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Studying Brown Ocean Re-Intensification of Hurricane Florence Using CYGNSS and SMAP Soil Moisture Data and a Numerical Weather Model

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Key Points:

- We hypothesize the wet antecedent soil moisture re-intensified Hurricane Florence
- We found that Hurricane Florence was re-intensified by wet antecedent soils, leading to intense and concentrated rainfall
- We found that cold antecedent soils impair the Brown Ocean effect in Hurricane Florence

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract

Hurricane Florence made landfall over the Carolinas 14 September 2018, bringing over 30 inches of rainfall. What remains understudied is the possible storm re-intensification by wet and warm antecedent soil moisture (ASM), known as the Brown Ocean Effect (BOE). This study investigates this effect with two approaches: (a) two satellite-based soil moisture (SM) data and (b) model simulation. The averaged Cyclone Global Navigation System and Soil Moisture Active Passive SM enables examination of land-atmosphere interaction at a sub-daily scale. Both observations and simulation results manifest positive feedback between ASM and rainfall intensity, with 3 days prior to landfall being the typical antecedent time scale. Wet (dry) ASM lead to intense (light) and concentrated (widespread) rains. We also found that soil temperature can modulate the BOE. This study aims to advance our understanding of land-atmosphere feedback and calls to acquire accurate antecedent land states to enhance forecast skills.

Plain Language Summary

Antecedent wet and warm soil conditions can maintain or re-intensify storms via vertical mixing of water vapor, a phenomenon called the Brown Ocean Effect (BOE). Previous studies investigating the existence of BOE have considered model simulations by perturbing antecedent soil moisture. Given the uncertainties in weather models, it is important to cross-validate the soil-rainfall feedback by both observations and simulations. It is also critical to understand the time scale of such feedback. The growing number of remote sensing soil moisture (SM) and weather radar rainfall products at various resolutions and spatial-temporal sampling offer unprecedented opportunities to examine this effect. Our results show consistent positive soil-rainfall feedback from both observations and simulations. Wet antecedent soils promote intense yet concentrated rains, while dry antecedent soils cause light and widespread rains. Meanwhile, soil temperature was also found to play an important role in mediating the feedback, with colder soils even leading to a negative correlation between wet antecedent soils and extreme rainfall rates. We advocate accurate representation of antecedent land surface states combined with assimilation of remote sensing SM products into models to enhance tropical cyclone forecasts.

1. Introduction

Hurricane Florence made landfall at 1115 UTC 2018-09-14, starting off as a category 4 hurricane on the East Coast but downgraded to category 1 over the Carolinas after landfall (Stewart & Berg, 2019). The winds and record-setting rainfall made it one of the billion-dollar weather and climate disasters in the US (NOAA NCEI, 2018). The risk of Hurricane Florence was likely overlooked by local residents who chose not to evacuate because of a misleading "low" hurricane category (Bosma et al., 2020). It is hypothesized that the land-atmosphere positive feedback intensified the storm after landfall.

The impact of SM on the atmosphere can be noted via two pathways (Guillod et al., 2015). One is as a direct impact (or positive feedback): warm and wet soils evaporate more water to participate in atmospheric recycling, resulting in more precipitation (Chang et al., 2009; Eltahir, 1998). The recent concept of the BOE—anomalously wet and warm soils can maintain or re-intensify storms, in a process similar to the warm ocean surface - has generated interest and led to a retrospective analysis of past storm events (Chang et al., 2009; Kishtawal, Niyogi, et al., 2012). The other mechanism is via an indirect impact (or negative feedback): enhanced sensible heat flux over dry soil deepens and warms the planetary boundary layer, creating a temperature gradient that is

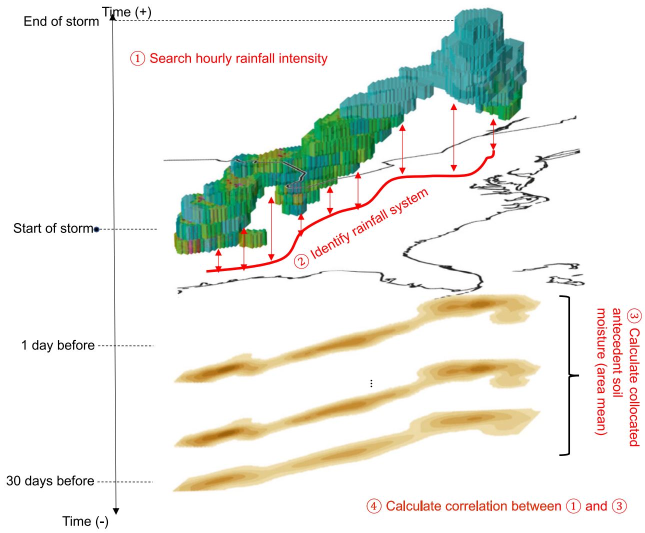

Figure 1. Illustration of tracking algorithm for rainfall and time-lag correlation analysis between rainfall intensity and antecedent soil moisture. The shading illustrates the rainfall intensity.

favorable for the formation of intense mesoscale convective systems, leading to intense rainfall rates (Guillod et al., 2015). On a synoptic scale, dry soils can modulate moisture convergence via thermal wind and wind shear and can re-intensify storms (Klein & Taylor, 2020). The impact of SM however is equivocal, depending on the atmospheric preconditions, which necessitates careful examination.

Identifying the feedback pathways, either negative or positive, is often through a set of numerical weather model simulations (Yoo et al., 2020). Many studies, however, have failed to reconcile the results from observations and model simulation (Guillod et al., 2015). For example, Taylor et al. (2012) found inconsistency in the results between satellite observations and climate models. From satellite observations, they found afternoon heavier rain falls on antecedent drier soils (i.e., negative feedback), while the model results suggested heavy rains favor wetter soils (i.e., positive feedback). Moreover, the time scale of such feedback is not well articulated in the literature. The main focus of most studies is to affirm the existence of the BOE and to examine its precursor environment. The scope of this study is to answer the scientific question—Did the BOE exist for Hurricane Florence? If so, can we reconcile the direction of feedback from observations and simulations? A related question is - What is the time scale of such feedback? To answer these questions, we propose a framework that utilizes two satellite remote sensing products—Cyclone Global Navigation System (CYGNSS) and Soil Moisture Active Passive (SMAP)—to investigate the existence of the BOE and its time scale. The advantage of using CYGNSS SM data lies in its provision of sub-daily SM estimates, making it suitable for investigating land-atmosphere interaction. However, since CYGNSS SM is still being calibrated, its accuracy in this study is considered inferior to SMAP SM. To address this limitation, we introduce a combined product that integrates the frequency of CYGNSS data while retaining the retrieval accuracy of SMAP. A set of control experiments are conducted to reinforce the exploratory data analysis. This study aims to provide insight for enhancing storm predictability with the importance of initiating weather forecast models with antecedent soil states and enhancing our understanding of land-atmosphere feedback in the extreme scenario.

2. Methods

To recap, this study seeks to investigate the BOE from both observations and model-based analysis. From the observational perspective, we correlate the rain-producing storms with n-days ASM from satellite-based SM retrievals. From the modeling analysis, we conduct experiments for the impact of ASM by isolating and changing its values in the initial condition of the model setup. We reference rain-producing storms and TC as follows. The rain-producing storms are extracted from an object-identification algorithm that is based on observed rainfall rates during Hurricane Florence (Wang et al., 2023). A TC is a large weather system (e.g., Hurricane Florence) with its intensity measured by sea level pressure (SLP) and wind speed.

2.1. Evaluation With Observations

The method used to correlate rainfall intensity and ASM is illustrated in Figure 1. First, we loop through hourly rainfall rates and identify rain-producing storms based on Peak-Over-Threshold method. A convolution filter is applied to split the rainfall fields into objects. A minimum threshold of 5 mm/hr and a filter size of 3 grid cells are used in the convolution process. The parameters are set to the same as Prein et al. (2017) for identifying mesoscale convective rain-producing storms. The convolution is conducted both in time and space to account for the continuity of rain-producing storm development. Second, each rain-producing storm is associated with its unique identifier which is organized into a time-space format. For the first two steps, we use the off-the-shelf Model Evaluation Tools software and the Method for Object-based Diagnostic Evaluation Time Domain (MTD) approach, developed by the Developmental Testbed Center (Brown et al., 2021). Readers are referred to the documentation for detailed description (https://met.readthedocs.io/en/latest/Users_Guide/mode-td.html). Third, we collocate rainfall intensity within each rain-producing storm (with 10th, 25th, 50th, 75th, 90th, and 99th percentiles) at time t with ASM (ranging from t-1 to t-30 days). The choice of a 1-month antecedent time window is motivated by the typical SM memory in this region (Dirmeyer et al., 2009; Wakefield et al., 2021). Lastly, we calculate the Spearman Correlation Coefficient (CC) between rainfall intensity and ASM (Details in Supporting Information S1). As a result, we identified 55 rain-producing storm tracks during Hurricane Florence.

To investigate the modulation of soil temperature on the SM-rainfall feedback loop, we conduct a partial correlation analysis besides normal correlation analysis. The partial CC (PCC) is calculated with the formula below.

$$r_{12,3} = \frac{r_{12} - r_{13}r_{23}}{\sqrt{1 - {r_{13}}^2}\sqrt{1 - {r_{23}}^2}}, \tag{1}$$

where the $r_{12,3}$ denotes the correlation between ASM and rainfall rates with controlling factor soil temperature, r_{12} is the correlation between ASM and rainfall rates, r_{13} is the correlation between rainfall rates and antecedent soil temperature, r_{23} is the correlation between ASM and antecedent soil temperature. We compared the difference between $r_{12,3}$ and r_{12}. If it is positive, it indicates that the controlling factor soil temperature is suppressing the relationship between ASM and rainfall rates. Likewise, if it is negative, that means soil temperature is strengthening the relationship.

2.2. Model Setup

It is challenging to disentangle the effects of SM from other environmental and atmospheric factors purely through observational data analysis. Therefore, we designed a set of control experiments using the Weather Research Forecast (WRF) model for the domain shown in Figure S1 in Supporting Information S1. Two domains are configured - one outer domain at a resolution of 12 km and the inner domain at a resolution of 4 km. A list of model physical schemes is shown in Table S1 in Supporting Information S1. One can find a similar model configuration for Hurricane Florence in Patel et al. (2021). We initialize the model from days two to seven with 1 day apart and allowed at least 1 day for the model to spin up (Figure S1b in Supporting Information S1). The reason for different initialization dates is to investigate the time scale of ASM that exerts the most influence on tropical storm intensity, which relates to the second research question—what is the time scale of such SM-rainfall feedback. For SM, we simulate wet (dry) soil conditions by multiplying the initial SM field by 150% (50%). A similar experiment setup for perturbing initial SM can be found in Kellner et al. (2012). For soil temperature, we perturbed the initial soil temperature by +10 K (warm) and −10 K (cool). To attest the soil temperature impact on the BOE, we use the wet ASM condition for the model input. In total, there are 18 experiements for SM perturbation and 18 experiments for soil temperature perturbation.

3. Data

3.1. Remote Sensing Soil Moisture Data

High temporal resolution, gridded SM data is needed in this study to construct a grid-to-grid comparison with rainfall data. The well-recognized SM Active Passive Level 3 data (SMAP) is used, as it is arguably the best available remote sensing data to date (Ford & Quiring, 2019). Due to its infrequent revisit time (typically 2–3 days), we incorporate another emerging satellite SM product - CYGNSS Level 3 data (Chew and Small, 2020). The CYGNSS data provides 6-hourly SM retrievals, which are on an ideal frequency to assimilate into Earth system models (Kim et al., 2021). With its similarity to L-band radar frequency, CYGNSS is calibrated against SMAP, so we assume a homogeneous retrieval of ASM when merging the two. The SMAP-Calibrated CYGNSS product has a resolutions of 36 km. To maintain the same uniform grid resolution as the rainfall data, the CYGNSS and SMAP data are averaged and then projected to the same grids using the nearest neighbors method. The temporal resolution of the newly generated CYGNSS-SMAP product is retained as the same as the CYGNSS resolution. Only quality-controlled SM data (set by the quality flag: retrieval_qual_flag = 0) are used in this study. The data from 2018-08-20 to 2018-09-20 are collocated with rainfall rates to analyze their correlations.

3.2. Stage IV Rainfall Data

The National Centers for Environment Prediction Stage IV rainfall data, referred to as Stage IV, is obtained from the NCAR/UCAR Earth Observing Laboratory for the coincident period. Stage IV is a radar-gauge merged

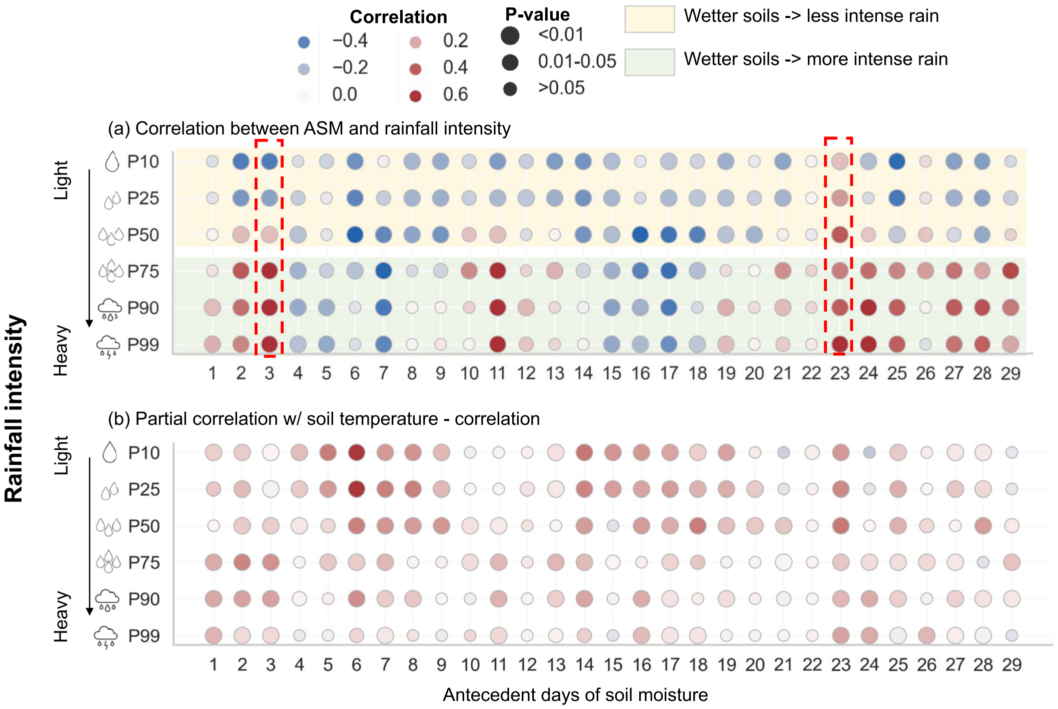

Figure 2. Map of (a) Correlation Coefficient (CC) between antecedent soil moisture (1–30 days) relative to the start of a rain-producing storm and precipitation intensity; (b) differences between PCC and CC. The precipitation intensity is grouped by different percentiles, that is, P10—10th percentile, P25—25th percentile, P50—50th percentile, P75—75th percentile, P90—90th percentile, and P99—99th percentile. The light yellow shaded region in figure (a) indicates that wetter soils lead to less intense rains (negative correlation), while the light green region indicates that wetter soils lead to more intense rains (positive correlation). The positive correlation difference in figure (b) indicates that soil temperature is a modulator of the ASM-rainfall feedback.

product, offering high spatiotemporal resolution over the continental US (4 km and hourly). Previous studies have used Stage IV as a benchmark to assess the performance of satellite precipitation products (Li et al., 2022).

3.3. Soil Temperature Reanalysis Data

Because no direct estimates of gridded soil temperature were available from remote sensing data, we used the North American Land Data Assimilation System project Phase 2 (NLDAS2) product, provided by NASA for the study period (Xia et al., 2012). This data set provides spatial and temporal resolutions at 0.125-deg and 1 hr. The Noah land surface model is used to resolve soil temperature at depths 0–5, 5–25, 25–70, 70–150 cm below the surface. In this study, we only retrieve the soil temperature at near surface level (0–5 cm) for detailed analysis. The model error is estimated to be less than 2 K when compared to in-situ measurements (Xia et al., 2013).

4. Results

4.1. Existence of BOE From Observations

Correlation analysis is conducted by correlating n-day ASM with precipitation intensity grouped by different percentiles (i.e., low-end: P10, P25, P50; high-end: P75, P90, P99), as shown in Figure 2a. The precipitation distribution is derived over a rainy area for an identified rain-producing strom at a given timeframe. First, results show that ASM has a negative correlation with low precipitation intensity (light yellow shaded block) while having a positive correlation with high precipitation intensity (light green shade block). The CC between 3-day ASM and P10 (P99) is lower (higher) than −0.4 (+0.6), both of which have significant statistics (p-value < 0.01). With that being said, wet ASM enhances extreme precipitation rates, as well as rain-producing storm intensity, pointing to the existence of the BOE.

Second, the time-varying CC is shown to have two prominent peaks in the CC: 3 days and 23–25 days prior to a rainfall system. The 3-day ASM infers a good estimate of atmospheric moisture residence time over the East Coast, aligning well with the results of Läderach and Sodemann (2016). Soil water from upper soil layers (10–50 cm) can directly contribute to increasing atmospheric humidity, also known as mobile water (Brooks et al., 2010). The 23–25 days ASM are likely the longest time that SM can exert its effect in participating land-atmosphere interaction, also known as the available SM memory (Dirmeyer et al., 2009). This part of the water is tightly bound water that is trapped in small pores and can be extracted via evapotranspiration (White & Toumi, 2012).

Despite a general positive correlation between wet ASM and extreme rainfall rates, it is possible to have a negative correlation (days 4–10), because of the imposed large-scale weather patterns. During antecedent days 4–10, air temperature suddenly dropped from 27 to 22°, and so did soil temperature (Figure S2 in Supporting Information S1). Cold soil temperature hampers soil water evaporation and vertical heat fluxes, leading to reduced ASM-rainfall correlation. Days 14–18 also present a negative correlation, which could be a result of large-scale weather dynamics. For instance, dry soils can modulate SM convergence via thermal wind and wind shear and thus enhance convective rainfall (Klein & Taylor, 2020). By breaking down the ASM into categorical—wet ASM (relative SM ≥ 0.5) and dry ASM (relative SM < 0.5) in Figure S3 in Supporting Information S1, we see that this period of negative correlations are only present in dry ASM (Figure S3a in Supporting Information S1), while wet ASM shows positive correlations (Figure S3b in Supporting Information S1).

To further analyze the soil temperature influences, we did a partial correlation analysis with soil temperature as a controlling factor (Figure 2b). The PCC measures the strength of a relationship between ASM and rainfall rates while holding antecedent soil temperature constant. We find increases in PCC relative to normal correlation for most of the antecedent days, meaning that soil temperature is a modulator to the ASM-rainfall feedback. We also separated the data into pre- (before 2018-09-14) and post-landfall (after 2018-09-14) episodes. The positive correlation between 3-day ASM and extreme rainfall intensity (P99) becomes stronger (CC > 0.7) in the pre-landfall period (Figure S4a in Supporting Information S1), yet it transitions to a negative correlation (CC < -0.2) for a post-landfall period (Figure S4b in Supporting Information S1). In essence, such a difference is mainly caused by the temperature change following hurricane landfall.

To interpret the results further, we show a two-dimensional histogram of 3-day ASM and rain rates (Figure S5 in Supporting Information S1) as a supplement to Figure 2. One can visually notice the changes from a negative correlation for light rains to a positive correlation for heavy rains. All the while, the rain-producing storm dynamics (i.e., storm lifetime, speed, etc.) present a significant correlation with ASM. As a result, ASM is positively correlated with rain-producing storm lifetime (Figure S5g in Supporting Information S1) but negatively correlated with translation speed (Figure S5f in Supporting Information S1). It implies that a rain-producing storm is likely to be sustained over wet soil, as the soil continuously supplies moisture fluxes.

4.2. Model Verification

4.2.1. Tropical Storm Intensity

All model experiemnts produce comparable SLP and sustainable wind speeds after landfall, as compared to the HURDAT2 data set (Figures 3a and 3b). The HURDAT2 data set is a compiled geospatial database maintained by NOAA, containing detailed information on tropical cyclones (Landsea et al., 2015). The simulated tracks in Figure S6 in Supporting Information S1 have small differences compared to the best track in the HURDAT2 data, prior to 2018-09-16 18Z. However, after that date, all simulations have difficulties in reproducing inland TC movement due to complex inland conditions and an extended number of forecast days. Although Zhang et al. (2019) reported wet ASM prolonged traveling distance of TC Bill, we did not observe significant differences in terms of traveled distances under different soil states. As manifested by observational analysis, ASM is positively correlated with rain-producing storm lifetime (Figure S5h in Supporting Information S1) but negatively correlated with translation speed (Figure S5g in Supporting Information S1). That is, higher ASM would mean higher likelihood of slower moving, longer duration rain-producing storm, which can lead to more storm inundation. Therefore, the insignificant correlation between ASM and traveling distance could be a result of increasing lifetime of rain-producing storms yet a slower translation speed (Kishtawal, Jaiswal, et al., 2012). This increases the likelihood of more storm-based rainfall accumulation over a given region.

The result from the 36 different WRF experiments confirms that varying initial SM and temperature at different initial times can have diverse impacts on TC intensity. This is also noted in the range of sea-level pressure and wind speed in Figure 3. Broadly, wet ASM lowers minimum sea-level pressure by 5 hPa on average (i.e., more intense) than dry and normal ASM (Figure 3a). Regarding maximum wind speed (Figure 3b), wet soils intensify

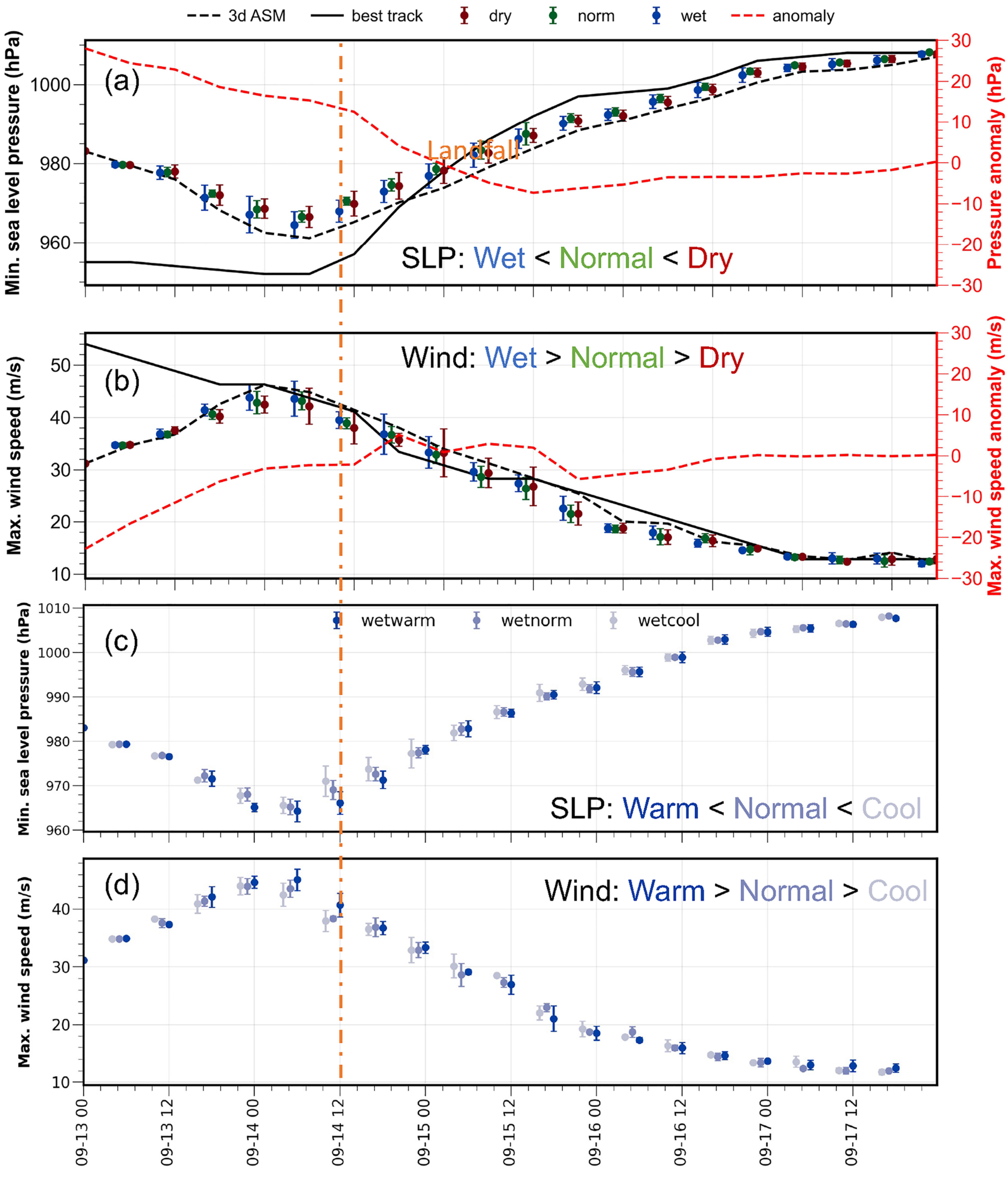

Figure 3. Time series of TC intensity from different initial soil moisture measured by absolute values (left *y* axis) and differences between 3-day normal antecedent soil moisture (ASM) run (initialized on 2018-09-11, 3 days prior to landfall) and HURDAT2 data (red dashed line and right *y* axis) of (a) mimimum sea level pressure (SLP) and (b) maximum 10-m wind speed. The error bar is estimated by the standard deviation of experiments from different initialization dates. Three-day wet ASM experiment is highlighted in red. The black line represents the HURDAT2 data. Time series of TC intensity from different initial soil temperature measured by (c) minimum SLP and (d) maximum wind speed.

surface winds by more than 1.35 m/s than dry soils. When ASM is wet, hot soils can further increase the TC intensity, indicated by 4.9 hPa lower minimum SLP (Figure 3c) and 2.75 m/s higher maximum wind speed (Figure 3d) than those from cold soils. It suggests that soil temperature is an important modulator for the BOE.

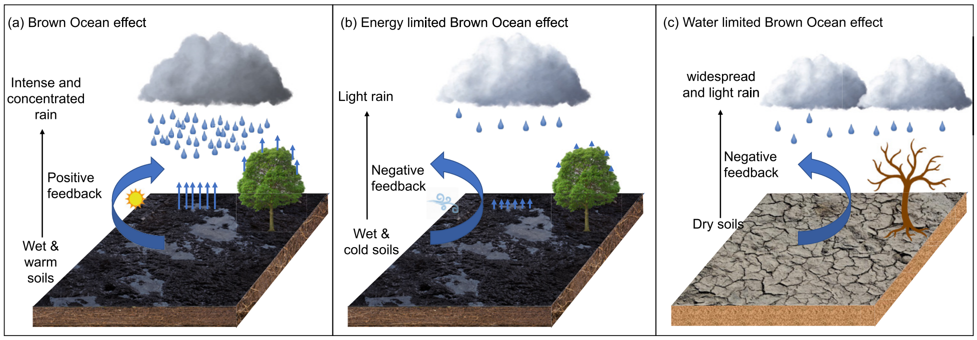

Figure 4. A summative schematic of (a) general Brown Ocean Effect (BOE), (b) energy-limited BOE, and (c) water-limited BOE.

The WRF simulation corroborates our observational finding that 3-day wet ASM (highlighted in Figure 3a) exerts the greatest impact on TC development. It produces the lowest sea-level pressure of 964.5 hPa and maximum sustainable wind speed of 157.7 km hr^{-1} across all model simulations.

4.2.2. Rainfall Intensity

The predicted rainfall time series averaged over three domains are shown in Figure S7 in Supporting Information S1. Over the rainfall core region (Figure S7a in Supporting Information S1), wet ASM results in more intense rainfall rates during the first 48 hr after landfall (2018-09-14 to 2018-09-16), which is 4.7% and 9.0% higher than normal and dry ASM, respectively. Yet, over the rain-producing storm region (Figure S7b in Supporting Information S1) and the whole region (Figure S7c in Supporting Information S1), dry ASM has a propensity to produce higher rainfall rates than both wet (2.2%) and normal ASM runs (4.3%). For the rainy area shown in Figure S8 in Supporting Information S1, dry ASM runs produce around 3.5% higher rainfall areas than both wet and normal ASM runs, averaging 7562 km^2. With that being said, drier ASM tends to result in less intense and more widespread rainfall, while the opposite for wet ASM. We further found that the wet ASM is linked to more extreme rainfall rates in the evening from 20Z UTC to 05Z UTC from a diurnal plot of rainfall rates (Figure S9 in Supporting Information S1).

For different initial soil temperatures, wet and hot soils produce 19.7% and 54.4% higher rainfall rates on average than wet soils with normal and cold temperature, respectively, over the rainfall core region (Figure S10a in Supporting Information S1). Outside the core region, the differences become limited (Figures S10b and S10c in Supporting Information S1).

5. Discussion

Through the observations and model-based analysis, we affirm the existence of the BOE during Hurricane Florence (research question #1) and discover that the time scales pertaining to the BOE are 3 and 23 days, respectively (research question #2). The 18 WRF runs by perturbing ASM manifest an intensified rain-producing storm if ASM is wet, a cross-reference to our observational analysis. We found consistent results between observations and simulations (Figure S11 in Supporting Information S1). Extreme rainfall rates (>30 mm/hr) are enhanced under wet ASM, which is found for both observation and simulation. Our simulation results also reveal that wet ASM promotes more intense and concentrated rains than dry ASM which leads to light and widespread rains (Figures S7 and S8 in Supporting Information S1). This is in fact counter to some studies that suggest the opposite for other storms (Kellner et al., 2012; Zhang et al., 2019). Both observation and simulation results converge on the 3-day ASM being the typical time scale for the soil-rainfall feedback during Hurricane Florence, which represents the atmospheric water vapor residence time. However, for a different setting, this value can vary. For instance, the aforementioned soil temperature can influence and possibly lengthen the time scale. Meanwhile, this value can vary by region according to Läderach and Sodemann (2016).

The feedback between rainfall and ASM is multifaceted and time-evolving. We summarize and show the key information in Figure 4. We found that two signs of feedback co-exist in this study. When antecedent soil is wet and warm, there exists positive feedback (BOE). Alternatively, when antecedent soil is wet and cold, negative feedback is present (Energy-limited BOE). When antecedent soil is dry, the water-limited BOE presents, leading to negative feedback. We convey an important message here—soil temperature is an important modulator to such BOE feedback. Despite existing studies suggest correlation between ASM and rainfall rates, less mentioned is the soil temperature modulation effect, which could also be a precursor to determining the sign of feedback. We see that cold antecedent soil temperature, possibly as a result of a cold pool, can result in negative feedback from observational analysis. This point has also been verified in our model simulation that wet and warm soils produce higher TC intensity and higher rainfall rates than soils with normal and cold temperatures. The underlying mechanism is that vertical heat fluxes are hampered by cold soil temperature, slowing the vertical mixing of water vapor (Nair et al., 2019).

6. Conclusions

This study investigates the possible existence of the BOE during Hurricane Florence from observational analysis and model simulations. Our main conclusions are:

1. Wet antecedent soils can promote extreme rainfall rates, referring to the existence of the BOE in Hurricane Florence. The antecedent time scales of such an effect are 3 and 24 days during Hurricane Florence, which reflect typical atmospheric water vapor residence time and SM memory, respectively.
2. Wet antecedent soils lead to intense and concentrated rains, while dry antecedent soils contribute to light yet widespread rains.
3. The sign of soil-rainfall feedback is modulated by soil temperature, with warm (cold) soils aiding positive (negative) feedback.

This study strives to advance our understanding of land-atmosphere feedback and calls to acquire accurate antecedent land states to enhance land falling tropical cyclone forecast skills.

Data Availability Statement

The CYGNSS Level 3 soil moisture data from UCAR/CU Version 1.0 is publicly available at https://doi.org/10.5067/CYGNU-L3SM1. The SMAP Level 3 Radiometer Global Daily 36 km EASE-Grid data Version 8 can be accessed from the NASA National Snow and Ice Data Center Dsitributed Active Archive Center (https://doi.org/10.5067/OMHVSRGFX38O). The configuration file for WRF and rain-producing storm tracking analysis can be found in Li (2023).

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