Contract No:

This document was prepared in conjunction with work accomplished under Contract No. 89303321CEM000080 with the U.S. Department of Energy (DOE) Office of Environmental Management (EM).

The Influence of Soil Properties on Sea-Breeze Circulations in the Southeast U.S.

Table of Contents

Scientific/Technical/Management Plan

Significance

Sea-breeze circulations (SBCs) are common weather phenomena at and near coastal regions [1]. They form because of a thermal gradient between the land surface at the coast and the sea surface. In a mid-day regime, a “thermal low” generated at the warm coast will lead to rising air motion, creating a wind shift coming from the sea near the surface displacing the coastal air. A “return flow” moving back towards the sea is generated by upper-level divergence because of the rising motion from the thermal low.

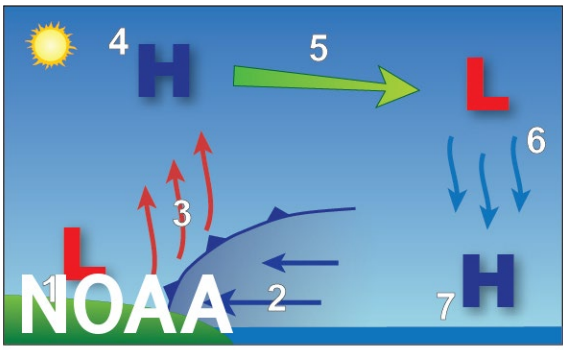

Figure 1. From NOAA: A graphic depicting the mid-day formation of a sea-breeze.

SBCs propagate and serve as a method of urban pollutant dispersion in the Los Angeles region of California and are constrained to the coast due to the topography of surrounding mountains serving as a boundary for further inland propagation. Within the northeast U.S. SBCs are seen in the warm season but tend to remain coastally bound due to Coriolis distortion over long distances. Within the southeast U.S. (SEUS), the paradigmatic example of SBCs occurs over the Florida peninsula, where thunderstorms form on a nearly daily occurrence due to the convergence of SBCs from the east and west sides of the peninsula. However, there are further examples of sea-breezes in the SEUS that warrant study.

Within the region bordering the SEUS and the Mid-Atlantic, just east of the southern Appalachian Mountains, warm-season SBCs form at the coast of Georgia and the Carolinas. Relatively flat topography ~150-200km inland allows for mostly unimpeded inland SBC propagation [2]. Through visual analysis, Viner et al. [3] catalogued several SBCs that propagated as far inland as the Central Savannah River Area surrounding Augusta, Georgia. Wermter et al. [4] found that while the land-sea thermal gradient at the coast can influence coastal SBC genesis, the inland-coastal thermal gradient over the land is the primary influencer on the speed and depth of inland propagation of SBCs in this region.

Additionally, soil moisture itself is a known correlative factor to sea-breeze formation, as it influences the soil temperature and the thermal gradient needed for SBC genesis and inland penetration. Physick [5] determined that higher latent heat fluxes associated with wetter soil dampen the land-sea thermal gradient and suppress the formation of a SBC. Physick [5] determined that higher latent heat fluxes associated with wetter soil dampen the land-sea thermal gradient and suppress the formation of a SBC. Conversely, drier soil enhances the thermal gradient and promotes SBC formation. However, while there is an inverse relationship between soil moisture and SBCs [6, 7], higher soil moisture can actually promote more convective rainfall following a SBC if it does not significantly impact the thermal gradient [6, 7].

While the relationship between soil moisture and SBC formation has been conceptually explored and modeled numerically, there is a research gap in observed connections. The Soil Moisture Active Passive (SMAP) satellite mission has been operational since 2015 and has been used to create high-resolution re-analytical Level 4 (L4) datasets of soil moisture and soil temperature at different soil depths: the surface (0-5cm) and rootzone (0-1m). The surface soil temperature effectively acts as the "skin temperature" of the surface at these levels, and a spatial map of the land-sea as well as the coastal-inland thermal gradients can be represented. SMAP data are also assimilated in some atmospheric models such at the High Resolution Rapid Refresh (HRRR; [8]) mesoscale model. We propose leveraging the use of SMAP products to fill in spatial gaps left by weather and mesonet stations within the SEUS region, as well as assessing the effectiveness of utilizing SMAP products towards SBC forecasting in both deterministic and machine learning (ML) models.

Science Question #1: What are observed climatological features of soil temperature and soil moisture in the Georgia/Carolinas region of the SEUS preceding and succeeding SBC events?

Science Question #2: How can SMAP data along with mesonet soil moisture measurements improve lead time and accuracy in forecasting SBC events?

Impact

SBCs have an impact on wind energy production [9] and impact the accuracy of solar power forecasts [10]. The use of geoengineering to promote SBC development has also been proposed by Mostamandi [11] to improve the availability of water. SBCs have been shown to increase the carbon uptake of mangroves [12]. Within the Georgia/Carolinas region, Noble et al. [13] have found that cloud cover increases on days following SBC events, especially during the early warm season in MAM (Figure 2). This has major implications on the solar energy industry which is rapidly expanding in the state of South Carolina. Improved SBC forecasts during the warm season would be beneficial to stakeholders in these industries.

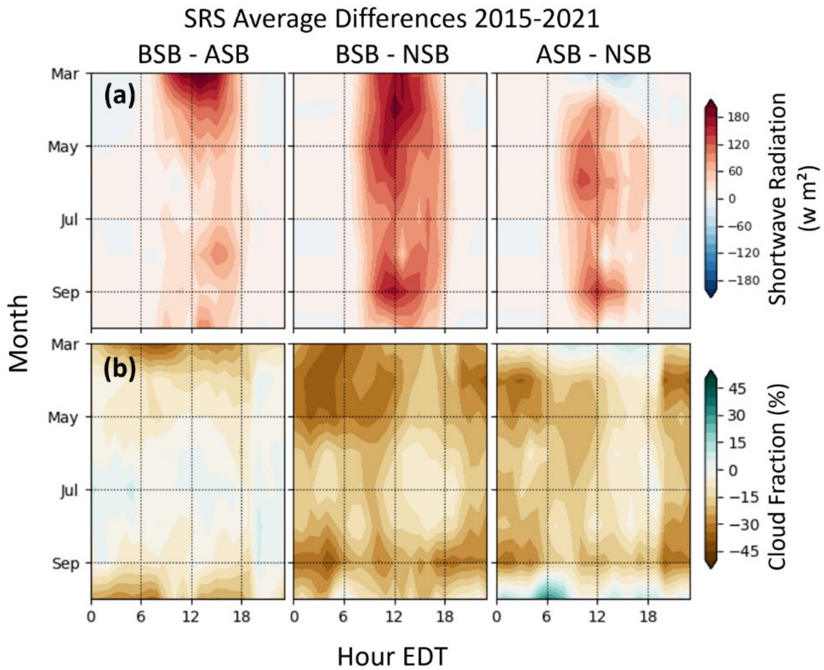

Figure 2. From Noble et al. [13]: (a) Shortwave radiation and (b) cloud fraction differences between before sea-breeze (BSB), after sea-breeze (ASB), and non-sea-breeze (NSB) days.

While spatial soil moisture patterns have not been measured at adequate resolution for a long period of time, there has been a climatic reduction of rainfall in parts of the Carolinas (Figure 3) during recent times. Sustained synoptic rainfall forced by "troughing" in the March-April-May (MAM) season influence soil moisture more significantly than short-lived convective storms that are more emblematic of the June-July-August (JJA) season [14]. As a result, it is reasonable to expect that there has been a modification of sea-breeze patterns because of the climatic drying, and that future patterns will be affected as the climate continues to warm.

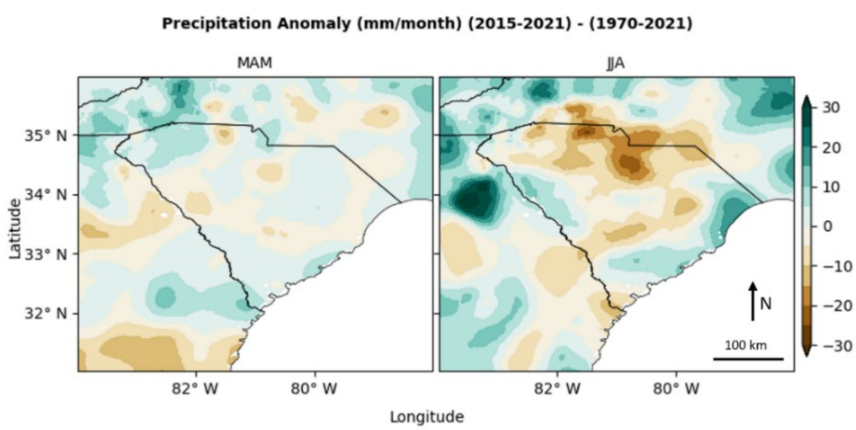

Figure 3. NCEI nClimGrid [15] gridded mean precipitation anomalies over the state of South Carolina during the sea breeze study period of 2015-2021, compared to seasonal means from 1970-2021.

Technical Approach

We will approach these scientific questions using a phased approach of numerical weather prediction (NWP) and ML methods integrated with SMAP satellite-derived products. We will address both questions in a series of three tasks. Science question 1 will be addressed by tasks 1 and 2, with the results of task 2 being used to lead into task 3 which addresses science question 2.

Task 1 – Sea-breeze detection method

To truly assess the climatology preceding and succeeding SBC events, we must consider how SBC events are defined. There is a plethora of methods for detecting SBCs. Bao et al. [16] devised a method that primarily examines wind patterns in the ECMWF ReAnalysis 5 (ERA5) product through comparison of radar and satellite patterns and utilized it over the warm season of 2019. We propose to expand this dataset beyond the 2019 dataset to span the years of 2015-2023 (Figure 4). ERA5 data SEUS subsets from 2015-2023 will be archived, with cross-shore (perpendicular to the coast) and along-shore (parallel to the coast) wind vector components derived from the gridded reanalyses.

While the Bao et al. [16] method is the most comprehensive method for detecting SBCs in the Georgia/Carolinas region of the SEUS, it relies on manual inspection of either satellite or RADAR data. Given that we intend to find 500-1000 SBC events, it is neither cost nor time efficient to give this task to an observer. We will instead leverage and train a ML convolutional neural network (CNN) model that is designed to analyze 2-D NEXt generation RADar (NEXRAD) composite images. The 2019 dataset compiled by Bao et al. [16] will be used as training data for the detection method, with the intent of the ML model having the ability to detect subtle patterns that an experienced observer would be able to find in radar imagery. We chose to base the detection method off this methodology as is it is useful for the discrimination between coastally bound and inland propagating SBCs. We will generate datasets for the MAM and JJA “warm season”.

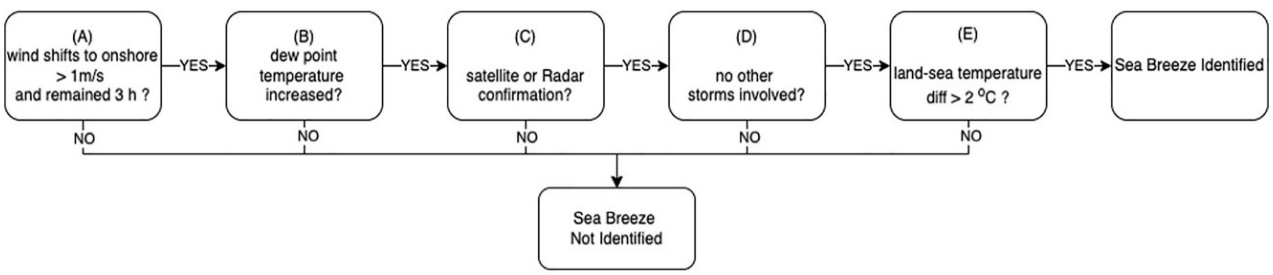

Figure 4. From Bao et al. [16]: The flow-chart used to catalog SEUS sea-breeze events in 2019 that the authors intend to apply to 2015-2023.

Subtasks:

- T1.1: Gather ERA5 data and write algorithm to detect wind shifts and temperature changes.
- T1.2: Gather NEXRAD imagery and train ML method.
- T1.3: Use ML to generate dataset of SBCs in 2015-2023 period. Revisit for 2024 & 2025 when data is timely.

Tentative Publication Title: Using Machine Learning to Detect Sea-Breezes in the Southeastern U.S.

Task 2 – Seasonal Soil Forcings on SBCs in the Warm Season

Soil moisture measurements will be used for verification of the SMAP gridded products as well as to be accessed for future tasks in the projects. Using the large catalog of SBCs in Georgia/The Carolinas spanning nearly a decade provided in Task 1, we will analyze soil moisture patterns between SMAP data as well as archives from a network of observed temperature/soil moisture stations in the University of Georgia Mesonet, the North Carolina State EcoNet, and soil moisture measurements from the Savannah River Site (SRS) in South Carolina (Figure 5). The soil moisture measurements will be used for verification of the SMAP gridded products as well as to accessed for future tasks in the project.

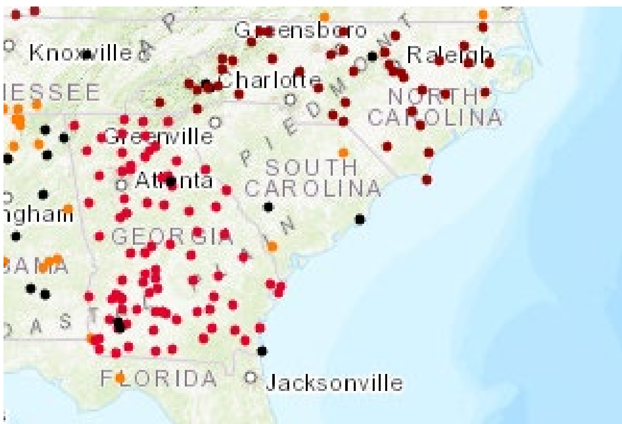

Figure 5. Soil moisture sensor network coverage of the focal region within the SEUS. (nationalsoilmoisture.com)

A preliminary analysis by our investigators of SMAP-estimated soil moisture patterns during the sea-breeze days identified by Bao et al. [16] is given as an example . With the exceptions of May and July, days in which an inland SBE occurred tend to have overall drier soil than days in which a coastal SBE occurred. May 2019 is a notable exception, however, in that inland SBCs were the predominant sea breeze scenario for that month, and average soil saturation fractions are ~0.08 higher in upstate South Carolina during those SBCs than during coastally bound SBCs. Another notable exception is during the month of September, while outside our focal periods of MAM and JJA, there is a large wet anomaly near the shore of South Carolina during coastal SBCs, while inland SBCs show drier soil throughout the state, and are nearly as common as non-SB days. However, in most cases drier soil upstate tends to be a more favorable environment for sea breezes to form. We will use an updated dataset with more sea-breezes detected to determine how the soil moisture and soil temperature climatology behaves preceding and succeeding SBC days. Any variance in soil moisture patterns will be contextualized with synoptic patterns using recorded synoptic weather types (WTs) over the SEUS [17].

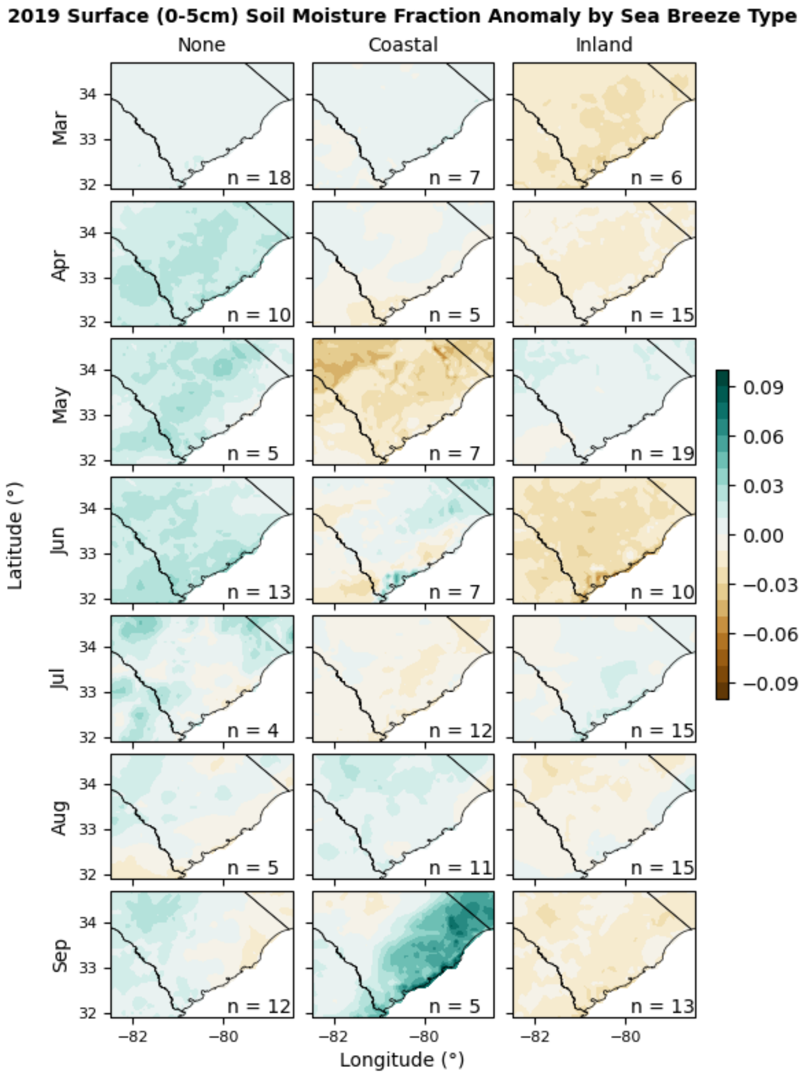

Figure 6. SMAP-derived soil moisture deviations from the monthly mean on days when (right) no sea-breeze occured, (middle) sea-breeze was bound to coast, and (right) sea-breeze propogated inland according to the methodology of Bao et al. [14].

To further examine the sensitivity of soil moisture and temperatures to sea-breeze dynamics, a set of NASA Unified Weather Research and Forecasting (NU-WRF; [18]) simulations will be conducted over the Georgia/Carolinas region of the SEUS. Entire seasons of MAM and JJA in a selected year will be simulated over a regional domain utilizing a grid spacing of 1,333 m, with boundary conditions provided by a parent domain of 4,000 m grid spacing. NU-WRF allows the use of SMAP when preprocessing the initial and boundary conditions. We will conduct seasonal simulations with and without using SMAP when preprocessing the land-surface model (LSM). We will assess both simulations' accuracy in producing SBCs detected in Task 1. We will also examine the vertical structure and propagation depth in a similar fashion to Wermter et al. [4], using a cross-section perpendicular to the coast in the SEUS (Figure 7). That study showed that a strong coastal-inland thermal gradient increases the propagation depth and speed of an SBC, so we expect that soil moisture will be a modulating factor in the soil temperature and that a SMAP-initialized NU-WRF simulation will more accurately represent SBC events.

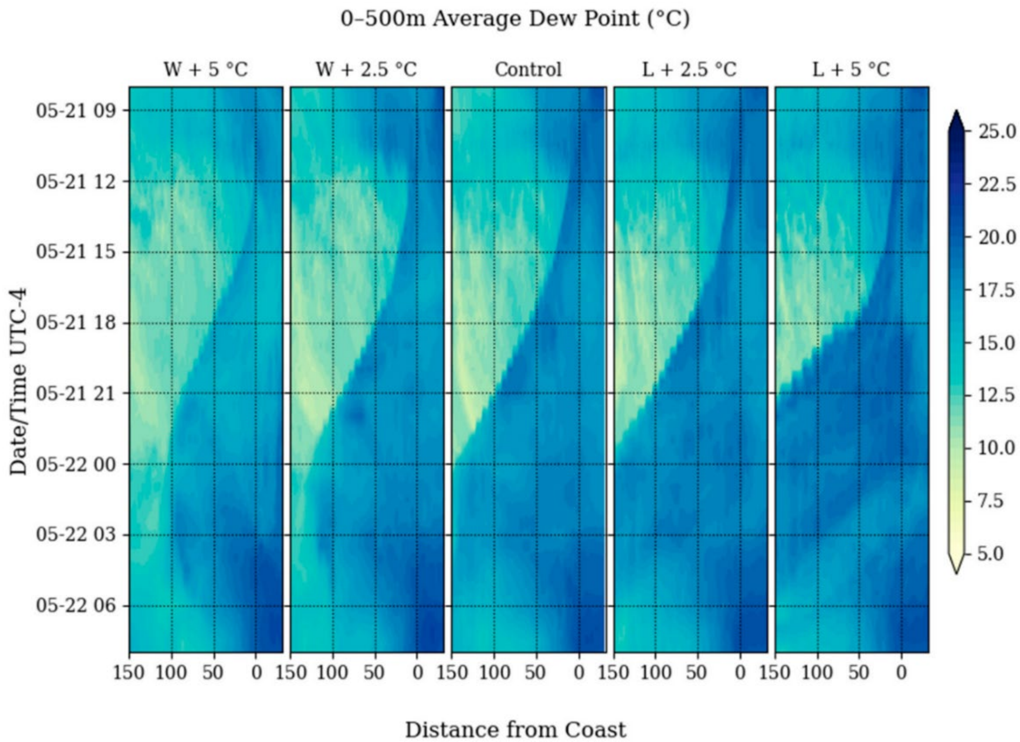

Figure 7. From Wermter et al. [4], a cross-sectional view of a simulated SBC from 21-22 May 2019. 0-500m dew point temperature is plotted with time as the vertical axis for a series of sensitivity simulations where the inland-coastal thermal gradient is modified.

Subtasks:

- T2.1: Utilizing SBC dataset from Task 1 and SMAP gridded products, determine the soil climatology preceding SBC days.
- T2.2: Conduct a series of month-long WRF sensitivity simulations using LSM spin-ups with and without SMAP integration.
- T2.3: Assess SMAP performance to the UGA and NCS Mesonets as well as SRS measurements.

Tentative Publication: A Soil Moisture Climatology of Sea Breeze Events in Georgia and the Carolinas, 2015-2023.

Task 3 – A prognostic model for SBCs

The final task of this project involves incorporating soil network measurements in a model that can forecast the occurrence sea breezes along several locations within the SEUS. The investigators of this project have experience in developing a ML method towards forecasting SBCs in Georgia and the Carolinas, using the land-sea thermal gradient and various measurements across multiple meteorological towers. We will expand on these methods and incorporate insight learned from Task 2 to create "land-aware" random forest (RF) and logistic regression (LR) methods for detecting SBCs. Since this model is intended for operational use, it will primarily rely on soil moisture measurement networks, but will also incorporate SMAP output when available and usable (e.g. clear enough cloud coverage to measure soil radiance).

Investigators on this proposal have experience in leveraging meteorological observations towards the ML prediction of SBCs in South Carolina using RF and LR methods to modest success (Figure 8). We will seek to improve these methods through the integration of soil moisture and temperature measurements wherever available. We will also select a series of locations within the Georgia/Carolinas region of the SEUS to apply these models to provide forecast guidance for the wide region. The objective of this task being to provide meteorological assistance to solar and wind energy forecasting.

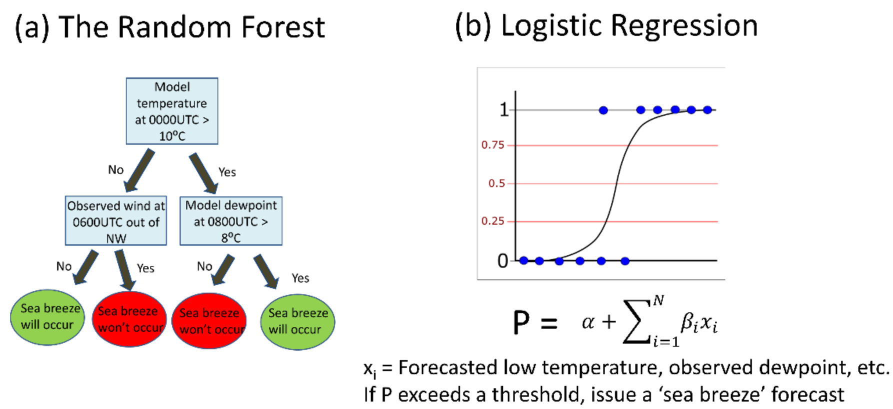

Figure 8. Examples of SBC forecasting using (a) Random Forest and (b) Logistic Regression ML methods.

Subtasks:

- T3.1: Using the SBC catalog from Task 1 and the soil moisture climatology from Task 2, incorporate soil moisture patterns from several SM sensors to ML methods.
- T3.2: Assess agreeance on both the diagnostic model from Task 1 and the prognostic model in Task 3.

Tentative Publication: Utilization of Soil Moisture Measurements in Forecasting Sea-Breeze Events with a Prognostic Machine Learning Method.

Implementation Plan

Personnel

Principal Investigator (PI): The PI will use their knowledge of numerical modeling towards Task 2 and will lead the NU-WRF modeling efforts within that task. They will also use their past experience in sea-breeze research to provide direction for the project. For Task 1, the PI will gather the ERA5 reanalysis data as well as write the code to detect initial SBC signatures (T1.1). For Task 2, the PI will process SMAP products to define the climatology for the region (T2.1) and will conduct the NU-WRF sensitivity studies to SMAP initialization. He will also retrieve and manage the mesonet data and assess their performance against SMAP (T2.3, T3.1).

Co-Investigator (Co-I) #1: Co-I #1 will leverage experience in ML to lead the development of the CNN model used to detect SBCs in Task 1. They will retrieve and process NEXRAD radar imagery to use as training data for the CNN model (T1.2). Additionally, Co-I #1 will use their vast expertise in numerical modeling to help in the simulation setup and analysis of NU-WRF output (T2.2).

Co-Investigator #2: Through their experience in using RF and LR models towards weather prediction, Co-I #2 will lead Task 3's development of the SBC prediction method (T3.1). They will also assist in the development of a soil moisture and temperature climatology, and the qualitative analysis of any notable patterns (T2.1). Towards Task 1, Co-I #2 will assess the reasonableness of the CNN SBC detection model (T1.3).

Co-Investigator #3: Co-I #3 will utilize their ML expertise to contribute to the development of both models in Tasks 1 and 2. They will help assess the reasonable thresholds for training data in both ML models (T1.2, T1.3, T3.1, T3.2). Additionally, they will test the forecast accuracy of the RF and LR models in Task 3 (3.2).

All investigators will contribute towards publications and presentations for research in all tasks throughout the duration of the project.

Schedule

Project tasks and subtasks identified through the project are expected to be completed along the following timelines (Table 1). Marked boxes indicate periods when each subtask is expected to be actively worked on.Some activities are applicable across multiple tasks (i.e. the CNN model for Task 1 is expected to be updated yearly). Tasks are arranged to progressively take advantage of the previous task.

Table 1. Timeline breakdown of tasks/subtasks. "X" indicates that the subtask will be undertaken during that quarter.

	2024				**2025**				**2026**			
	Q1	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**
T1.1	X											
T1.2		X										
T1.3			X		X				X			
T2.1				X								
T2.2					X	X	X					
T2.3							X	X	X			
T3.1										X	X	
T3.2												X

Summary

Our proposed research will improve the forecasting of SBCs which has major impacts on the weather forecasting within the SEUS and will provide the groundwork to implement similar methods to other lower/midlatitude coastal regions. This project will be conducted using analysis of soil moisture observation, both by station and by SMAP satellite estimates, as well as implementing those data into NWP and ML models.

References

1. Miller, S.T.K., et al., *Sea breeze: Structure, forecasting, and impacts.* Reviews of Geophysics, 2003. **41**(3).

2. Buckley, R.L. and R.J. Kurzeja, *An observational and numerical study of the nocturnal sea breeze. Part I: Structure and circulation.* Journal of Applied Meteorology, 1997. **36**(12): p. 1577-1598.

3. Viner, B., et al., *Frequency and Characteristics of Inland Advecting Sea Breezes in the Southeast United States.* Atmosphere, 2021. **12**(8).

4. Wermter, J., S. Noble, and B. Viner, *Impacts of the Thermal Gradient on Inland Advecting Sea Breezes in the Southeastern United States.* Atmosphere, 2022. **13**(7).

5. Physick, W.L., *Numerical Experiments on the Inland Penetration of the Sea Breeze.* Quarterly Journal of the Royal Meteorological Society, 1980. **106**(450): p. 735-746.

6. Baker, R.D., et al., *The influence of soil moisture, coastline curvature, and land-breeze circulations on sea-breeze-initiated precipitation.* Journal of Hydrometeorology, 2001. **2**(2): p. 193-211.

7. Da Silva, R.R. and R. Avissar, *The hydrometeorology of a deforested region of the Amazon basin.* Journal of Hydrometeorology, 2006. **7**(5): p. 1028-1042.

8. Benjamin, S.G., et al., *A North American Hourly Assimilation and Model Forecast Cycle: The Rapid Refresh.* Monthly Weather Review, 2016. **144**(4): p. 1669-1694.

9. Steele, C.J., et al., *Modelling sea-breeze climatologies and interactions on coasts in the southern North Sea: implications for offshore wind energy.* Quarterly Journal of the Royal Meteorological Society, 2015. **141**(690): p. 1821-1835.

10. Rodríguez-Benítez, F.J., et al., *A short-term solar radiation forecasting system for the Iberian Peninsula. Part 1: Models description and performance assessment.* Solar Energy, 2020. **195**: p. 396-412.

11. Mostamandi, S., et al., *Sea Breeze Geoengineering to Increase Rainfall over the Arabian Red Sea Coastal Plains.* Journal of Hydrometeorology, 2022. **23**(1): p. 3-24.

12. Zhu, X., Z. Qin, and L. Song, *How Land-Sea Interaction of Tidal and Sea Breeze Activity Affect Mangrove Net Ecosystem Exchange?* Journal of Geophysical Research: Atmospheres, 2021. **126**(8): p. e2020JD034047.

13. Noble, S., B. Viner, and J. Wermter, *Identification and Summary of Inland Penetrating Sea Breezes at the Savannah River Site from 2015-2021.* Submitted to Atmospheric Science Letters, 2022.

14. Hu, H., L.R. Leung, and Z. Feng, *Early warm-season mesoscale convective systems dominate soil moisture–precipitation feedback for summer rainfall in central United*

States. Proceedings of the National Academy of Sciences, 2021. **118**(43): p. e2105260118.

15. Vose, R.S., et al., *NOAA Monthly U.S. Climate Gridded Dataset (NClimGrid), Version 1.*, N.N.C.f.E. Information, Editor. 2014.

16. Bao, S., et al., *Mapping the Spatial Footprint of Sea Breeze Winds in the Southeastern United States.* Journal of Geophysical Research: Atmospheres, 2023. **128**(7): p. e2022JD037524.

17. Qian, J.H., et al., *Precipitation Characteristics of Warm Season Weather Types in the Southeastern United States of America.* Atmosphere, 2021. **12**(8).

18. Peters-Lidard, C.D., et al., *Integrated modeling of aerosol, cloud, precipitation and land processes at satellite-resolved scales.* Environmental Modelling & Software, 2015. **67**: p. 149-159.

Open Science and Data Management Plan

Measurements

No new measurements will be made as part of this research. All measurements and observational products that will be used are currently publicly available to the scientific community through data repositories containing SMAP satellite data, NEXRAD radar data, mesonet data, or other data. Measurements and observed data used towards publications or presentations will be cited and the repositories linked to, and subsets of data used will be made available to be distributed by the investigators upon request.

Numerical Modeling

All NU-WRF simulation results will be backed up on our organization's computer systems. Namelists and model setup information for simulations used towards publications and presentations will be archived and will be made available upon requests.

Machine Learning Modeling

Training data and output data for the ML models used in this project will be archived in our organization's computer systems. Methods and ML model specifications will be provided along with the results in any publication or presentation that utilizes our ML methods. Output will be made available upon request.

Table of Personnel and Work Effort

Name	Role	Commitment (months per year)											
		Year 1			*Year 2*			*Year 3*			*Sum*		
		This Project		*Other Funded Projects*	*This Project*		*Other Funded Projects*	*This Project*		*Other Funded Projects*	*This Project*		*Other Funded Projects*
		NASA Support	*Total*		*NASA Support*	*Total*		*NASA Support*	*Total*		*NASA Support*	*Total*	
PI	PI	1.2	1.2	0	1.8	1.8	0	1.2	1.2	0	0	0	0
Co-I #1	Co-I	1.2	1.2	0	1.2	1.2	0	1.2	1.2	0	0	0	0
Co-I #2	Co-I	1	1	0	0.6	0.6	0	1	1	0	0	0	0
Co-I #3	Co-I	1	1	0	0.6	0.6	0	1	1	0	0	0	0
Sum of work effort:		4.4	4.4	0	4.2	4.2	0	4.4	4.4	0	0	0	0

Budget Narrative

Principal Investigator – The PI will be the manager of the project and will provide direction to its tasks. They will gather and detect potential sea-breeze events in ERA5 data, provide training datasets for the machine learning sea-breeze detection algorithm, devise SMAP temperature and soil moisture climatologies for the SEUS, and will lead the NU-WRF modeling efforts. They will provide direction for publications and presentations for the project.

Co-Investigator #1 – Co-I #1 will lead in the development of the CNN machine learning model in the first task. They will additionally gather and plot 2-D NEXRAD radar imagery to use as training data for the model. They will aid the NU-WRF modeling as well as publication writing.

Co-Investigator #2 – Co-I #2 will lead development of the ML methods to forecast sea-breeze events and will also assist in qualitative analysis in determining seasonal and climatological patterns in soil properties. They will contribute towards writing publications and presentations for the project.

Co-Investigator #3 – As an expert in machine learning, Co-I #3 will be involved in the development of both machine learning models that this project proposes. They will help determine if training datasets are sufficient enough and will evaluate the effectiveness of each model in both cataloguing and forecasting sea-breeze events. They will also assist in publication writing.

The budget includes funds for roughly 1 person month per year for all investigators (total of 4 person months) which includes data analysis, modeling and preparation of manuscript and presentations.

Budget Details

Domestic travel support for one professional conference/meeting per year. Each trip cost is estimated based on prior attendance at AGU and AMS conferences and current conference and GSA rates, which include transportation, registration, 5 days of per diem, and lodging each, and miscellaneous travel expenses.

1 Conference/meeting per year: $4,000

- Airfare: $1,000
- Conference registration: $700
- 5 days per diem/lodging $400/day
- Miscellaneous (ground transportation, materials, etc.): $300

Total Travel: $12,000