the high quality and completeness of our data sources, 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 subindustry level (grocers, home improvement, casual dining.) at a daily frequency. This serves as our target variable (predictand) for all forecasting models. The data is derived from a longitudinally consistent panel of credit and debit cardholders with modest geographic balancing applied across all 50 states to reflect population distribution. The panel skews slightly older and higher income relative to the overall U.S. population, as it excludes the unbanked segment. While the underlying data infrastructure supports analysis at fine geographic granularity (Combined Statistical Area, first three-digits of ZIP code, and merchant address levels), we obtained the spending data pre-aggregated at the state level. This aggregation level provides sufficient sample sizes for robust model training across all 50 geographic units and three retail industries, though it limits our ability to examine intra-state heterogeneity such as urban-rural consumption differences.

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).

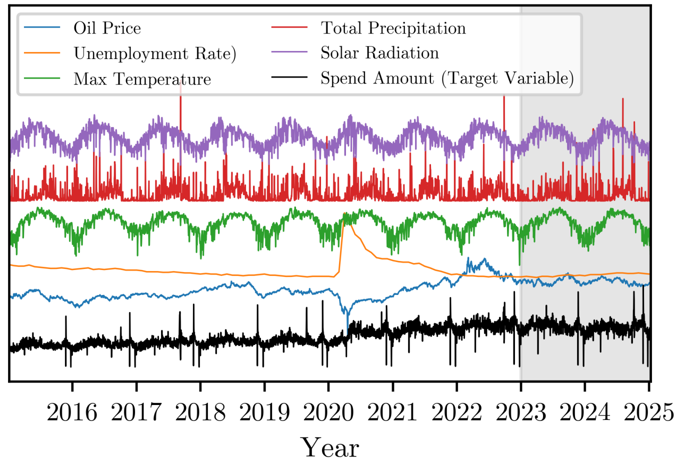


Fig. 2. Sample time series from our dataset including predictors and our predictand (Spending Amount). Values scaled and shifted for visualization clarity. The gray area represents our test period with the remaining date range used for training and validation. The train and test periods are mutually exclusive (non-overlapping) to assure no data leakage between them.

3) Weather Data: We incorporate comprehensive weather data from ERA5 reanalysis [47] 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. Complete definitions of all weather variables with units and processing methods are provided in Appendix A.

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 subindustry, illustrating typical variable relationships, is provided in Appendix P.

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 Models):** We engineered features from a window of 7 days prior to the target date and 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. For the Climatology configuration, each computed rolling mean value was replaced with the historical weekly average of rolling means for the corresponding week of year.
- *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 subindustry and state, every model was trained and evaluated for both the Baseline and Weather-Informed feature sets.

1) **Linear Regression [48]:** 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 [49]:** 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 [50]:** 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 [51]:** 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 [52]:** 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 [53]:** 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 [54]:** 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 [55] 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, 2022, and a hold-out test set covering January 1, 2023 to January 11, 2025 (see Figure 2 for depiction). This approach prevents data leakage between train and test sets.

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 14 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 configuration mirrors operational deployment, where predictions use only information available at prediction time.

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.

Feature Collinearity Handling for Linear Methods: For the linear least squares-based methods (Linear Regression, Elastic Net Regression, and SGD Regression), we employed Variance Inflation Factor (VIF) filtering as a pre-conditioning step. In each cross-validation run, we computed VIF scores for the features and, if any exceeded the selected threshold, iteratively removed the feature with the highest VIF score before recomputing the scores. This process repeated until all remaining VIF scores were below the threshold. The threshold itself was treated as a hyperparameter and optimized during the Optuna process. This procedure was implemented to address multicollinearity, which can result in unstable coefficient estimates and degraded model performance in linear models.

Hyperparameter Optimization Protocol: Each model undergoes extensive hyperparameter tuning using the Optuna framework (details in Appendix G4) with 100 optimization trials per configuration with each trial composed of a 5-fold temporal split cross validation (CV). We employ CV by splitting the data into 5 uniformly spaced consecutive temporal blocks to preserve time series integrity and minimize leakage between train and validation sets, with the average MSE across folds serving as the optimization objective. Our approach treats each forecast initialization as an independent learning sample. Unlike iterative autoregressive methods that chain predictions together (using predicted values to generate subsequent predictions), we predict each day independently using only actual observed features. This avoids dependencies that would be disrupted by autoregressive predictions with temporal gaps in the training data (e.g., when blocks 1, 2, 4, 5 are used for training and block 3 serves as validation). Upon completion of hyperparameter optimization, we retrain each model on the entire training dataset using the optimal parameters identified through cross-validation to produce the final model used for test evaluation.

Training Scale and Scope: We train models across 3 industries - 50 US states - 2 weather configurations - 8 ML algorithms, yielding 2,400 unique model configurations. With 100 Optuna trials per configuration and 5-fold cross-validation per trial, our evaluation encompasses 1.2M 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: symmetric Mean Absolute Percentage Error (sMAPE) [56] 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 industries.

Symmetric Mean Absolute Percentage Error (sMAPE) [56]: sMAPE expresses prediction accuracy as a symmetric percentage error, enabling direct comparison across states and industries with vastly different spending scales. It is defined as:

$$\text{sMAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{0.5(|y_i| + |\hat{y}_i|)} \tag{2}$$

sMAPE improves upon traditional MAPE by providing symmetric treatment of over- and under-predictions while avoiding numerical instability when values approach zero [19]. The metric's scale-invariant property is essential for our multi-state analysis, given that daily consumer spending ranges from thousands of dollars in smaller states to millions in larger markets. This enables meaningful aggregation of results across heterogeneous geographic and sector contexts without bias toward high-volume states. Lower sMAPE values indicate better forecast accuracy.

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):

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

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.

TABLE I
TOP PERFORMING MODEL-WEATHER CONFIGURATIONS

Rank	ML Model	Weather Info	sMAPE (95% CI)	Gap from Best
1	XGBoost	Perfect Forecast	14.0 (13.1–14.8)	—
2	XGBoost	Climatology	14.1 (13.3–15.0)**	+0.9%
3	LightGBM	Climatology	14.2 (13.4–15.1) ns	+1.8%
4	Elastic Net	Perfect Forecast	14.3 (13.6–15.1) ns	+2.5%
5	Elastic Net	Climatology	14.4 (13.7–15.1) ns	+2.6%
6	LightGBM	Perfect Forecast	14.4 (13.6–15.2) ns	+2.7%
7	Elastic Net	No Weather	14.4 (13.7–15.1) ns	+2.8%

Note: Rankings of the best-performing forecasting configurations by sMAPE, evaluated across eight machine learning models and three weather information scenarios. Gap from Best shows the percentage increase in forecast error relative to the top performer. Statistical significance compares each configuration against the best performer using Heteroskedasticity and Autocorrelation Consistent (HAC)-robust Diebold-Mariano tests with Benjamini-Hochberg correction for multiple comparisons (23 comparisons = 8 ML models x 3 weather scenarios - 1 reference). Results provide practitioners with evidence-based guidance for selecting optimal forecasting configurations. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; ns = not significant; — = baseline.

Statistical Significance Testing: We report 95% confidence intervals for all performance metrics using bootstrap resampling (1,000 iterations, percentile method). To validate the robustness of our findings, we apply HAC-robust Diebold-Mariano (DM) tests [57] with Benjamini-Hochberg correction [58] to compare forecast errors between model configurations. The DM test is specifically designed for comparing predictive accuracy of competing forecasts and accounts for the temporal dependence inherent in forecast errors. We pool forecast errors at the corresponding aggregation level to maintain 741-day error series for valid temporal testing. We implement HAC-robust standard errors using the Newey-West (NW) estimator [59] with a bandwidth of 30 lags, chosen based on the empirical autocorrelation function of forecast errors, which exhibits significant autocorrelation at weekly and seasonal intervals reflecting the cyclical nature of consumer spending patterns (e.g., higher spending on weekends). Benjamini-Hochberg correction controls the false discovery rate across our numerous model-scenario combinations. Importantly, we did not conduct 2,400 separate hypothesis tests requiring correction. Our statistical framework follows standard forecasting evaluation protocols where model training (including the 1.2M runs for hyperparameter tuning via cross-validation) is methodologically distinct from model comparison (the statistical inference performed on final test set predictions). The Benjamini-Hochberg correction applies only to the comparisons of final model configurations, not to the internal optimization process. This approach provides statistical confidence in our results while properly accounting for heteroskedasticity and autocorrelation characteristic of economic time series forecast errors.

Reporting Conventions: Throughout this paper, performance metrics (sMAPE, RMSE) and confidence intervals are reported rounded to one decimal place for readability. Percentage improvements and statistical comparisons are calculated using full-precision values prior to rounding. This ensures accurate statistical inference while maintaining readable tables.

IV. RESULTS & ANALYSIS

A. Overall Performance Results

Our comprehensive evaluation demonstrates that incorporating weather data substantially improves consumer spending prediction accuracy. Table II shows that Weather-Informed models achieve a mean sMAPE reduction of 11.5% compared to baseline models across all algorithms, industries, and geographic regions. This improvement is consistent whether using climatological averages (11.5% reduction) or a perfect forecast (11.5% reduction), indicating that most predictive value comes from capturing weekly historical weather patterns rather than a calendar-informed Baseline.

Table I identifies the best-performing model-weather configurations. XGBoost with Perfect Forecast achieves the lowest overall error (sMAPE = 14.0%), though the performance differences among top configurations are modest. Notably, XGBoost with Climatology performs nearly identically (sMAPE = 14.1%), reinforcing that operational models using only historical weather averages can capture most of the available weather signal without requiring sophisticated forecast models.

Figure 3 presents the distribution of sMAPE values across all state-subindustry combinations for each model and weather configuration. Weather-Informed models (violet and green) often show lower error distributions than Baseline models (red) across all eight evaluated algorithms.

Sector-specific analysis (Table III) reveals differential weather sensitivity. Grocers demonstrate the strongest response to weather information (20.2% mean improvement with Climatology), consistent with necessity goods exhibiting stockpiling behavior during adverse weather. Casual dining shows moderate improvements (12.2%), reflecting discretionary spending's mobility dependence. Home Improvement exhibits the smallest gains (3.3%), suggesting that project-based purchases are less sensitive to short-term weather variations.

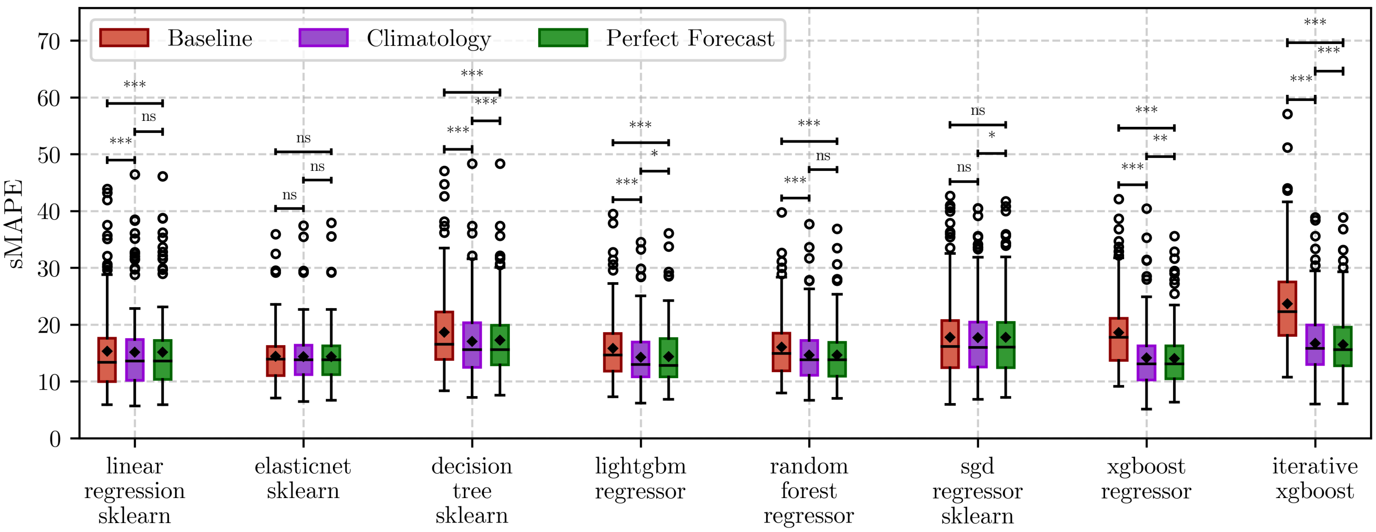


Fig. 3. Comparison of sMAPE distributions for eight ML models with and without weather data. sMAPE values were calculated separately for each state-subindustry then averaged to treat each economic context as an equal experimental unit. Box plots show the distribution of sMAPE values across U.S. states and industries. Weather-Informed models (green and violet) often demonstrate lower prediction errors compared to Baseline models (red) across most of the tested algorithms. 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. Black diamonds represent the mean sMAPE values for each distribution. Statistical significance assessed using the HAC-robust Diebold-Mariano test with Benjamini-Hochberg correction for multiple comparisons (3 pairwise comparisons for each group). Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; ns = not significant. More detail available in Table V.

Examining individual model-subindustry combinations (Table V) confirms these sector patterns hold across diverse algorithmic approaches: grocers consistently show the largest improvements, casual dining shows moderate gains, and home improvement exhibits the smallest benefits regardless of model architecture. This consistency demonstrates that underlying demand elasticity, rather than algorithmic choice, primarily determines weather's predictive value.

B. Geographic Distribution of Improvement

Weather data provides benefits across all U.S. geographic regions, not just areas with extreme weather volatility. Figure 4 displays state-level RMSE improvements for XGBoost (the top-performing model per Table I) across all three industries. Improvements may range to over 60%, with a median improvement of 15.7% across all state-subindustry combinations.

Regional patterns (Table IV) show weather benefits across climate zones. The Pacific region achieves the largest gains (19.9% sMAPE improvement), while high-variability regions like Great Plains (17.1%) and South Central (16.5%) also show substantial benefits. The Northeast demonstrates the smallest but still statistically significant improvements (4.8%). Notably, the magnitude of improvement does not correlate simply with weather volatility. The Pacific region (CA, OR, WA), characterized by relatively stable, temperate conditions, achieves the highest improvement of any region, suggesting that weather's predictive value depends on sector mix and consumer behavior patterns rather than merely climate variability.

Statistical testing confirms these geographic improvements are robust across state-subindustry combinations as shown in Figure 5. HAC-robust Diebold-Mariano testing with Benjamini-Hochberg correction comparing Baseline vs. Climatology XGBoost models show significant improvements ($p < 0.01$) in 111 of 150 state-subindustry combinations (74%). Only 25 state-subindustry pairs show non-significant differences, primarily in the Home Improvement sector where we observe weather sensitivity is inherently lower.

While the majority of states show substantial improvements, a small number of state-subindustry combinations (notably Maine, Massachusetts, Minnesota) exhibit minimal or negative effects with weather data, suggesting geographic or data-specific factors that warrant future investigation.

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 (2023-2025) where ground truth appears in grey and Weather-Informed predictions in green. The visualization reveals how 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 Climatology 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

TABLE II
IMPACT OF WEATHER INFORMATION ON FORECAST PERFORMANCE

Weather Condition	Mean (95% CI)	Median (SD)	% Improvement Mean	Sig.
Baseline	17.5 (17.1–17.9)	15.7 (7.1)	—	—
Climatology	15.5 (15.1–15.8)	14.1 (6.1)	11.5	***
Perfect Forecast	15.5 (15.2–15.9)	14.2 (6.1)	11.5	***

Note: The table presents sMAPE statistics for consumer spending forecasts under three weather information conditions: Baseline (no weather data), Climatology (historical weather averages), and Perfect Forecast (idealized perfect forecast). Mean sMAPE values are reported with 95% confidence intervals (CI) obtained via bootstrap resampling. Median and standard deviation (SD) are also reported. Percentage improvement is calculated relative to the no-weather baseline. Statistical significance assessed using the HAC-robust Diebold-Mariano test with Benjamini-Hochberg correction for multiple comparisons (2 comparisons). Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; ns = not significant; — = baseline.

TABLE III
FORECAST PERFORMANCE BY SUBINDUSTRY

Subindustry	Baseline (95% CI)	Climatology (95% CI)	% Imp. (vs. Base)	Sig.	Perfect Forecast (95% CI)	% Imp. (vs. Base)	Sig.
Casual Dining	19.2 (18.5–20.1)	16.9 (16.3–17.6)	12.2	***	17.0 (16.4–17.7)	11.5	***
Grocers	15.5 (14.8–16.2)	12.3 (11.9–12.8)	20.2	***	12.5 (12.1–12.9)	19.4	***
Home Improvement	17.8 (17.2–18.4)	17.2 (16.6–17.8)	3.3	***	17.0 (16.4–17.5)	4.6	***

Note: Mean sMAPE statistics with 95% bootstrap confidence intervals for each retail subindustry, pooled across all eight forecasting models and aggregated over daily periods. Data were first grouped by subindustry, weather condition, and day, then averaged across all days within each subindustry-weather combination. Both percentage improvements are calculated relative to the no-weather baseline. Significance testing compares climatology vs. baseline and perfect forecast vs. baseline using HAC-robust Diebold-Mariano tests with Benjamini-Hochberg correction for multiple comparisons (6 comparison = 3 subindustries x 2 weather scenarios). Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; ns = not significant; — = baseline.

TABLE IV
FORECAST PERFORMANCE BY US CLIMATE REGION

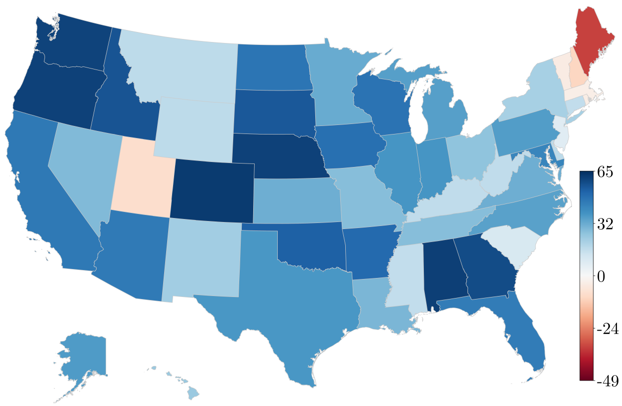
Region	Baseline (95% CI)	Climatology (95% CI)	% Imp. (vs. Base)	Sig.	Perfect Forecast (95% CI)	% Imp. (vs. Base)	%Imp. (Perf. Vs. Clim.)	Sig.
Arctic	21.9 (18.6–25.2)	19.6 (16.7–22.5)	10.7	***	19.8 (16.8–23.0)	9.7	-1.1	*
Arid West	14.5 (13.5–15.6)	12.7 (11.8–13.8)	12.4	***	12.8 (11.9–13.8)	11.5	-1.1	*
Great Lakes	18.9 (17.8–20.0)	16.6 (15.8–17.4)	12.1	***	16.6 (15.8–17.4)	12.3	0.2	ns
Great Plains	20.1 (18.6–21.7)	16.7 (15.8–17.7)	17.1	***	16.6 (15.7–17.6)	17.2	0.1	ns
Mountain West	16.8 (15.5–18.2)	14.7 (13.5–16.0)	12.4	***	14.8 (13.6–16.0)	12.2	-0.3	ns
Northeast	18.7 (17.9–19.5)	17.8 (17.0–18.6)	4.8	***	17.7 (17.0–18.6)	5.0	0.2	ns
Pacific	14.4 (12.9–16.0)	11.5 (10.3–12.9)	19.9	***	11.7 (10.5–13.2)	18.5	-1.7	***
South Central	14.6 (13.4–15.9)	12.2 (11.4–12.9)	16.5	***	12.0 (11.3–12.7)	17.8	1.5	*
Southeast	16.1 (15.5–16.8)	13.9 (13.4–14.4)	13.6	***	13.9 (13.4–14.5)	13.6	0.0	ns
Tropical	22.6 (19.4–25.9)	19.7 (17.6–22.3)	12.5	***	19.8 (17.3–22.1)	12.4	-0.1	ns

Note: Forecast Performance by Climate Region. sMAPE statistics with 95% bootstrap confidence intervals for each U.S. climate region, pooled across all eight forecasting models, three retail subindustries, and aggregated over daily periods. Data were first grouped by region, weather condition, and day, then averaged across all days within each region-weather combination. Both percentage improvements are calculated relative to the no-weather baseline. Significance testing compares both climatology vs. baseline using HAC-robust Diebold-Mariano tests on regionally-pooled forecast errors, with Benjamini-Hochberg correction for multiple comparisons (20 comparison = 10 regions x 2 weather scenarios). Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; ns = not significant; — = baseline.

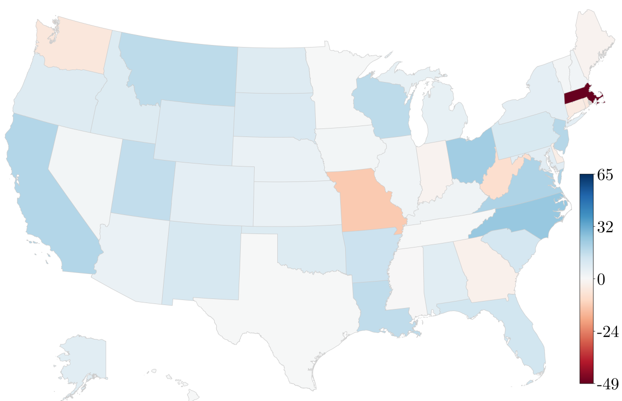
TABLE V
DETAILED MODEL PERFORMANCE BY SUBINDUSTRY

Model	Subindustry	sMAPE (95% CI)			% Improvement		Overall Model Performance		
		Baseline	Climatology	Perfect	vs. Base (Clim)	vs. Base (Perf)	Baseline Mean	Climatology Mean	Perfect Forecast Mean
Decision Tree	Casual Dining	17.5 (15.7–19.4)	15.7 (14.4–17.3)	15.8 (14.5–17.4)	10.0***	9.4***	18.6	17.0	17.2
	Grocers	17.6 (16.1–19.5)	15.1 (13.7–16.5)	15.5 (14.1–17.0)	14.5***	12.3***			
	Home Improvement	20.7 (18.8–22.8)	20.2 (18.3–22.2)	20.3 (18.7–22.4)	2.4*	1.7 ns			
Elastic Net	Casual Dining	16.0 (14.9–17.2)	16.0 (14.9–17.2)	16.1 (15.0–17.5)	0.0 ns	-0.6*	14.4	14.4	14.3
	Grocers	10.8 (10.2–11.5)	10.8 (10.2–11.5)	10.9 (10.2–11.6)	0.1 ns	-0.3 ns			
	Home Improvement	16.3 (15.1–17.7)	16.3 (15.0–17.7)	16.1 (14.9–17.4)	0.4 ns	1.6***			
Iterative XGBoost	Casual Dining	27.3 (25.7–29.0)	17.8 (16.7–19.2)	17.7 (16.6–19.0)	34.7***	34.9***	23.6	16.7	16.5
	Grocers	23.8 (21.5–26.3)	13.8 (12.4–15.3)	13.7 (12.5–15.1)	41.9***	42.4***			
	Home Improvement	19.9 (18.1–22.2)	18.4 (16.4–20.5)	18.0 (16.1–20.1)	7.6 ns	9.7*			
LightGBM	Casual Dining	14.9 (13.6–16.2)	14.1 (13.0–15.7)	14.4 (13.2–15.8)	5.0***	3.2***	15.8	14.2	14.4
	Grocers	14.9 (13.6–16.3)	12.6 (11.6–13.7)	12.9 (11.9–14.1)	15.3***	13.2***			
	Home Improvement	17.5 (15.9–19.3)	16.0 (14.4–17.5)	15.8 (14.2–17.5)	8.9***	10.1***			
Linear Regression	Casual Dining	20.6 (18.0–23.2)	19.8 (17.5–22.2)	20.0 (17.7–22.4)	3.8***	3.1***	15.3	15.1	15.1
	Grocers	9.5 (9.0–9.9)	9.8 (9.2–10.4)	9.8 (9.2–10.6)	-3.2***	-3.9***			
	Home Improvement	15.7 (14.4–17.0)	15.8 (14.4–17.3)	15.6 (14.3–17.1)	-0.1 ns	1.0**			
Random Forest	Casual Dining	14.4 (13.0–15.9)	14.1 (12.7–15.6)	14.1 (12.7–15.6)	2.6**	2.4**	16.0	14.7	14.6
	Grocers	15.4 (14.3–16.5)	12.4 (11.6–13.3)	12.6 (11.8–13.4)	19.1***	18.2***			
	Home Improvement	18.2 (16.5–19.9)	17.5 (15.9–19.1)	17.2 (15.6–18.7)	4.1***	5.8***			
SGD	Casual Dining	23.7 (21.5–25.9)	23.1 (21.0–25.1)	23.3 (21.2–25.5)	2.5***	1.5***	17.7	17.7	17.8
	Grocers	12.8 (11.8–13.9)	12.9 (11.9–13.9)	13.0 (12.0–14.0)	-1.3*	-1.8**			
	Home Improvement	16.7 (15.5–18.1)	17.0 (15.7–18.4)	17.0 (15.7–18.4)	-1.7***	-1.2*			
XGBoost	Casual Dining	19.6 (17.9–21.4)	14.5 (13.3–15.9)	14.8 (13.6–16.0)	25.9***	24.6***	18.6	14.1	14.0
	Grocers	19.1 (17.5–21.1)	11.4 (10.2–12.5)	11.5 (10.3–12.6)	40.5***	39.9***			
	Home Improvement	17.0 (15.3–18.9)	16.5 (14.8–18.5)	15.7 (14.0–17.5)	3.2*	7.6***			

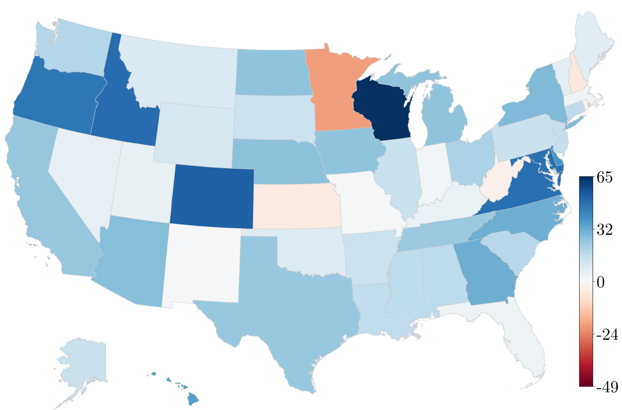
Note: Model Performance by Subindustry and Overall Aggregate. sMAPE statistics with 95% bootstrap confidence intervals for each model-subindustry-weather combination, aggregated over 741 daily forecast periods across all geographic regions. Subindustry-specific columns show performance for each of the three retail categories (grocers, home improvement, casual dining). Percentage improvements are calculated relative to the Baseline (no weather), with significance testing comparing Climatology vs. Baseline and Perfect Forecast vs. Baseline using HAC-robust Diebold-Mariano tests with Benjamini-Hochberg correction for multiple comparisons (48 comparisons = 8 models × 3 subindustries × 2 weather scenarios). Overall Model Performance columns show aggregate sMAPE across all subindustries for each weather condition, displayed only on the first row of each model. Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; ns = not significant; — = baseline.



(a) Grocers



(b) Home Improvement



(c) Casual Dining

Fig. 4. Percentage improvement in RMSE for consumer spending prediction across three retail industries and all U.S. states when incorporating weather data. The heatmap shows the performance gain of Perfect Forecast models compared to Baseline models using XGBoost for each state-subindustry combination (similar results for Climatology model). Weather data improves prediction accuracy across diverse geographic regions and retail sectors, with median improvements of 16.1% (mean improvements of 18.2%) and even exceeding 60%, demonstrating the value of meteorological features in demand forecasting.

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 Perfect Forecast 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 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 our theoretical mechanisms in action. Casual dining shows sharp collapses during the storm period, consistent with mobility barriers severely constraining discretionary restaurant visits. The Weather-Informed models (green lines) consistently track these dramatic spending drops more accurately than baseline models (red lines), capturing both the magnitude and timing of weather-driven behavioral responses. These patterns validate that weather effects operate through correlated economic mechanisms: mobility-dependent discretionary services show immediate, sharp demand destruction during adverse conditions as the theoretical framework predicts.

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 [60], [61]. 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 [61]. 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 [62], [63]. The restaurant subindustry 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 [64].

Spending Pattern Analysis: Figure 8 presents South Dakota casual dining spending data during the Winter Storm

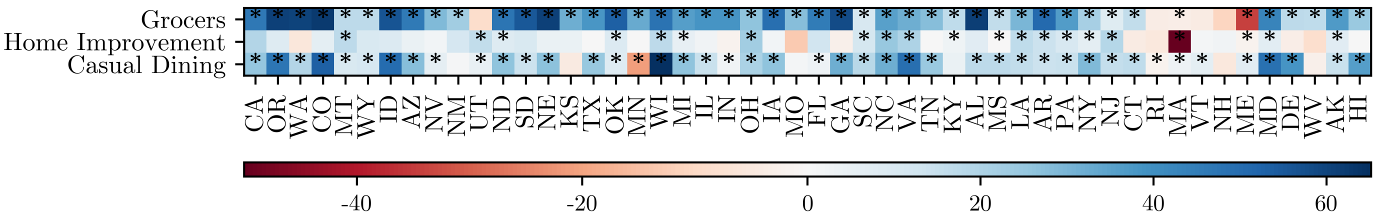
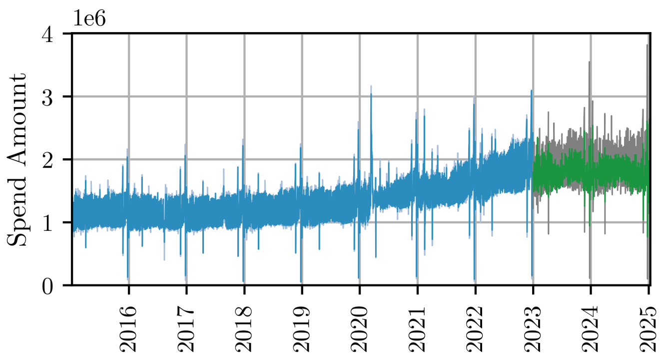
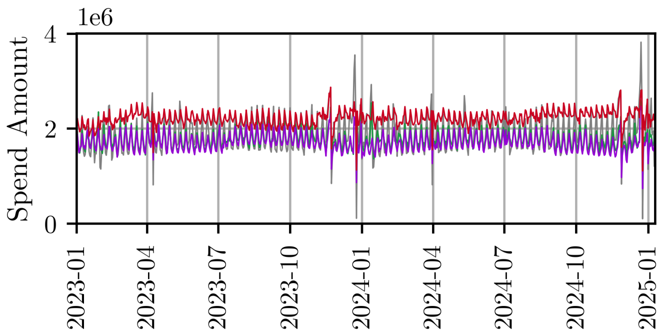


Fig. 5. Percentage improvement in RMSE for consumer spending prediction across three retail industries geographically arranged for the XGBoost model (the best performing model from Table I). The heatmap shows performance gains when comparing Climatology to Baseline (identical data as Figure 4); Perfect Forecast vs. Baseline exhibits nearly identical improvement patterns. Asterisks (*) indicate statistically significant differences ($p < 0.01$) determined by HAC-robust Diebold-Mariano testing with Benjamini-Hochberg correction (150 comparisons = 50 states × 3 industries). Weather data integration demonstrates widespread benefits (111 out of 150 configurations, 74%) across diverse geographic regions and retail sectors, confirming the robust value of incorporating meteorological features into demand forecasting models.



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



(b) Test Period Detail Against Ground Truth (gray) sMAPE: Baseline (red) = 21.1%, Climatology (violet) = 11.5%, Perfect Forecast (green) = 10.5%

Fig. 6. Sample time series demonstrating model performance on consumer spending prediction for Texas grocers over ten years for XGBoost method. (a) Complete time series showing training/validation period (2015-2023) with ground truth (light blue) and Perfect Forecast model predictions (blue), followed by test period (2023-2024) with ground truth (grey) and Perfect Forecast predictions (green). (b) Detailed view of the test period ground truth (gray) comparing Perfect Forecast model predictions (green) against Baseline model predictions (red) that exclude weather data, and Climatology predictions (violet) using only weekly historical weather averages. The Weather-Informed models demonstrate improved accuracy in capturing spending patterns.

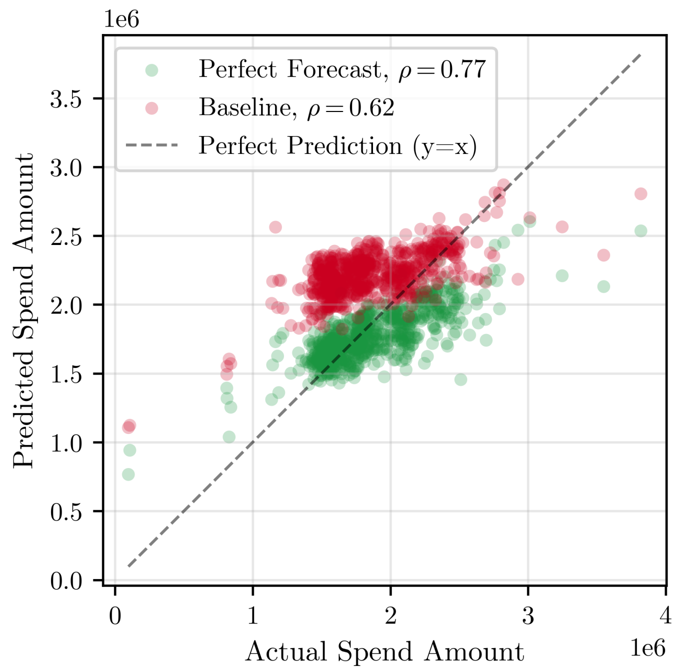


Fig. 7. Scatter plot comparing predicted versus actual spending on the test set. Each point represents a prediction, and the diagonal dashed line indicates a perfect forecast (y=x). The Perfect Forecast model (green) clusters more tightly around the prediction line than the Baseline model (red), demonstrating improved forecasting performance. The Pearson correlation coefficient (ρ) quantifies this relationship for the Perfect Forecast ($\rho = 0.77$) and Baseline ($\rho = 0.62$) models

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) **Pre-Storm Period (1 week before):** One week before the storm, both weather-informed models substantially outperform Baseline (26.2% sMAPE), with Climatology achieving 11.5% sMAPE (56.0% improvement) and Perfect Forecast achieving 14.9% sMAPE (43.0% improvement). Notably, Climatology outperforms Perfect Forecast during normal conditions, capturing typical pre-winter seasonal spending patterns more effectively than daily precision.
2) **Storm Impact Period (February 20-24):** During peak storm days (highlighted in red), casual dining spending collapses dramatically. The Perfect Forecast model captures this extreme deviation better than Climatology, achieving 36.4% sMAPE (17.5% improvement over Baseline's 44.1%) compared to Climatology's 41.1% sMAPE (6.8% improvement). This demonstrates Perfect Forecast's value during extreme events that deviate substantially from historical seasonal norms—precisely

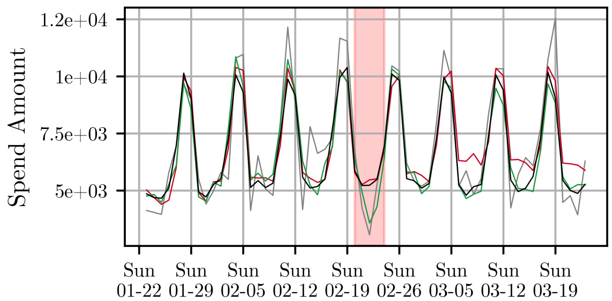


Fig. 8. South Dakota casual dining spending and predictions during Winter Storm Olive (February 21-23, 2023) using XGBoost. The storm period is highlighted in red, showing dramatic spending disruptions during the extreme weather event. The Perfect Forecast model (green) demonstrates substantially improved tracking against the ground truth (gray) compared to Baseline (red) and Climatology (black). The Perfect Forecast model accurately captures the sharp spending collapse during the storm event, while both baseline and climatology models fail to predict the magnitude of the behavioral response. This illustrates a theoretical upper bound of weather-informed forecasting performance.

when forecast precision matters most.

3) **Recovery Period (1 week after):** Following the storm, both weather-informed models show strong performance. Perfect Forecast achieves 12.4% sMAPE (55.3% improvement over Baseline's 27.6%), while Climatology achieves 13.4% sMAPE (51.7% improvement), demonstrating sustained value as spending patterns normalize post-disruption.

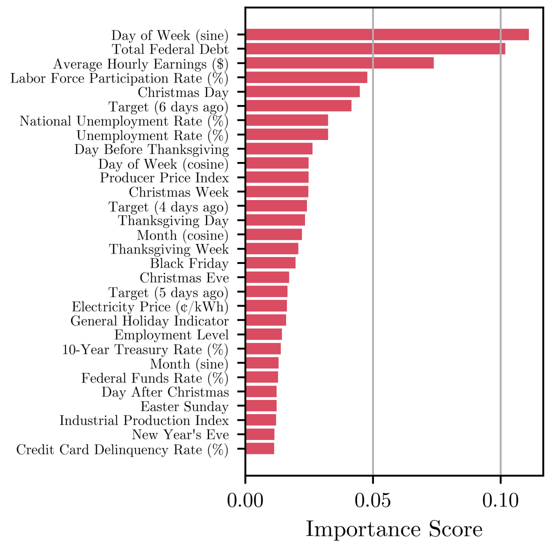
E. XGBoost Feature Importance Analysis

Figure 9 displays the mean feature importance for the top 30 features comparing (a) Baseline with (b) Perfect Forecast models. Both models demonstrate that economic indicators play a crucial role in prediction accuracy, including total federal debt, average hourly earnings, 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.

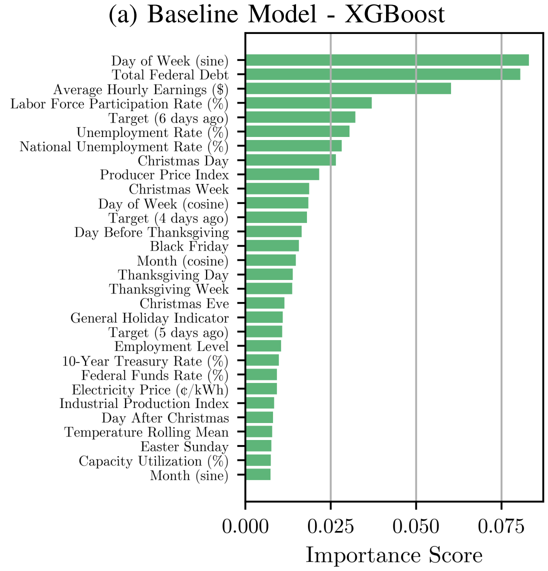
The Perfect Forecast model maintains similar rankings for these core economic and temporal features, though with reduced relative importance as the feature space expands to include meteorological variables. Notably, the Perfect Forecast model assigns significant importance to rolling mean temperature illustrating 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.

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



(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 Perfect Forecast model identifies the weather variable temperature rolling mean among the highest-ranked features, indicating a significant contribution to predictive performance.

(TPE) sampling approach in efficiently exploring the XGBoost hyperparameter space.

The optimization exhibits rapid initial improvement, with the best objective value decreasing from approximately 0.6 to 0.2 over the course of 100 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.

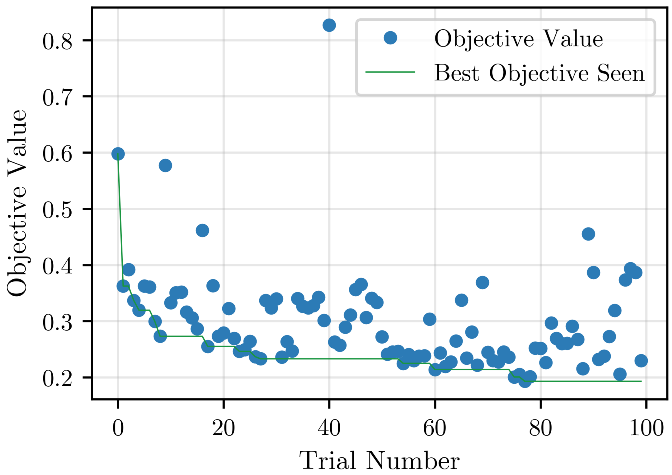


Fig. 10. Optuna hyperparameter optimization progress showing trial objective values and the best objective seen curve. The optimization converges as trials progress, demonstrating the effectiveness of the Bayesian optimization approach [65].

V. Limitations and Directions for Future Research

Despite the comprehensive scale and methodological rigor of this study, several limitations must be acknowledged to contextualize the findings and guide future investigations in weather-integrated consumer spending prediction.

First, while our credit and debit card transaction data provides a longitudinally consistent panel with geographic balancing across all 50 states, several sampling limitations exist. The panel excludes cash transactions and the approximately 4-5% of U.S. households that remain unbanked. Recent Federal Reserve research shows that cash users and the unbanked are disproportionately concentrated among older, less educated, lower-income, and Black consumers [66]. This systematic exclusion is particularly relevant given that cash comprised 16% of all U.S. transactions in 2023, with usage rates reaching 27-28% among the lowest-income and least-educated segments. Combined with the panel's skew toward older and higher-income cardholders, this introduces demographic bias that may affect the generalizability of weather-spending relationships. Future research could integrate multi-source payment datasets to enhance representativeness across the full demographic spectrum.

Second, the state-level aggregation of data enables broad geographic coverage across 50 U.S. states but obscures intra-state heterogeneity. Variations in urban versus rural lifestyles, infrastructure, or microclimates (e.g., coastal vs. inland weather sensitivities) may lead to divergent spending patterns that are not captured at this granularity. To address this, subsequent studies should explore finer spatial resolutions, such as ZIP code or municipal levels, potentially using geospatial ML techniques to model localized dynamics more precisely. While the underlying transaction data captures consumption at Combined Statistical Area granularity, enabling urban-suburban-rural differentiation, our state-level aggregation was necessary to ensure sufficient sample sizes for robust model training across all geographic units and industries. This aggregation choice represents a trade-off between geographic precision and statistical power.

Third, the intentional exclusion of deep learning architectures (e.g., LSTMs or Transformers) prioritizes interpretability and computational efficiency but limits benchmarking against state-of-the-art time-series models that may handle non-linear weather interactions more effectively. Extending the framework to include these models could yield additional error reductions, though at the cost of increased complexity and reduced transparency.

Fourth, our climatology approach uses only historical weekly averages, representing realistic operational deployment without requiring weather forecast models. The perfect forecast scenario establishes a theoretical upper bound, though real-world forecast accuracy degrades beyond 3-5 days [67]. The near-identical aggregate performance of Climatology (11.5%) and Perfect Forecast (11.5%) suggests that seasonal patterns capture most predictive value under normal conditions. However, this likely masks differential performance during extreme weather events—our Winter Storm Olive case study demonstrates that weather-informed models excel during rare but impactful deviations from seasonal norms, where even imperfect forecasts provide critical timing and intensity information that climatology cannot. Additionally, our next-day (+1 day) prediction horizon may underestimate the relative value of weather forecasts at shorter horizons (same-day predictions using real-time observations) or overestimate their value at longer horizons (3-7 days) where forecast skill degrades substantially. Future research should quantify forecast value separately for extreme versus normal weather regimes to guide retailer investment decisions in forecast services.

Fifth, the focus on three retail industries (grocers, home improvement, casual dining) and U.S.-centric data provides depth but constrains generalizability to other sectors (e.g., apparel, e-commerce) or international contexts with diverse climates, cultural norms, and economic structures. Cross-cultural validations or expansions to global markets would broaden the applicability of weather-informed predictions.

Sixth, our training data (2015-2022) includes the COVID-19 pandemic period, which created unprecedented spending disruptions that may confound weather-spending relationships. We did not exclude pandemic years because: (1) cleanly isolating pandemic effects would require arbitrary modeling assumptions, (2) removing 2-3 years would substantially reduce training data, and (3) our test period (2023-2025) captures post-pandemic consumer behavior most relevant to operational deployment.

VI. Conclusion

These contributions establish weather integration as a valuable enhancement for retail demand forecasting that balances accessibility with performance trade-offs. By providing a comprehensive, multi-subindustry, multi-geography, multi-algorithm evaluation of weather's predictive value, this study quantifies weather's contribution across diverse operational contexts and identifies patterns consistent with theoretical mechanisms from the S-O-R framework and demand theory, though causal validation through controlled experiments remains an important direction for future work.

These findings reveal heterogeneous weather sensitivity across industries and contexts. The magnitude of forecasting improvement varies substantially by sector. Grocers (20.2%) and casual dining (12.2%) show strong weather dependence, while home improvement (3.3%) exhibits more limited sensitivity. This suggests that weather integration delivers the highest return on investment for necessity goods prone to stockpiling and mobility-dependent discretionary services, while providing marginal value for project-based durable goods. Beyond industry differences, aggregate results show climatology and perfect forecast achieving similar overall performance (both 11.5% improvement). Yet the Winter Storm Olive analysis exposes critical differences during extreme events: climatology achieved only 6.8% improvement during the storm period versus 17.5% for perfect forecast. This indicates that real-time or short-term weather forecasts may provide substantial additional value precisely when forecast errors are most costly to business operations. These findings suggest a tiered implementation strategy: historical weather patterns suffice for routine forecasting and long-term planning, while high-sensitivity sectors (grocers, casual dining) with significant exposure to extreme weather disruptions may justify investment in operational weather forecast services.

Future research should quantify forecast value separately for normal versus extreme weather regimes to guide investment decisions, examine finer geographic granularities to capture urban-rural heterogeneity and microclimate effects, extend analysis to additional retail sectors and international markets with diverse climates, and empirically test the proposed behavioral mechanisms through natural experiments or field studies that can establish causal relationships beyond the correlational patterns observed here.

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APPENDIX

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. **All weather data are sourced from ERA5 reanalysis [47], with population-weighted geographic aggregation applied to create state-level indicators.**

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.

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.

H. Decision Tree Regressor

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

I. 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”}
- **VIF threshold:** Log-uniform float range $\{5, 100\}$

J. Linear Regression

- **fit_intercept:** Categorical choices {True, False}
- **positive:** Categorical choices {False, True}
- **VIF threshold:** Log-uniform float range $\{5, 100\}$

K. 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}

L. 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 $\{0.0, 1.0\}$
- **VIF threshold:** Log-uniform float range $\{5, 100\}$

M. 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 $\{0.0, 10.0\}$

N. 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 $\{0.6, 1.0\}$

O. 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.

P. Optimization Settings

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

- **Number of trials:** 100 per model configuration
- **Sampling algorithm:** TPESampler (Tree-structured Parzen Estimator)
- **Cross-validation:** 5-fold uniformly spaced, 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.

This appendix presents the correlation matrix for the Florida home improvement subindustry 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.

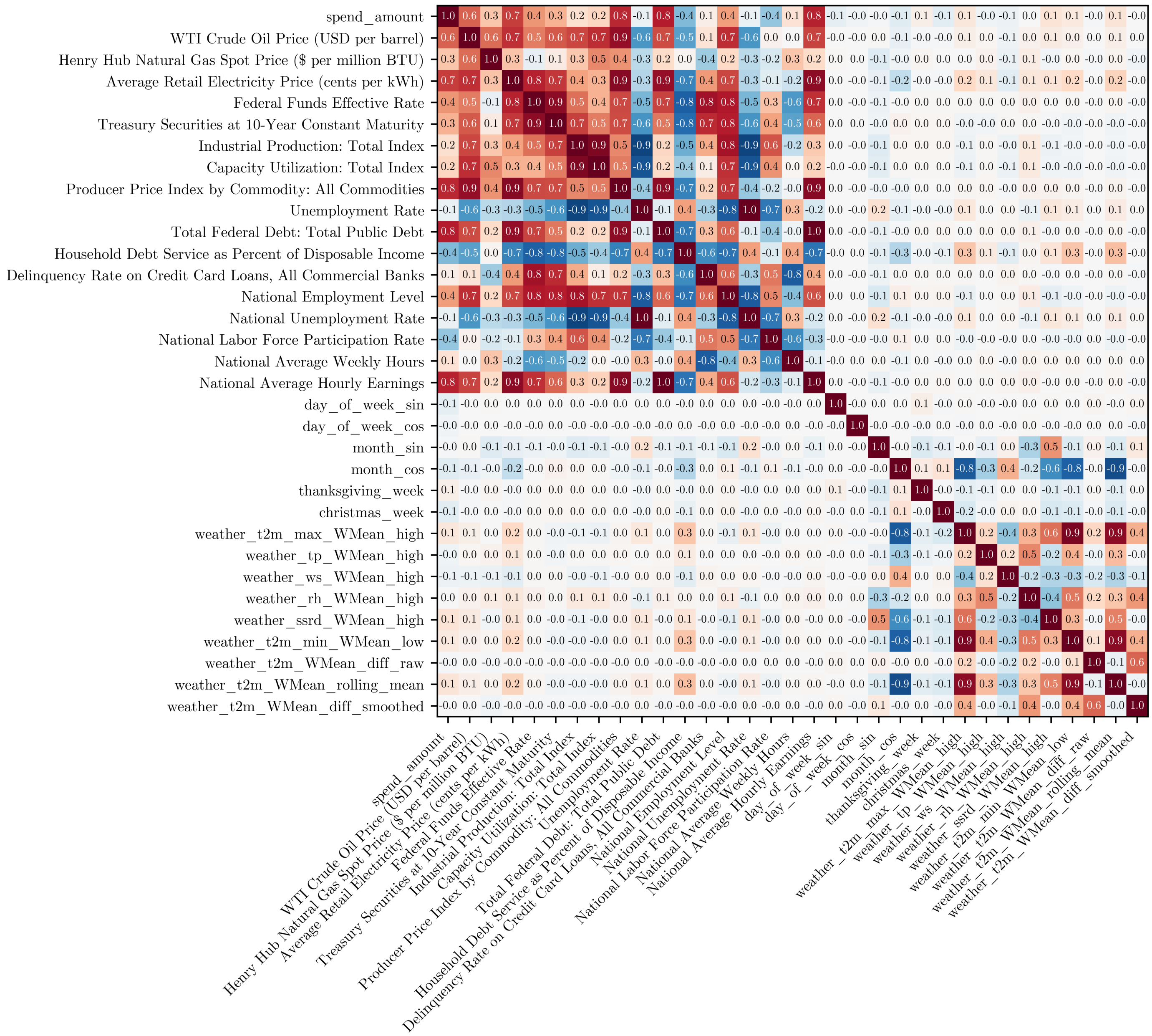

Fig. 11. Correlation matrix for Florida home improvement industry showing pairwise correlations between economic indicators, weather variables, and consumer spending. The color scale ranges from -1 (perfect negative correlation, dark blue) to +1 (perfect positive correlation, dark red), with white indicating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

TABLE VI
REGIONAL CLASSIFICATION OF STATES

Region	States
Arctic	AK
Arid West	AZ, NM, NV, UT
Great Lakes	IA, IL, IN, MI, MN, MO, OH, WI
Great Plains	KS, ND, NE, SD
Mountain West	CO, ID, MT, WY
Northeast	CT, DE, MA, MD, ME, NH, NJ, NY, PA, RI, VT, WV
Pacific	CA, OR, WA
South Central	OK, TX
Southeast	AL, AR, FL, GA, KY, LA, MS, NC, SC, TN, VA
Tropical	HI