Enhancing Regional Climate Accuracy Through Earth Balance and Regional Climate Models

A Technical Report submitted to the Department of Computer Science

Presented to the Faculty of the School of Engineering and Applied Science

University of Virginia • Charlottesville, Virginia

In Partial Fulfillment of the Requirements for the Degree

Bachelor of Science, School of Engineering

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Spring, 2025

On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

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CS4991 Capstone Report, 2025

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ABSTRACT

The challenge of accurately predicting climate change impacts at regional scales stems from the limited resolution and adaptability of current global climate models. Specifically, there exist sub-pockets of weather that do not embody the characteristics of the regional weather prediction in every region in the United States. To address this, this project will couple an Earth Balance Model (EBM) with a Regional Climate Model (RCM) to improve the precision of climate projections for specific regions, namely North Florida where disastrous weather events frequently occur. The solution integrates physical modeling of global energy balance with high-resolution regional simulations, leveraging Python, data processing tools, and skills in numerical modeling and geospatial analysis. Initial results show encouraging accuracy in reproducing temperature and precipitation patterns for North Tampa in years past, demonstrating the model's capability to refine regional forecasts. Future work involves expanding the model to other regions, refining the coupling mechanisms to improve the accuracy of regional forecasts, and conducting rigorous testing to ensure scalability for diverse climate scenarios.

1. INTRODUCTION

Climate change poses a paramount and escalating threat to the future of our planet including its ecosystems, economies, and inhabitants, increasing the significance for accurate climate projections in terms of mitigation, adaption, and constructing adequate infrastructure to counter the effects of climate change. Current global climate models (GCMs) provide valuable insights into long-term climate trends and are extremely accurate, however they are limited in their ability to capture localized weather variations in areas due to the nature of its coarse resolution limits. Regions such as North Florida experience significant microclimatic phenomena stemming from coastal and inland interactions, diverse terrain, and frequent tropical storms and hurricanes. This microclimatic behavior differs significantly from broader regional predictions leading to a unnoticed but important discrepancy. This highlights the need for improved climate modeling techniques that can provide higher-resolution tailored to specific geographic areas.

To address this challenge, the project couples an Earth Balance Model (EBM) with a Regional Climate Model (RCM) to enhance the accuracy of specifically, local climate predictions. Both models have contrasting focuses with the EBM model concentrating on the large-scale energy balance which dictates the planet's climate. The RCM model will focus on refining these initial projections by incorporating finer-scale environmental and atmospheric conditions on relevant areas. This approach aims to bridge the gap between broader climate trends and localized weather variations in certain subpockets of regions. Initial tests have demonstrated promising results in replicating past temperature and precipitation patterns in North Tampa, a region prone to extreme weather events.

2. RELATED WORKS

Salathé, et al. (2009) posited that Global Climate Models (GCMs) lack sufficient spatial resolution to capture local terrain, environmental and atmospheric processes, which leads to inaccuracies in predicting temperature, precipitation and extreme weather events at the regional level. Salathé, et al. noted that through the use of high-resolution regional modeling techniques, "…regional climate models explicitly simulate the interactions between the large-scale weather patterns simulated by a global model and the local terrain" (p. 1). These high-resolution regional climate models account for terrain interactions, coastal influences and local climatic variations, which significantly improved forecast accuracy. This improvement in regional forecast accuracy aligns with the motivation behind my report, which is to refine climate projections at even smaller subregional scales by integrating an Earth Balance Model with a high-resolution RCM for the region of North Tampa.

Ho-Hagemann, et al. (2024), focused on regional climate model projections within the GCOAST-AHOI regional Earth system model. Their work highlights the fact that traditional independent atmosphere and ocean models fail to capture the complex interactions and feedback mechanisms influencing regional climate changes due to global warming. Enormous benefits were produced by coupling the ICON-CLM regional climate model with an Earth system modeling framework, accounting for land-sea interactions, hydrological processes and mesoscale atmospheric dynamics. This coupled framework improved seasonal and annual mean prediction of near-surface air temperature, precipitation, and mean sea level pressure compared to that of traditional models. The study highlights the limits of uncoupled climate models stating that "a possible reason for the cold SST bias could be the underestimation of the downward shortwave radiation at the surface of ICON-CLM" (p. 7816). This highlights the importance of optimizing the coupling process between different Earth system components and how crucial a coupled climate model is for making accurate localized predictions. This is directly applicable to the project as the Earth system model (ESM) that Ho-Hagemann utilized is extremely similar to the EBM model in this project, demonstrating that the coupling between the EBM and RCM model can capture localized climate interactions relevant to the North Tampa model. This is especially important for the North Tampa region, which experiences coastal influences, urban heat island effects, and frequent extreme weather events. All of these occurrences make it so that a high-resolution, coupled modeling approach is required to improve prediction accuracy.

3. PROJECT DESIGN

This project integrates an Earth Balance Model (EBM) with a Regional Climate Model (RCM) to enhance the accuracy of climate predictions for localized regions—North Tampa for this project. The system was coded utilizing numerical modeling, machine learning techniques, and past weather data to refine climate projections at finer resolutions. The implementation consists of three key components: the EBM for large-scale energy balance modeling; the RCM for local climate refinement; and a machine learning-based forecasting system that attempts to dynamically update predictions using historical and real-time data.

3.1 Earth Balance Model (EBM) Implementation

The EBM component of the project simulates global energy balance by considering factors like solar radiation, greenhouse gas emissions and outgoing longwave radiation. The model uses a simple equation to update temperature values based off radiative forcing. The parameters included are:

- Solar constant (1361 W/m²) to account for incoming solar energy;
- Albedo (0.3) to model Earth's reflectivity;
- Emissivity (0.612) for greenhouse gas impact; and
- Stefan-Boltzmann constant for outgoing radiation calculations.

The function that was coded computes temperature changes over time, incorporating external climate values. This provides a baseline estimate of temperature trends, which the RCM later works on with localized data.

3.2 Regional Climate Model (RCM) for Local Refinement

The RCM refines the broad-scale temperature predictions from the EBM by incorporating localized atmospheric variables, such as temperature, humidity, pressure, wind speed and precipitation. Other considerations that are included are local terrain effects, urban heat island influences and coastal weather dynamics (i.e. sea breeze effects).

A Random Forest Regressor is trained on historical weather data from North Tampa to predict short-term temperature variations based on these features. The dataset was preprocessed by extracting key climate variables from a CSV file containing relevant information. From this, the model is trained using 80% of the dataset, while 20% is used for testing. The trained model used to predict temperature values for the next day, providing high-resolution refinements to the initial EBM forecasts. The performance of the RCM is evaluated using RMSE (Root Mean Squared Error), which provides a quantitative measure of prediction accuracy.

3.3 Time Series Prediction Using LSTM

In addition to the RCM, a Long Short-Term Memory (LSTM) neural network was trained to capture time-dependent weather trends. Long Short-Term Memory neural networks are particularly useful for climate modeling as they can recognize patterns in historical temperature and precipitation fluctuations over extended periods. The LSTM model was trained on sequences of past ten days of weather data to predict next-day temperature. The implementation included two LSTM layers to process sequential climate data, dropout layers to prevent overfitting, a fully connected dense layer for temperature predictions and a loss optimizer (Adam optimizer). After training**,** the LSTM model was evaluated on test data, and RMSE is used to compare its performance with the RCM's Random Forest model.

3.4 Model Integration and Real-Time Predictions

To improve forecast accuracy, the EBM, RCM and LSTM predictions are integrated into a final hybrid climate model. This was done by running the EBM to generate a global temperature baseline, then refining the EBM prediction with the RCM mode. After these short-term predictions were enhanced using LSTM, which captures temporal climate fluctuations, outputs from all three models were combined using a weighted average approach. On a trial basis, the model is structured to dynamically update based on new weather observations, allowing for more precise forecasting of temperature trends, precipitation changes and extreme weather events in North Tampa.

4. ANTICIPATED RESULTS

Initial results from the integrated Earth Balance Model (EBM) and Regional Climate

Model (RCM) demonstrate promising improvements in capturing localized climate variations for North Tampa. The model seems to successfully incorporate high-resolution weather data and real-time atmospheric variables in the machine-learning mechanisms, producing more accurate regional climate predictions compared to standalone Global Climate Models.

However, while the model has shown some enhancements in local prediction accuracy, the overall improvements compared to GCM projections remain marginal. The results suggest that further refinement of the coupling mechanisms between EBM and RCM are necessary to achieve significant gains in precision.

For now, additional work is necessary to investigate a different machine learning model or a completely different model in general. Different variables may need to be considered and the weights of certain variables may be hindering the model's performance. Additionally, the GCM model that the project's model is being compared against was extremely hard to select as it serves as the benchmark for the project. Further research into possibly selecting a different set of results may prove to fruitful to the project.

5. CONCLUSION

Accurate regional climate forecasting is becoming increasingly vital as climate change intensifies in both the frequency and severity of extreme weather events. Yet, most current prediction systems rely heavily on Global Climate Models, which lack the spatial resolution to effectively account for local terrain, coastal influences, and urban effects in regional areas.

The importance of this project lies in its ability to provide communities with more precise and actionable climate information. North Tampa, a region particularly vulnerable to hurricanes, heat waves, and flooding, serves as an ideal testbed for demonstrating the model's effectiveness. Key features of the system include its integration of physical modeling, machine learning, and real-time data, enabling high-resolution forecasts that can adapt to changing conditions. The hybrid model in this paper provides more accurate short-term predictions of temperature and precipitation than traditional models, supporting better decision-making in urban planning, disaster response, and infrastructure design.

From a strictly stakeholder perspective, the anticipated value of this project is enormous. Local governments, emergency planners, engineers, and even homeowners could use the output to prepare for the effects of extreme weather events better. For instance, improved localized forecasts could guide the construction of flood-resistant buildings in certain areas or inform specific evacuation strategies in storm-prone areas.

Beyond practical utility, the project deepened technical knowledge in areas like numerical simulation, climate modeling, machine learning, and model coupling techniques. Also, I learned valuable insights through the integration of combining climate science with computer science and data engineering to solve real-world problems like this. This work lays the foundation for future efforts to scale and generalize the model to other vulnerable regions, contributing to a better data-informed approach to climate adaptation.

6. FUTURE WORK

Future work will focus on refining the coupling the mechanisms, expanding the model's applicability to other regions, and ensuring that the model is scalable for diverse climate scenarios. Furthermore, the project will operate on real-time data to potentially make more accurate predictions in a multitude of ways. These range from improving localized weather pattern accuracy, where microclimates and small-scale variations in temperature and precipitation are better captured, to enhancing severe weather forecasting by identifying flooding hotspots and tornado risks within large storm systems. Additionally, the model aims to refine urban and coastal climate predictions to account for higher temperatures in urban areas known as urban heat islands, as well as sea breeze effects which help support climate adaptation strategies.

To increase the usability of the system, future iterations of the model will incorporate additional environmental data sources, such as soil moisture, vegetation cover, and satellite imagery, to improve prediction accuracy. Model retraining and hyperparameter tuning will be conducted across multiple climate zones to ensure generalizability. Additional techniques for uncertainty quantification, such as Monte Carlo dropout or ensemble modeling will be explored to help assess forecast confidence.

Furthermore, the project will integrate climate change projection data, such as Representative Concentration Pathways (RCPs), the prediction of future greenhouse gas concentrations, to assess how future emissions scenarios may influence regional forecasts. As the model matures, it will inform long-term planning by providing insights into how climate change may affect specific regions under various global emissions situations which ultimately contribute to proactive resilience planning.

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