Results Summary and Business Recommendations

Executive Summary: Weather & Sales Analysis

Goal: Evaluate how the weather affects the weekly sales of Items 45, 5, and 9 and offer practical forecasting and inventory suggestions.

Key Findings:

- Station Pressure as the Most Consistent Weather-Related Predictor: Atmospheric stability is the most consistent weather predictor. In contrast, wind speed, temperature, and extreme events (snow, thunderstorms) offer marginal or erratic predictive value.
- Weather explains a limited proportion of sales variance (validation R^2 generally below 0.10, with test performance peaking at 0.22 for Item 45).

Item-Specific Sensitivity:

- Item 45: Moderately responsive to high-pressure systems; resilient to short-term shocks.
- Item 5: Highly seasonal; demand peaks during colder months and shorter daylight hours.
- Item 9: Weather-insensitive; sales are best predicted by historical averages.

Summary of Weather Impacts

In order to determine the best forecasting technique for each item, this section compares Ordinary Least Squares (OLS) regression with Decision Tree models to assess the relationships between weather variables and sales.

Item 45:

Important Drivers: Precipitation volume and atmospheric stability were the most statistically relevant predictors for Item 45. In the OLS model, Precipitation total (β = 8,942, $p = 0.009$) and station pressure (β = 3,747, $p = 0.015$) were significant predictors, though coefficient magnitudes reflect variable scaling and should not be interpreted as literal one-unit changes.
This is supported by the Decision Tree, which ranks Station Pressure as the most important feature (47.3%).
The Decision Tree was selected as the model (R2 = 0.22, RMSE = 2,300). The non-linear "step-change" in demand when barometric pressure exceeds a threshold likely explains why the OLS model could not generalise (R2 = -0.18). As it identified this relationship, the Decision Tree is the only model demonstrating a modest out-of-sample predictive signal.

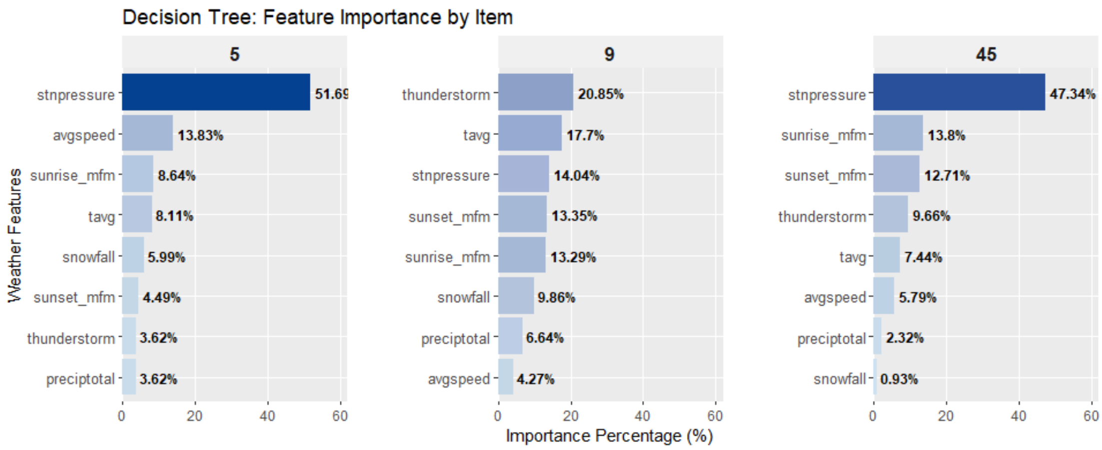
Item 5:

Although the Decision Tree assigned importance to these variables, neither station pressure nor precipitation reached statistical significance in the OLS model ($p > 0.10$), suggesting they might be proxies for more general seasonality, even though the Decision Tree gave Sunrise/Sunset a high importance (roughly 19% combined).
Although overall performance remained weak, the Decision Tree was retained for structural interpretation, as it captured seasonal non-linearities not visible in the OLS framework.
During validation, the Decision Tree achieved $R^2 = 0.08$ compared to -0.18 for the OLS model, which justified selecting it for structural interpretation. The model overfitted to training noise, though, as indicated by the final test R2 of -0.30. Despite being the best structure for capturing the complexity of item 5, the Decision Tree's negative R2 indicates that it is currently more useful as a diagnostic tool than a trustworthy forecasting engine.

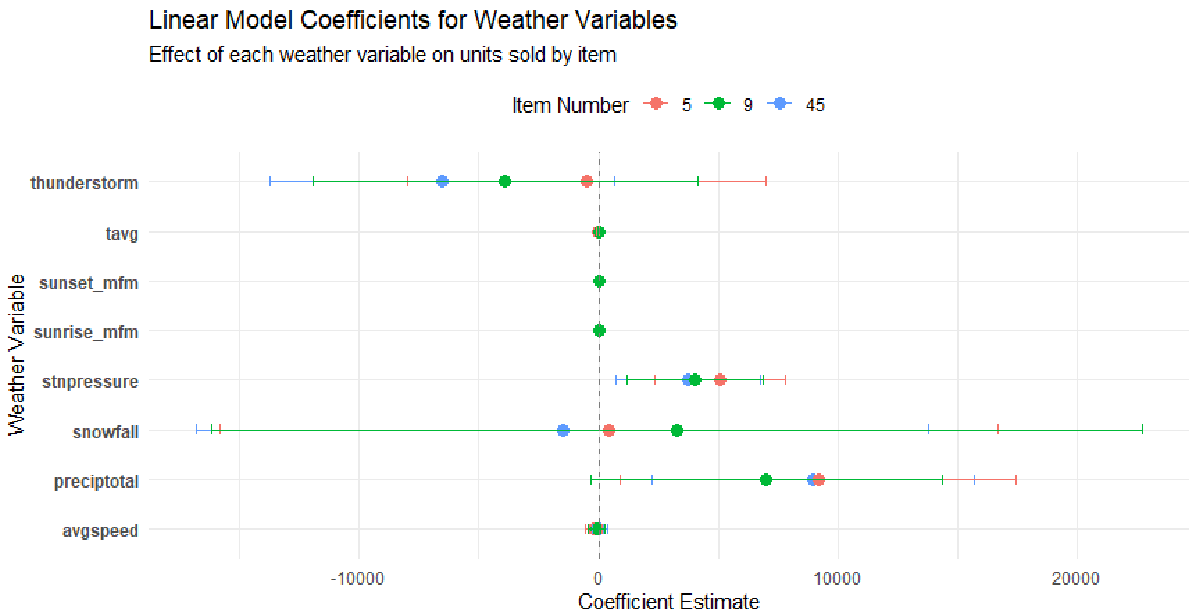
Item 9:

Station pressure was the only statistically significant linear predictor ($p = 0.006$), though its practical impact was limited. It's interesting to note that while thunderstorms were deemed the most significant feature by the Decision Tree (20.8%), the linear model determined that they were statistically insignificant ($p = 0.33$), indicating a lack of consistent signal.
Linear regression was chosen as the model due to its simplicity.
Neither model performed better than a straightforward historical average, with a final test R^2 of -0.02. In a high-noise environment, the Linear model's simpler structure introduces less volatility than the Decision Tree, which is why it was chosen.
Weather-based logic for Item 9 increases operational complexity without yielding a discernible improvement in accuracy.

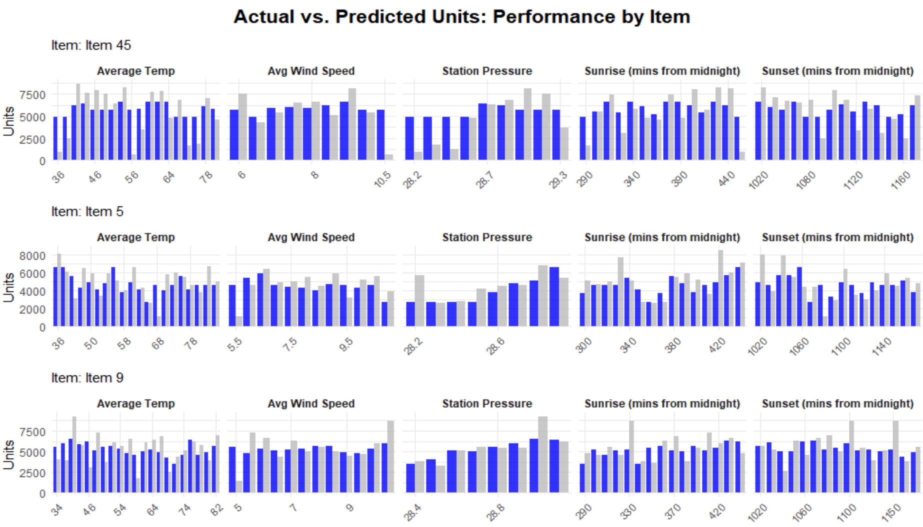
Model Visualisations



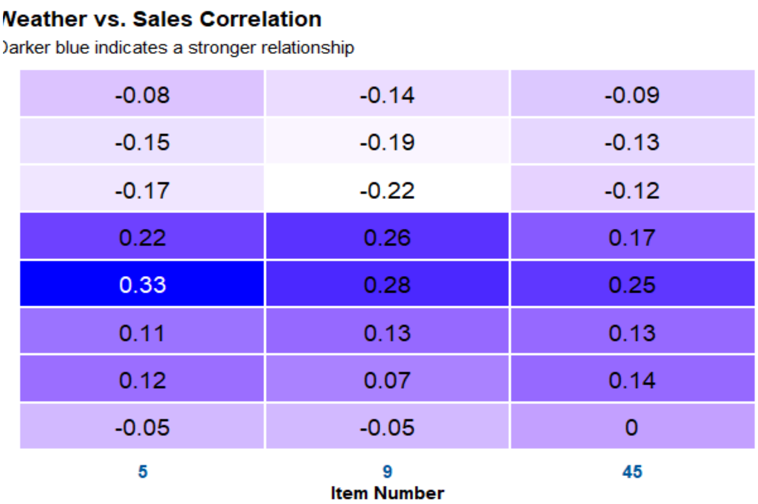
This visualisation shows the importance of the weather variables for each item. This was used during the model testing phase to see initial results from the Decision Tree Models. Station pressure consistently ranked among the top predictors, although Item 9 showed thunderstorms as the highest-ranking variable in the Decision Tree. and items yielding a high importance for the variable, with only Item 9 being the outlier with Thunderstorms as its top predictor.



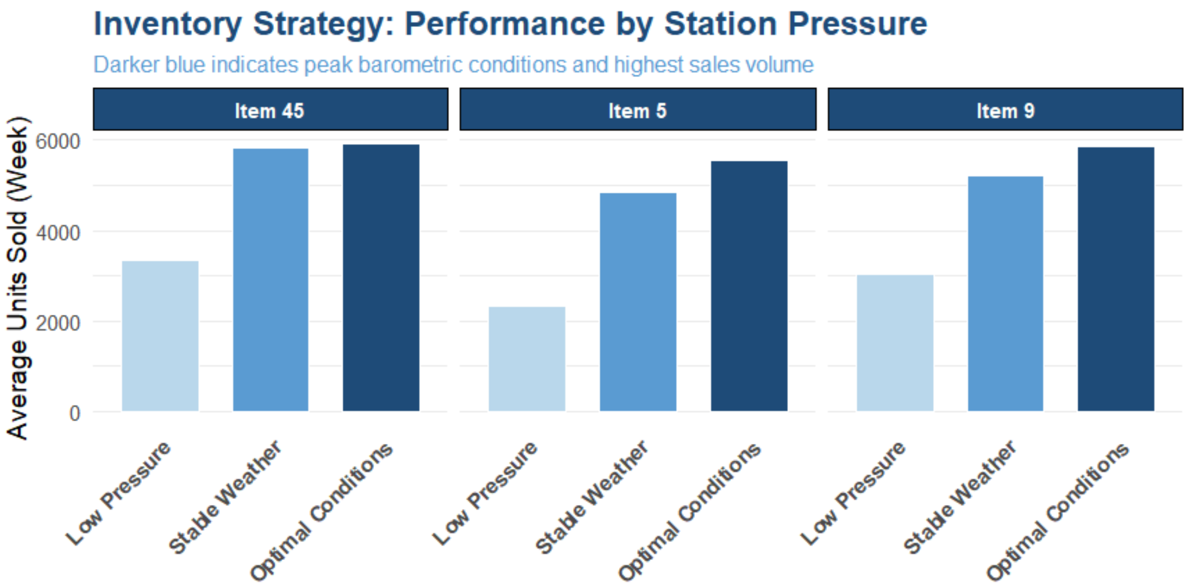
The Linear Model Coefficients plot shows that while variables like Thunderstorms, Snowfall, and Average Wind Speed are included in your model, they contribute less predictive value compared to the more influential predictors. The key takeaway is that Precipitation and Station Pressure are the only variables with strong, consistent positive effects across all three items, whereas the others show "zero-crossing" confidence intervals. This tells us that even though these factors are part of your model, they are not reliable predictors of sales because their impact is statistically indistinguishable from zero.



The visual features bar charts comparing actual weekly units sold (grey) with model-predicted units (blue) across five weather variables: Average Temperature, Average Wind Speed, Station Pressure, Sunrise, and Sunset, for Items 45, 5, and 9. Each panel categorizes weather values and shows mean sales, aiding evaluation of prediction alignment. For Item 45, predicted values align well with actual sales, particularly for Station Pressure and daylight, indicating moderate alignment despite some discrepancies. Item 5 shows greater variability, with notable gaps between predicted and actual bars in temperature and daylight categories, suggesting weaker model stability. Item 9 displays minimal variation across weather bands, with flat patterns and inconsistent alignment, supporting findings of low weather sensitivity. Overall, while atmospheric variables provide some structure—especially for Item 45—weather does not significantly explain sales volatility for Items 5 and 9.



The Weather vs. Sales Correlation Heatmap provides a high-level, diagnostic summary of how meteorological factors linearly influence the sales of Items 5, 9, and 45. The visual identifies station pressure and sunrise timing as the most significant drivers across the dataset, with station pressure showing the strongest moderate positive correlation of 0.33 for Item 5. Conversely, variables such as average wind speed and thunderstorms show negligible or slightly negative correlations, suggesting they are less reliable predictors of purchasing volume for these specific products. The key takeaway for stakeholders is that these items are primarily "fair-weather" or atmospheric-stability driven; as barometric pressure increases and daylight shifts, sales trends show a modest upward association.



The Inventory Strategy: Performance by Station Pressure bar chart illustrates the direct relationship between atmospheric stability and sales volume across all three items. By categorising barometric data into three distinct tiers, the visual reveals that "Optimal Conditions" were associated with the highest observed average weekly sales, while "Low Pressure" environments correlate with the lowest demand. This effect is most pronounced for Item 45, which shows a sharp increase in sales as pressure stabilises, consistent with the observed moderate correlation ($r \approx 0.25$). While Items 5 and 9 show varying levels of overall weather sensitivity, this visualisation suggests that high pressure is associated with elevated sales, particularly for Item 45.

Model Limitations

Omitted Variable Bias:

- The current models ignore critical drivers like price elasticity, promotions, and holidays.

Data Smoothing:

- Weekly aggregation reduces daily noise and zero-sale skewness, improving stability for seasonal analysis, but it limits the ability to capture immediate responses to single-day weather events.

Overfitting Risk:

- Decision Trees capture non-linear trends but require stress-testing against larger datasets to ensure long-term reliability.

Business Insights and Recommendations

Item 45: Optimise Inventory for High-Pressure Conditions

The analysis identifies Item 45 as the only product with a predictive signal (R2 = 0.22) linked to atmospheric stability rather than "bad weather". The data shows a distinct non-linear surge in sales when station pressure exceeds 28.9 inHg, confirmed by the Decision Tree model which effectively captured this threshold behaviour where the Linear model failed (R^2 = -0.18). To capitalise on this moderate "fair weather" demand:

- When the 7-day forecasted average station pressure surpasses 28.9 inHg, set the inventory planning system to automatically raise reorder quantities by 12–18% above baseline. This is recommended due to ‘stnpressure’ being the dominant driver from the weather variables, accounting for 47.34% of feature importance.
- To avoid stockouts during documented sales peaks, increase safety stock coverage by one week of demand buffer during these periods of high pressure. This is recommended because the Decision Tree model for Item 45 shows a non-linear "step-change" in demand at specific pressure thresholds. The benefit is that by proactively securing shelf availability during documented demand surges, it avoids lost revenue during the item's highest units sold in atmospheric windows, this is only a small buffer, as it has been noted that weather only explains a minor portion of variance.

Item 5: Restructure for Cold-Weather Demand

Item 5 displays clear seasonal sensitivity rather than daily weather responsiveness. The models indicate that demand is driven by broader environmental regimes—specifically cold temperatures and shorter daylight hours—making daily weather-based ordering ineffective. Analysis shows a positive correlation with sunrise timing (r = 0.22) and a negative correlation with average temperature (r = -0.15), hinting at a minor demand increase during the winter months.

- After analysis, switching Item 5 from daily reactive forecasting to a seasonal allocation plan is advised. Increase base forecasts for winter-region stores by 10–15% from November to February, excluding daily "noise" variables like wind or rain, which had little correlation. This is advised since Item 5's daily weather models showed significant testing failures (R2 = -0.30), suggesting that "day-to-day" weather variations are not a reliable indicator of sales. Nonetheless, the data demonstrates consistent associations with average temperature (r = -0.15) and sunrise timing (r = 0.22), demonstrating that demand is linked to the entire winter season rather than specific weather occurrences.

Item 9: Disengage from Weather Prediction

The results for Item 9 indicate that weather variables introduce operational "noise" rather than predictive value. Both the Linear Regression and Decision Tree models produced negative R^2 values, meaning they are less accurate than a simple historical average. With a final test R2 effectively at zero (-0.02), all weather variables for Item 9, including the "important" thunderstorm feature, were statistically insignificant ($p > 0.05$).

- From the analysis, it is advised that the weather-driven forecasting module for Item 9 be decommissioned right away. In order to stabilise replenishment accuracy and simplify model maintenance, switch back to an 8-week Rolling Simple Moving Average (SMA). This will naturally outperform current models, as it ignores irrelevant environmental fluctuations.

Conclusion

This analysis focused on evaluating the weather's effect on sales, with the final analysis looking at the weather variables – with the most statistical insight – and their predicted sales and correlation to the total weekly units sold.
Both Linear Regression and Decision Tree models were applied, supported by correlation analysis and feature importance metrics to validate variable selection.

Station pressure emerged as the most consistent atmospheric variable across models, though even its strongest performance explained a limited portion of total variance. This indicates that broader stable weather systems have more influence on sales patterns than short-term events such as rainfall or thunderstorms. However, even for the most responsive product (Item 45), weather variables explained a modest proportion of variance. Validation performance was weak across all items ($R^2 < 0.10$), though Item 45 demonstrated improved generalisation on the test set ($R^2 = 0.22$), indicating a modest but stable weather-demand relationship. This confirms that weather acts as a secondary influence rather than a primary determinant of purchasing behaviour.

With a Decision Tree model, a slight improvement in prediction was obtained for item 45, which shows the most obvious weather dependency. This implies that structured, albeit non-dominant, demand fluctuations are influenced by stable atmospheric conditions. Though model performance suggests limited forecasting power, item 5 exhibits mild seasonal sensitivity associated with colder temperatures and daylight variation. Item 9, on the other hand, shows very little weather responsiveness, and both models perform worse than a straightforward historical average.

From a modelling standpoint, Linear Regression is adequate for Item 9 because of its simplicity and similar performance, while Decision Trees offer slight improvements for Items 45 and 5 by capturing non-linear effects. The low or negative R^2 values for all products, however, suggest that weather should not be viewed as the primary forecasting driver, but rather as a secondary influence.

The results indicate that while weather-based modifications might improve inventory planning for some products, especially Item 45, the majority of sales variation is probably due to more general commercial factors, such as pricing strategy, promotional activity, seasonality, and consumer behaviour. Future models would significantly increase forecasting reliability and explanatory power by incorporating these factors.

In conclusion, weather forecasting should be targeted, evidence-based, and product-specific rather than applied generally because it offers little but useful information for some products.