Region-Specific Economic Impacts of Extreme Weather Events

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(1) Introduction and Aims

Our study aims to answer two key research questions:

- We investigate the profound impacts of climate change on multiple sectors in the region, identifying industries already affected by these changes.
- We develop a machine-learning forecasting model specifically tailored to these industries, enabling us to provide sector-specific insights, identify vulnerable industries, and offer a predictive tool for future climate-related impacts.

By addressing these questions, our research contributes to a better understanding of the complex relationship between climate change and productivity, empowering stakeholders to make informed decisions and develop strategies for building resilience in the face of ongoing climate challenges.

(2) Susceptibility of each Region to Climate Change

We study the distribution of productivity in each sector in British Columbia and by the end of this report we hope to :

→ Determine the relationship between the productivity of the dominant industry and factors affecting climate change

→ Based on the results, we predict the temperature and the productivity for the next 5 years.

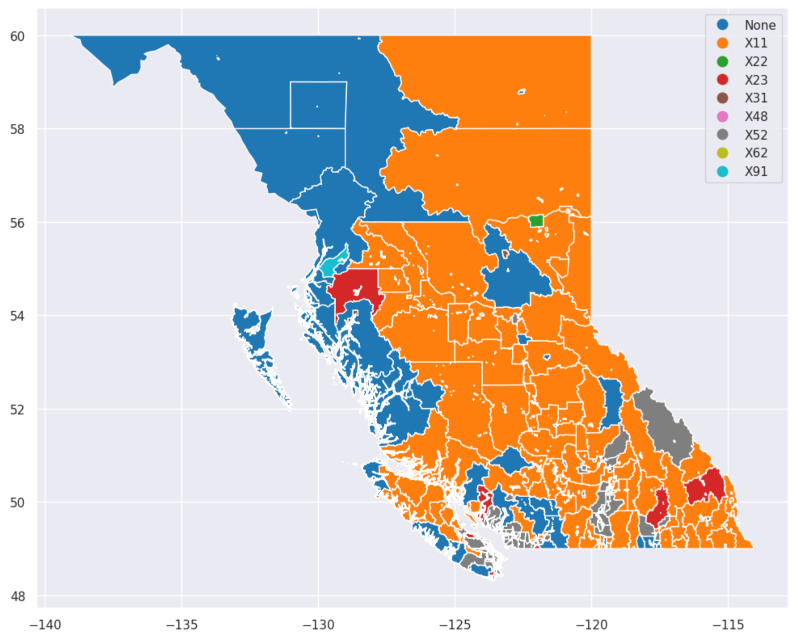

Figure 1: Region-specific Impact on Productivity due to Climate

(3) Linear Regression Model

We plotted the Residual vs Fitted model of skewed univariate regression with the difference in the temperature as a factor and observed that the data here seems to be randomly scattered depicting a **linear relationship** between the two.

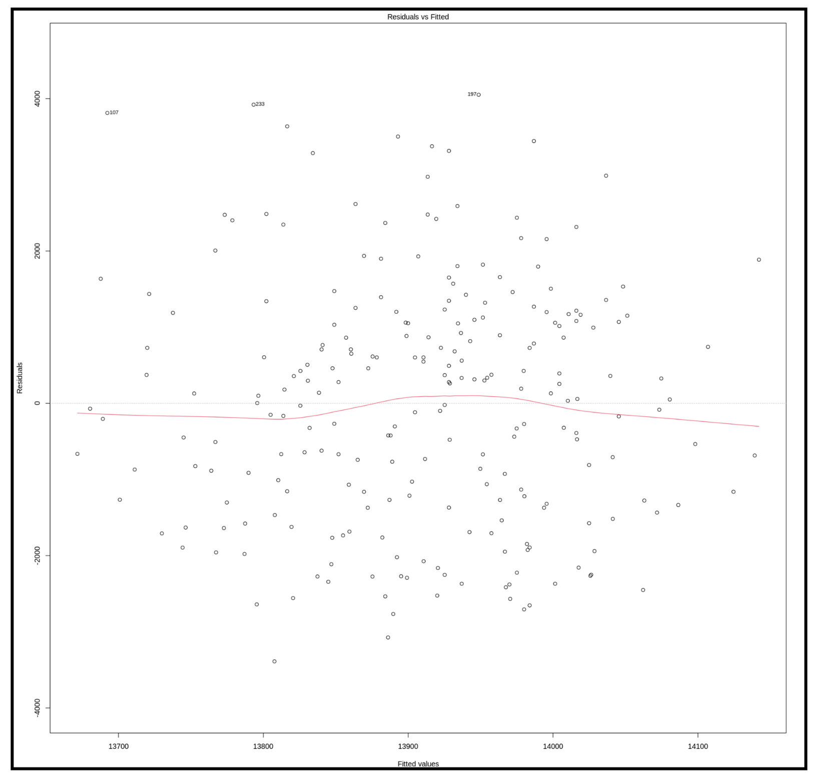

Figure 2: Residual vs Fitted Value Plot for Volatility in Temperature vs Productivity

(4) Identifying the Heterogeneity of Variance

On analyzing the Q-Q plot we observed the presence of **heavy tails** in the distribution, characterized by deviations from the 45˚ straight line at both ends and a straight center line.

This can however be due to **Heteroscedasticity** which refers to the variability of the residuals increasing as the predicted values increase. This can result in extreme values in the residuals, contributing to fat tails in the distribution of the residuals.

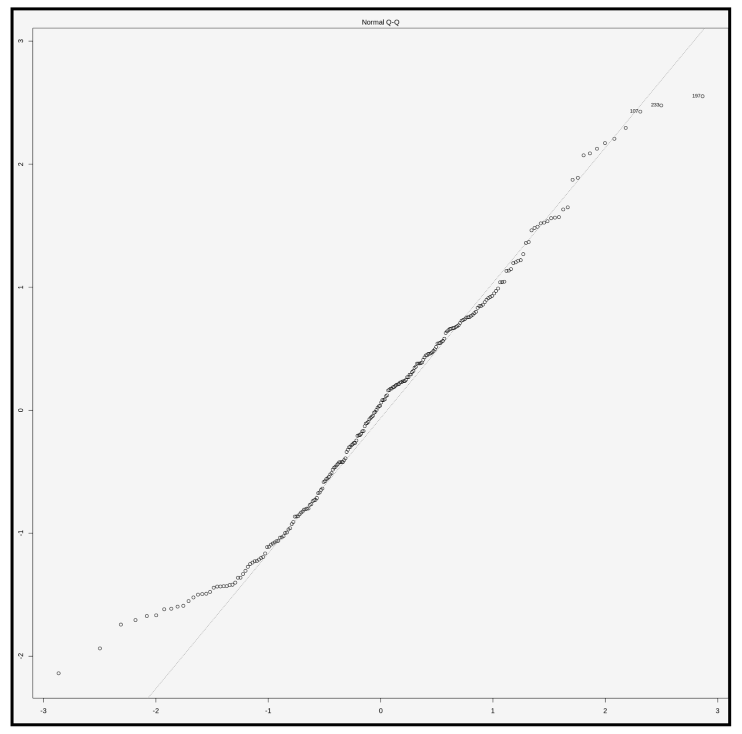

Figure 3: Normal Q-Q Plot for Volatility in Temperature vs Productivity

(5) Machine Learning Model for Forecasting

Goal: To train a general purpose forecasting model using machine learning. We use an LSTM model trained with MSE Loss.

- This will allow us to learn periodic patterns in weather data, and impacts on productivity.

We train on 3 variables: **max temp**, **min temp** and **productivity**, from 1998-2017.

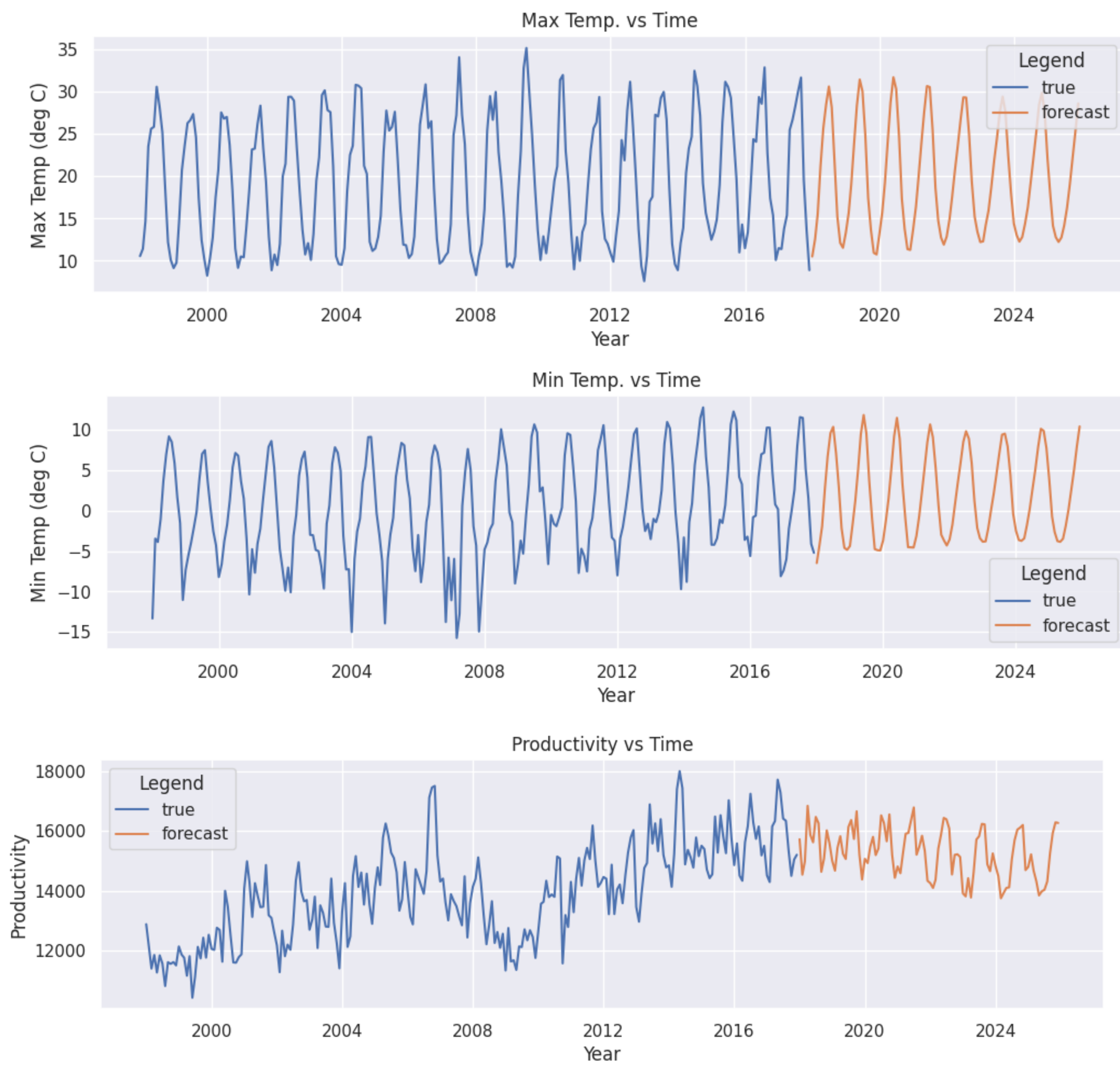

Figure 4: Max Temp, Min Temp and Productivity over time, with future prediction till 2025.

With vs *Without* Temperature data

We train models with data from 1998 2015, and test on known data from 2016 and 2017.

Without temp data, RMSE is: **10.91**

With temp data, RMSE is: **13.77**

However, we see that the model *with* temp data (right) shows periodic behaviour we expect.

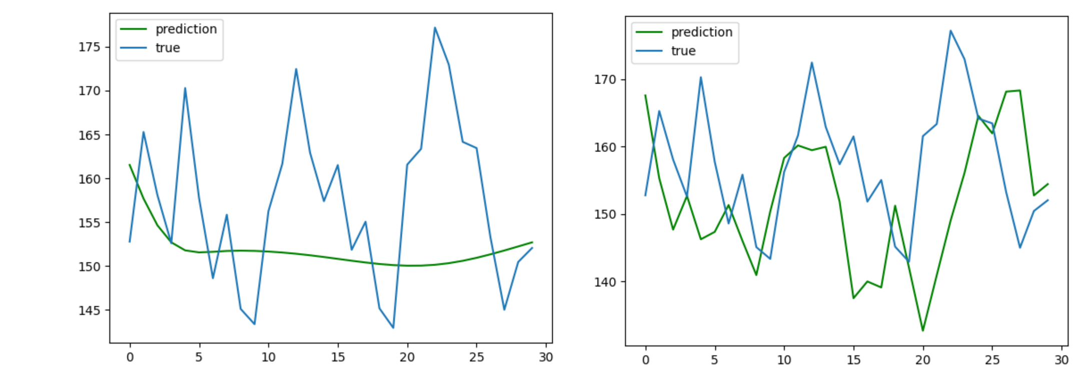

Figure 5: Without temp variables and With temp variables

(6) Conclusion

- Heteroscedasticity indicates varying residual variability across predictor values.
- Lower precision in coefficient estimates can result from Heteroscedasticity, leading to potential deviations from true population values.
- Climate change is projected to cause a substantial decline in productivity in sectors such as Agriculture, Forestry, Fishing, Hunting, Mining, Quarrying, and Oil and Gas Extraction in British Columbia.

We developed an LSTM-based forecasting model to predict future trends in productivity and temperature, assessing its strengths and limitations. We observed that we had limited data, and productivity was influenced by other variables like immigration, laws, and even the pandemic.

(7) Acknowledgment

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(8) References

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