Dynamical Structures of Cross-Domain Forecast Error Covariance of a Simulated Tropical Cyclone in a Convection-Permitting Coupled Atmosphere–Ocean Model

XINGCHAO CHEN, ROBERT G. NYSTROM, CHRISTOPHER A. DAVIS, AND COLIN M. ZARZYCKI

ABSTRACT: Understanding the dynamics of the flow-dependent forecast error covariance across the air–sea interface is beneficial toward revealing the potential influences of strongly coupled data assimilation on tropical cyclone (TC) initialization in coupled models, and the fundamental dynamics associated with TC air–sea interactions. A 200-member ensemble of convection-permitting forecasts from a coupled atmosphere–ocean regional model is used to investigate the forecast error covariance across the oceanic and atmospheric domains during the rapid intensification of Hurricane Florence (2018). Forecast uncertainties in both atmospheric and oceanic domains, from an Eulerian perspective, increase with forecast lead time, mainly from TC displacement errors. In a storm-relative framework, the ensemble forecast uncertainties in both domains are predominantly caused by differences in the simulated storm intensity and structure. The largest ensemble spread in the atmosphere, temperature, and wind fields can be found within the TC inner-core region. Alternatively, the largest ensemble spread in the upper-ocean currents and temperature fields are located along the cold wake behind the storm. Cross-domain ensemble correlations suggest that it is possible to use atmospheric and oceanic observations to simultaneously update state variables associated with the coupled atmosphere–ocean prediction of TCs using strongly coupled data assimilation. Sensitivity experiments demonstrate that at least 60–80 ensemble members are required to represent physically consistent cross-domain correlations and minimize sampling errors.

KEYWORDS: Tropical cyclones; Air-sea interaction; Coupled models; Data assimilation

1. Introduction

Tropical cyclones (TCs) are one of the most devastating and frequently occurring natural disasters, causing catastrophic damage to coastal areas by producing extreme wind, rainfall, storm surge, and flooding (Stone et al. 1997; Emanuel 2003; Peduzzi et al. 2012). TCs typically form over warm ocean, with sea surface temperature (SST) of 26°C or higher (Palmen 1948; Tuleya and Kurihara 1982; DeMaria and Kaplan 1994), and represent an extreme case of air–sea interactions (e.g., Leipper 1967; Price 1981; Emanuel 1986; Schade and Emanuel 1999; Ginis 2002; Balaguru et al. 2012; Haakman et al. 2019). The energetics of TCs can be idealized as an atmospheric Carnot heat engine, with the ocean as the primary source of heat and the main sink of kinetic energy via surface winds (Emanuel 1986, 2018). The frictionally driven inflowing air parcels receive moist enthalpy from the ocean at nearly constant temperature and thereby provide most of the heat for TCs (Emanuel 1986; Pauluis and Zhang 2017). On the other hand, TCs also elicit a vigorous response in the upper ocean and induce turbulent entrainment mixing of colder water from below the seasonal thermocline (Price 1981; Cione and Uhlhorn 2003; Mei et al. 2015; Emanuel 2018; Haakman et al. 2019). The associated SST cooling, in turn, results in a reduction of the moist enthalpy flux into the atmosphere, thereby limiting TC intensification (Emanuel 1986; Schade and Emanuel 1999; Wu et al. 2016; Zhu et al. 2016). These competing processes near the air–sea interface are critical to TC development. Consequently, air–sea interactions lie at the heart of TC energetics and dynamics.

The primary features of TC air–sea interactions can be simulated using high-resolution fully coupled atmosphere–ocean models (e.g., Bender and Ginis 2000; Chen et al. 2007; Zarzycki 2016). The first coupled model used for operational TC prediction was developed by NOAA’s Geophysical Fluids Dynamics Laboratory (GFDL) in 1995 (Bender et al. 1993; Kurihara et al. 1998; Bender et al. 2007). By incorporating the TC air–sea interactions, the GFDL model became the first operational numerical model to be competitive with purely statistical models (DeMaria and Kaplan 1999; Emanuel 2018). Nowadays, most operational TC forecast models have been upgraded to coupled atmosphere–ocean or atmosphere–wave–ocean models (e.g., Chen et al. 2007; Doyle et al. 2014; Kim et al. 2014). However, a particular challenge still exists for coupled TC prediction, how to initialize the forecasts in a dynamically consistent fashion. Currently, all operational TC forecasts are initialized in uncoupled mode, i.e., atmospheric observations are only assimilated into the atmosphere model, and oceanic observations are only assimilated into the ocean model (also called weakly coupled data assimilation).
Given limited oceanic observations (especially observations in the subsurface ocean) near TCs, the ocean upper-ocean temperature, salinity, and location of eddies and fronts, which can be critical to TC development, remain poorly initialized in operational TC forecast models (Zhang and Emanuel 2018). Another shortcoming of weakly coupled data assimilation (WCDA) is that it may create dynamically and thermodynamically imbalanced initial conditions near the air–sea interface, which leads to initialization shocks that accelerate the development of forecast errors and degrade TC prediction (Mulholland et al. 2015).

Strongly coupled data assimilation (SCDA) is a method to improve the initialization of coupled models (Penny and Hamill 2017). By using the cross-domain error covariance, SCDA is able to propagate information across the air–sea interface, and update atmospheric and oceanic state variables simultaneously. In principle, SCDA is more efficient in extracting useful information from available observations than WCDA. That is, the oceanic initial conditions can be improved by assimilating atmospheric observations, and the atmospheric initial conditions can be improved by assimilating oceanic observations. Additionally, SCDA should theoretically lead to a more dynamically and thermodynamically balanced initial state between the atmosphere and ocean than that produced by WCDA. SCDA has been explored in the past few years, and previous studies have indicated that it is superior to WCDA (e.g., Smith et al. 2015; Frolov et al. 2016; Laloyaux et al. 2016b,a; Sluka et al. 2016; Penny and Hamill 2017; Laloyaux et al. 2018; Penny et al. 2019). However, it has not yet been widely used for the high-resolution coupled prediction of TCs. Li and Toumi (2018) used the Data Assimilation Research Testbed (DART) package (Anderson et al. 2009) to study the potential impacts of coastal high-resolution surface current observations on the forecasts of seven idealized TC cases. They demonstrated that TC intensity forecasts can be improved by assimilating synthetic ocean current observations into the atmosphere using SCDA. Chen and Zhang (2019, hereafter CZ19) developed a convection-permitting SCDA system for TC prediction. They evaluated the system using observing system simulation experiments of Hurricane Florence (2018). The results indicate that SCDA can also correct the atmospheric initial condition of Florence by assimilating oceanic observations, which further improves the track and intensity forecasts of Florence.

By both of these studies used the ensemble Kalman filter (EnKF) to perform the SCDA. The EnKF uses a flow-dependent error covariance estimated from an ensemble of short-term forecasts to propagate information between observed and unobserved variables. The flow-dependent error covariance is ultimately decided by the model dynamics, which quantifies the uncertainty of the ensemble forecast (or ensemble spread) and the linear multivariate relationships between different model state variables and observations (or ensemble correlations). The extent to which different model state variables can be updated by the EnKF is determined by the flow-dependent error covariance. For this reason, understanding the dynamics and structures of the forecast error covariance is very useful toward revealing the potential benefits of the EnKF. Poterjoy and Zhang (2011, hereafter PZ11) studied the evolution of the flow-dependent error covariance for Hurricane Katrina (2005) from a 60-member atmosphere-only ensemble forecast. They found that the error covariance between simulated atmospheric observations and atmospheric model state variables is highly anisotropic, and is variable dependent, as determined by the underlying TC dynamics.

For an ensemble of coupled forecasts, one can calculate not only the error covariance within the atmospheric and oceanic domains, but also the error covariance across the two domains. This cross-domain error covariance enables ensemble-based DA, like the EnKF, to transport observed information from one domain to another. The dynamical structures of the cross-domain error covariance reflect the advantages of SCDA on TC initializations when compared to WCDA. In this study, the TC cross-domain error covariance structures are examined using a large (200-member) ensemble of convection-permitting coupled forecasts for Hurricane Florence (2018) during its rapid intensification. The spatiotemporal evolution of forecast errors and the potential cross-domain impacts of different simulated atmospheric/oceanic observations are assessed. Sensitivity experiments with varying ensemble size are also conducted to determine how many ensemble members are required in order to represent physically consistent cross-domain error correlations and to minimize sampling errors.

2. Methods

a. Model description and experiment design

The Coupled Ocean–Atmosphere–Wave–Sediment Transport Modeling System (COAWST) (Warner et al. 2010) is used for the ensemble forecasts of Hurricane Florence. The model configurations and physics used in this study are the same as that used in CZ19. The Weather Research and Forecasting (WRF) Model (Skamarock et al. 2008) and the Regional Oceanic Modeling System (ROMS; Shchepetkin and McWilliams 2005) are coupled within the COAWST framework. The coupling interval is set to 900 s. During the coupling step, COAWST coupler provides ROMS with the wind stress, latent/sensible heat flux, sea level pressure, and longwave/shortwave radiation from WRF, and provides WRF with the updated SST field from ROMS. The WRF model uses the WRF single-moment 6-class microphysics scheme (Hong and Lim 2006), the Dudhia shortwave radiation scheme (Dudhia 1989), the Rapid Radiative Transfer Model longwave radiation scheme (Mlawer et al. 1997), and the Yonsei University planetary boundary layer scheme (Hong et al. 2006). The surface flux scheme introduced in Chen et al. (2018), which uses a decreasing surface momentum flux exchange coefficient at hurricane-forced wind speeds, is used in WRF to calculate the surface wind stress. The sensible heat and latent heat exchange coefficients are as in Brutsaert (1975). The surface wind stress and heat fluxes are calculated through the surface flux scheme in WRF and provided to ROMS through COAWST. There is no wave coupling in this study. No cumulus parameterization has been used in WRF Model. The horizontal grid spacing of WRF is...
We acknowledge that this chosen horizontal grid spacing is not able to resolve individual convective cells, but it is enough to resolve the basic dynamics of organized mesoscale convective systems and TCs (e.g., Osuri et al. 2013; S. Wang et al. 2015; Chen et al. 2018; Chen et al. 2020; Ruppert and Chen 2020). The WRF domain covers most of the Atlantic Ocean and eastern United States with 445 × 267 grid points (Fig. 1a). A total of 43 vertical levels are used with a pressure top at 50 hPa.

The ROMS model has a similar model domain configuration to WRF, with 9 km grid spacing and 441 × 261 grid points (not shown). There are 36 stretched terrain-following vertical levels, with at least 15 levels within the upper 50 m in order to better resolve the ocean mixed layer. The generic length scale method with the $k$-$\varepsilon$ closure scheme (Warner et al. 2005) is used to parameterize the ocean vertical turbulent mixing. CZ19 shows that the model setup can realistically simulate the structures and intensity of Florence during its rapid intensifying and weakening stages from 8 to 16 September 2018.

The 200-member ensemble forecast is initialized at 0000 UTC 8 September. The NOAA’s Global Ensemble Forecast System (GEFS) real-time 21-member analyses from 1800 UTC 5 September to 0000 UTC 8 September (available every 6 h, 10 analysis times in total) are used to generate the initial atmospheric perturbations. At each analysis time, we collect 20 ensemble perturbations by subtracting the control member (member 0) from members 1–21. The atmospheric initial conditions at 0000 UTC 8 September are then obtained by adding the collected 200-member perturbations (20 ensemble perturbations at each analysis time ×10 analysis times) estimated from the GEFS analyses to the GEFS member 10 analysis at 0000 UTC 8 September (which is used as the initial condition of the nature run in CZ19). Because Florence was very weak before 0000 UTC 8 September (minimum surface
pressure is higher than 1000 hPa), this procedure does not generate multiple TC signatures along the simulated TC track, which would result in highly non-Gaussian ensemble spread at the initial time (not shown here). The GEFS member 0 analyses from 0000 UTC 8 September to 0000 UTC 16 September are used as the atmospheric boundary conditions for the 200-member ensemble forecasts. As with CZ19, the initial and boundary conditions of ROMS are obtained from Hybrid Coordinate Ocean Model with Naval Research Laboratory Coupled Ocean Data Assimilation Global 1/12° Reanalysis (Cummings 2005). Namely, all members have identical ocean conditions at the initial time. The ensemble forecast is integrated forward 8 days to 0000 UTC 16 September. Blue lines in Fig. 1 show the ensemble forecast mean of Florence’s track and intensity from the 200-member ensemble. Overall, the ensemble mean well captures the evolutions of Florence’s track and intensity during the 8-day integration, though northward track biases can be found in the first 6 days (Fig. 1c). This study will focus on the rapid intensification stage of Florence from 0000 UTC 10 September to 0000 UTC 12 September.

b. Ensemble covariance and correlation

In the EnKF, the analysis equation is defined as

$$ x^a = x' + K(y - Hx'), $$

(1)

where $x'$ and $x^a$ are the prior estimate (or first guess) and posterior estimate (or analysis) of model state variables, respectively. In the equation, $y$ represents the observation vector and $H$ is the observation operator. The innovation $(y - Hx')$ represents the distance between observations and model forecasts, in observation space. The Kalman gain matrix $K$ is defined as

$$ K = P^f H^T (HP^f H^T + R)^{-1}. $$

(2)

Here, $R$ represents the observational error covariance, and $P^f$ is the flow-dependent forecast error covariance between model state variables estimated from the ensemble forecast. The dynamical structures of the error covariance $P^f$ are fundamentally determined by the dynamics of model error growth (e.g., Cohn and Parrish 1991; Evensen 1994; Zhang 2005; Poterjoy and Zhang 2011). $P^f H^T$ represents the error covariance between model state variables and simulated observations calculated via observation operator ($H$). An EnKF uses the error covariance $P^f H^T$ to propagate information from the innovation across space and to different model state variables. As in PZ11, the error covariance $P^f H^T$ can be decomposed into a product of the ensemble standard deviation of each quantity and the correlation between them as

$$ \text{cov}(x_{ijk}, y_{ijk}) = \sigma_{x_{ijk}} \sigma_{y_{ijk}} \times \text{corr}(x_{ijk}, y_{ijk}), $$

(3)

where $\sigma_{x_{ijk}}$ and $\sigma_{y_{ijk}}$ are the standard deviations of $x_{ijk}$ and $y_{ijk}$ estimated from the ensemble forecasts; $x_{ijk}$ and $y_{ijk}$ represent model state variable at model grid $(i, j, k)$ and simulated observation at observation location $(i', j', k')$. The component $\sigma_{x_{ijk}} \sigma_{y_{ijk}}$ quantifies the uncertainty of the ensemble forecasts. The correlation component $\text{corr}(x_{ijk}, y_{ijk})$ quantifies the linear multivariate relationship between model state variable and simulated observation. In SCDA, the ensemble correlations between simulated atmospheric (oceanic) observations and oceanic (atmospheric) variables reveal the potential impacts of observations across the air-sea interface. As shown in Eq. (3), a larger ensemble error covariance $P^f H^T$ can thus be produced by a larger ensemble spread or larger correlation between model state variable and simulated observation. Bearing in mind the importance of the ensemble error covariance in SCDA, we will focus on the forecast uncertainties in each domain and the cross-domain ensemble correlations in the following sections to illustrate the potential influences of SCDA on TC initialization in the coupled model.

3. Eulerian and storm-relative ensemble means and uncertainties

The ensemble spread component of the forecast error covariance will be analyzed in this section. Means of atmospheric and oceanic variables from the ensemble coupled forecast are also studied. Figure 1a shows the ensemble of track forecasts for Hurricane Florence. All 200 ensemble members follow a northeast track after initialization and turn to the southeast on 16 September. Green dots in Fig. 1a show the forecasted storm positions at 0000 UTC 10, 11, and 12 September from different ensemble members. Compared to the best track data from the National Hurricane Center (NHC) Atlantic hurricane database (Landsea and Franklin 2013), we find that the translation speed of Florence is slightly slower in the ensemble forecasts. The spread of storm positions increases from 0000 UTC 10 September to 0000 UTC 12 September, which reflects an increase of TC displacement errors with forecast lead time. The TC position spread in the meridional direction is around 3° at 0000 UTC 10 September and increases to approximately 8° at 0000 UTC 12 September. The prestorm ocean stratification and SST near the TC centers are similar between ensemble members until 0000 UTC 12 September (not shown here). The ensemble forecast realistically captures the intensity of Florence (Figs. 1b,c). Florence intensified from a category-1 hurricane to a category-4 major hurricane from 0000 UTC 10 September to 0000 UTC 12 September (Fig. 1c). The spread of ensemble intensity forecasts slightly decreases from 0000 UTC 10 September to 0000 UTC 12 September with the standard deviations of the TC minimum surface pressure and maximum surface wind decrease from 8.0 hPa and 4.8 m s$^{-1}$ to 7.2 hPa and 4.2 m s$^{-1}$ (Figs. 1b,c). An increase in intensity spread can be found after 0000 UTC 15 September, which is closely related to the TC displacement errors, i.e., Florence made landfall in only some ensemble forecasts by this time (Fig. 1a). Because the study will focus on the rapid intensification of Florence (from 0000 UTC 10 September to 0000 UTC 12 September), the differences in the TC landfalling time will not influence the analysis.

The ensemble mean (color shading) and standard deviation (contours) of surface pressure, surface wind speed, sea surface meridional ($V$) current, and sea surface temperature (SST) fields at 0000 UTC 10, 11, and 12 September are shown in Fig. 2. In the original model (Eulerian) coordinates, the forecast
uncertainties (or standard deviations) of the TC surface pressure and wind speed fields gradually increase with forecast lead time, and evolve from a compact centralized structure to an asymmetric elliptical distribution. From 0000 UTC 10 September to 0000 UTC 12 September, the maximum standard deviation of the surface pressure field increases from 10.4 to 17.8 hPa, and the maximum standard deviation of the surface wind speed field increases from 8.2 to 13.3 m s$^{-1}$. The increase of forecast uncertainty within the atmospheric surface fields are mainly from storm displacement errors (Fig. 1a). The result is consistent with the findings in PZ11. Due to the increasing TC displacement errors, the Eulerian mean minimum surface pressure and maximum surface wind speed of Florence does not show clear changes during the 2-day forecast from 0000 UTC 10 September to 0000 UTC 12 September (Figs. 2a–f), despite all ensemble members intensifying during this period (Figs. 1b,c). Behind the storm, enhanced sea surface current (Figs. 2g,h,i) and SST cooling (Figs. 2j,k,l) can be found along the TC track. These features are produced by the TC-generated surface wind stress and oceanic near-inertial internal gravity waves (Price 1981; Ginis 2002). Similar with the TC surface pressure and wind speed fields, the standard deviation of sea surface current and SST fields also increase from 0000 UTC 10 September to 0000 UTC 12 September, with the largest forecast uncertainties located behind the TC center (Figs. 2g–l). The maximum standard deviations of the sea surface meridional current and SST fields increase from 0.65 m s$^{-1}$ and 0.70$^\circ$C to 0.78 m s$^{-1}$ and 1.01$^\circ$C during the 2 days. The forecast uncertainties of the ocean variables are also mainly from the TC position differences.

For practical TC DA, the TC displacement errors usually reduce considerably after the first few DA cycles (with a 1–6 h DA interval) by assimilating TC position and minimum surface pressure observations (e.g., Chen and Snyder 2007; Chen and Zhang 2019; Zhang et al. 2019). To remove the effects of TC displacement errors, the mean and uncertainties of the

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**FIG. 2.** Eulerian mean (a)–(c) surface pressure, (d)–(f) surface wind speed, (g)–(i) sea surface meridional current, and (j)–(l) sea surface temperature at (left) 0000 UTC 10 Sep, (center) 0000 UTC 11 Sep, and (right) 0000 UTC 12 Sep. Gray contours show the standard deviation (a)–(c) every 4 hPa starting from 4 hPa, (d)–(f) every 4 m s$^{-1}$ from 4 m s$^{-1}$, (g)–(i) every 0.2 m s$^{-1}$ starting from 0.2 m s$^{-1}$, and (j)–(l) every 0.4$^\circ$C starting from 0.4$^\circ$C.
ensemble coupled forecasts of Florence are further analyzed in a storm-relative reference frame at each forecast lead time (i.e., ensemble members are recentered based on the forecasted locations of the TC minimal surface pressure). The analysis of the forecast error covariance (ensemble variance and correlation) in the storm-relative coordinate system provides further insight into the fundamental TC dynamics independent of TC position. Hence, the following analysis will focus on the evolutions of ensemble variance and correlation in the storm-relative coordinate unless otherwise specified.

Figures 3a–f show the storm-relative mean and standard deviation of the surface pressure and wind speed fields. The TC motion vector has been subtracted from the atmospheric velocity fields in the analysis. Different from the analysis in the Eulerian coordinate system, Florence shows a clear rapid intensification from 0000 UTC 10 September to 0000 UTC 12 September in the storm-relative coordinates. The surface minimum pressure decreases from 973 to 948 hPa (Figs. 3a–c), and the maximum surface wind speed increases from 35 to 59 m s\(^{-1}\) (Figs. 3d–f) through the 2 days. An asymmetric surface wind speed distribution can be found during these 2 days, with the surface wind speed maximized on the southwest side of the TC center. This asymmetric surface wind speed structure may be produced by the combined effects of environmental mean flow (west-southwesterly in the lower troposphere), vertical wind shear (southwesterly during most of these 2 days), asymmetric SST cooling, or other factors. Further analysis of the detailed mechanism is left for future work. The maximum standard deviation of surface pressure can be found near the TC center, and the maximum standard deviation of surface wind speed can be found near the radius of maximum wind (RMW), reflecting a larger forecast uncertainty over the TC inner-core region than the environment. The results are consistent with PZ11. During the intensification, the maximum
standard deviation of surface wind speed increases from 8.2 to 11.7 m s\(^{-1}\) from 0000 UTC 10 September to 0000 UTC 12 September (Figs. 3d–f), while the maximum standard deviation of surface pressure does not show noticeable change (Figs. 3a–c), likely because of a lag in the mass field in response to the enhanced wind speed.

Consistent with the asymmetric surface wind field, Florence also exhibits a strong asymmetric vertical structure of wind speed throughout the troposphere during these 2 days of the simulation (Figs. 4a–c). Stronger wind speeds can be found on the southwest side of the TC center from surface to around 15 km altitude. The forecast uncertainty of wind speed peaks near the eyewall (~35 km from the TC center), with the largest uncertainty confined to lowest levels (\(z < 1.5 \text{ km}\), Figs. 4a–c). The standard deviation of wind speed decreases in the eye but increases near the eyewall from 0000 UTC 10 September to 0000 UTC 12 September, which reflects the increasing dependence of the wind speed field on the wavenumber-0 vortex structure, as the ensemble intensity forecasts diverge with the model integration (Figs. 1b,c).

Cross sections of the ensemble mean temperature field shows Florence’s primary warm core in the midtroposphere (4–8 km) becoming stronger throughout the rapid intensification (Figs. 4d–f), which may be induced by the radial eddy flux and mean vertical advection of potential temperature (Stern and Zhang 2013). A secondary upper-level (12–15 km) warm core near the TC center can also be found during the latter part of the rapid intensification (Figs. 4e,f), which is closely related to the enhanced subsidence warming within the eye. Different from the standard deviations of wind speed, the ensemble standard deviation of temperature is mostly axisymmetric throughout the forecast. The maximum standard deviation of the temperature increases from 1.85 to 2.18 K through the 2 days (Figs. 4d–f). The altitude of the maximum standard deviation, with respect to temperature, decreases with greater lead time, which may be related to the enhanced subsidence in the eye.

The water vapor mixing ratio cross sections show that the eyewall region has higher humidity than the surrounding areas (Figs. 4g–i) due to the strong convective updrafts within the eyewall. In the midtroposphere (3–9 km), the eye becomes dryer with greater lead time, corresponding to enhanced subsidence in the eye. The ensemble spread of the water vapor mixing ratio peaks below 5 km altitude beyond 400 km from the TC center (Figs. 4g–i), which is mainly contributed by the forecast uncertainty related to TC size and rainband activity (not shown here). A secondary maximum of the mixing ratio standard deviation can be found near the TC center at 3–6 km altitude, which is closely related to the ensemble variance of TC intensity and the related subsidence within the eye.
The temporal evolution of the mean and standard deviation of sea surface meridional current and SST are shown in Figs. 3g–l. As the TC-generated wind stress provides a continuous force on the ocean surface, the sea surface current underneath the TC is dramatically enhanced (Figs. 3g–i). The magnitude and area of enhanced meridional current near the TC center increases gradually with the intensity of Florence from 0000 UTC 10 September to 0000 UTC 12 September. In the wake of the storm, enhanced sea surface currents associated with near-inertial gravity waves can be found on the right side of the storm track, which are shown as alternating positively and negatively enhanced sea surface meridional currents in Figs. 3g–i. This pronounced rightward bias occurs because the near-inertial rotating ocean currents on the right side of the storm track are quasi-resonate with the rotation of wind stress produced by the translating TC, while the clockwise near-inertial rotating ocean currents are decelerated by the TC wind stress on the left side of the track (Price 1981). The magnitude of the enhanced currents on the right side of the track reduce after the TC passage due to the horizontal dispersion of the near-inertial gravity waves (Ginis 2002). Due to the enhancement of surface wind stress, the TC-generated near-inertial ocean currents are stronger and able to last for longer time at 0000 UTC 12 September than that at 0000 UTC 10 September and 0000 UTC 11 September.

Consistent with the ocean current field, stronger SST cooling can be found on the right side of the TC track (Figs. 3j–i). The maximum SST cooling induced by Florence increases from 2.2°C to 2.9°C with the intensity of Florence from 0000 UTC 10 September to 0000 UTC 12 September. The strongest SST cooling occurs around 100–180 km behind of the TC center during the 2 days (Figs. 3j–i). The largest forecast uncertainties associated with the ocean current and SST fields can be found along the TC track. The forecast uncertainties with regard to the ocean current and SST are mainly from the forecast uncertainty with respect to TC intensity, and are also partially contributed by the uncertainties in the TC translation speed and direction (Fig. 1).

Figure 5 shows the cross sections of oceanic meridional current, vertical velocity, and temperature fields along the TC cold wake (shown by dashed lines in Figs. 3j–l, from northwest to southeast) at (left) 0000 UTC 10 Sep, (center) 0000 UTC 11 Sep, and (right) 0000 UTC 12 Sep. Gray contours show the standard deviation (a)–(c) every 0.05 m s⁻¹ starting from 0.05 m s⁻¹, (d)–(f) every 0.2 mm s⁻¹ starting from 0.2 mm s⁻¹, and (g)–(i) every 0.3°C starting from 0.3°C.
behind the upwelling region by about 90 km (110 km behind the TC center in Fig. 5g). Around 170 km behind the TC center, the OML currents converge back to the TC track due to the near-inertial oscillation and produce downwelling below the OML (Fig. 5d), which deepening the OML thickness to ~40 m at a location approximately 300 km behind the TC center (Fig. 5g). The distance between the upwelling and downwelling regions is determined by the inertial wavelength, which is a function of the local inertial period and the TC translation speed (Perrie 2006).

Strong ocean temperature cooling (~2°C) can be found in the OML underneath and behind the TC center (Fig. 5g). The cooling is mainly the result of shear-induced turbulent entrainment of cold water from below the seasonal thermocline, and also partially from the sensible and latent heat loss to the TC and the upwelling of colder thermocline water (Price 1981; Ginis 2002; Jaimes and Shay 2015). The upwelling process shallows the OML depth while turbulent entrainment increases the OML depth (Ginis 2002). The OML cooling is stronger over the regions where the OML depth is reduced by upwelling and is weaker over the regions where the OML depth is increased by downwelling (Fig. 5g). The cross sections at 0000 UTC 11 September and 0000 UTC 12 September are similar with that at 0000 UTC 10 September. With stronger surface wind stress, the OML near-inertial currents are also much stronger at these two times. As a result, stronger upwelling and downwelling can be found below the OML at 0000 UTC 11 September and 0000 UTC 12 September (Figs. 5e,f). In addition, stronger vertical shear associated with the enhanced oceanic current near the OML base induces stronger turbulent entrainment of cold water from below the thermocline, and further increases the magnitude of SST cooling. Although the OML currents are much stronger at 0000 UTC 11 September and 0000 UTC 12 September, the SST cooling is only slightly larger in magnitude than that at 0000 UTC 10 September. The main reason is the simulated TC translation speeds are much faster at 0000 UTC 11 September and 0000 UTC 12 September (13 and 15 m s⁻¹) than that at 0000 UTC 10 September (7 m s⁻¹), which reduces the duration of the cooling processes.

The standard deviation of the ocean currents is largest over the enhanced current region in the OML and peaks near the base of the OML, where strong upwelling occurs (Figs. 5a–c). The standard deviation of vertical velocity, on the other hand, is strongest below the OML base and peaks near the strongest upwelling or downwelling regions (Figs. 5d–f). The ocean temperature standard deviation maximum is near the base of the OML (Figs. 5g–i), which is fundamentally associated with the forecast uncertainties of the TC wind and OML current. In addition, the forecast uncertainties of the OML temperature are larger within the TC cold wake than ahead of the TC center (Figs. 5g–i), which is also mainly from the TC intensity forecast uncertainty.

4. Storm-relative ensemble correlation across air–sea interface

The correlation component of the forecast error covariance will be examined in this section. As mentioned in the introduction, we will focus on the cross-domain correlations in this study to reveal the potential impacts of SCDA across the air–sea interface. Figure 6 shows the ensemble correlations between a simulated surface pressure observation at the TC center (TC minimum surface pressure observations) and different oceanic state variables. The statistical significance of the cross-domain correlations are tested using the t test. Black dots in Fig. 6 show regions where the cross-domain correlations are statistically significant at the 95% confidence level. For practical TC DA, the TC position and minimum surface pressure observations can be obtained from the Tropical Cyclone Vitals (Trahan and Sparling 2012). At 0000 UTC 10 September, the TC central surface pressure is positively correlated with the sea surface meridional current ahead of the TC center and negatively correlated with the sea surface meridional current behind the TC center (Fig. 6a), with the maximum and minimum correlation values around 0.74 and −0.68. This correlation dipole suggests the cyclonically rotating sea surface currents underneath the TC will become stronger with the reduction of the TC central pressure (or the intensification of the TC). Since the TC intensity is relatively weak and the TC translation speed is small at 0000 UTC 10 September, the correlation between the TC central pressure and the near-inertial ocean currents along the TC track is weak, which reduces below ±0.2 beyond 400 km from the TC center (Fig. 6a). This wavelike correlation pattern along the cold wake is likely associated with the propagation of the TC-generated near-inertial gravity waves (Ginis 2002).

The SST along the track is positively correlated with the TC central pressure at 0000 UTC 10 September (Fig. 6d). The result indicates that the SST cooling is stronger with a stronger TC. On the TC periphery, the SST field is negatively correlated with the central pressure. This can be explained by the upwelling near the TC center (Figs. 5d–f) and the compensating downwelling of the displaced warm water outside the upwelling region, which acts to warm the sea surface and OML temperature (Jullien et al. 2012; Jaimes and Shay 2015).

At 0000 UTC 11 September and 0000 UTC 12 September, the correlation patterns between the TC central pressure and the sea surface current and SST fields are similar with that at 0000 UTC 10 September, but the magnitude becomes much stronger with the intensity and acceleration of Florence (Figs. 6b,c,e,f). Meaningful correlations (which we define as >0.5) between the central pressure and near-inertial surface current can still be found beyond 1000 km distance from the TC center at 0000 UTC 12 September (Fig. 6c). In addition, we find that the central pressure is positively correlated with the SST to the north of the TC center at 0000 UTC 12 September (Fig. 6f). The reason is that the ensemble members with stronger simulated TC intensity generally have larger northward track bias, and the SST is slightly colder at higher latitudes.

Besides the sea surface variables, the TC central pressure is also meaningfully correlated with the oceanic current throughout the OML (Figs. 6g–i), the oceanic vertical velocity (upwelling and downwelling) below the OML base (Figs. 6j–l), and the oceanic temperature from the sea surface to the thermocline (Figs. 6m–o). The ensemble correlations show that, with lower central pressure and stronger TC intensity, the ocean near-inertial current in the OML and the upwelling and downwelling processes below the OML will become stronger.
FIG. 6. Cross-domain correlations between surface pressure at the storm center and (a)–(c) sea surface meridional current (SSC), (d)–(f) sea surface temperature (SST), (g)–(i) oceanic meridional current (OC), (j)–(l) vertical velocity (OW), and (m)–(o) temperature (OT) along vertical cross sections through the storm wake [dashed lines in (d)–(f), same as the dashed lines in Figs. 3j–l] at (left) 0000 UTC 10 Sep, (center) 0000 UTC 11 Sep, and (right) 0000 UTC 12 Sep. Black vectors in (a)–(c) show the TC moving direction. Black dots show regions where the cross-domain correlations are significant at the 95% level.
In addition, the temperature of the OML will decrease underneath and behind the TC center because of the increased vertical mixing induced by enhanced wind stress and ocean currents. In the thermocline, the oceanic temperature will decrease over the upwelling regions and increase over the downwelling regions (Figs. 6m–o).

Figure 7 shows the ensemble correlations between TC surface wind speeds and oceanic state variables. The simulated surface wind speed observations are located on the southwest side of the TC center within the RMW (red squares in Figs. 3d–f). TC inner-core surface wind speed can be observed by satellite scatterometers like the Cyclone Global Navigation Satellite System (CYGNSS; Ruf et al. 2016) and airborne Stepped Frequency Microwave Radiometer (SFMR; Jones et al. 1981). The correlations in Fig. 7 show similar patterns with those in Fig. 6 but the signs are flipped. The reason is the TC surface wind speed is negatively correlated with the TC central pressure. The correlation magnitudes in Fig. 7 are slightly stronger than that in Fig. 6, because the TC surface wind speed is more directly correlated with the enhanced ocean current and SST cooling than the TC central pressure.

In addition to atmospheric surface observations, the potential impacts of atmospheric observations throughout the troposphere on the analysis of oceanic state variables are also examined. Figures 8 and 9 demonstrate the ensemble correlations between simulated temperature observations near the TC center at 2 and 9 km altitudes (shown by the blue squares in Figs. 4d–f) and different oceanic state variables. The TC inner-core temperature in the lower troposphere can be obtained from TC dropsonde observations (J. Wang et al. 2015). Compared to the simulated surface wind speed observation within the RMW, a 2 km temperature observation of the TC eye region shows a weaker but similar correlation pattern (Fig. 8). It reflects that the lower-level warming in the eye is less correlated to the TC intensity and air–sea interactions than the surface wind speed. However, the simulated temperature observation within the TC eye at 9 km has similar correlations with the oceanic temperature, current, and vertical velocity fields as the surface wind speed observations in terms of the amplitudes and structures (Fig. 9). This suggests upper-level warming associated with the subsidence in the eye is meaningfully correlated with the TC intensity (Munsell et al. 2018). The upper troposphere temperature near the TC center can be observed by high-altitude dropsondes (Braun et al. 2016) and satellite microwave temperature sounders (Knaff et al. 2004).

Overall, the simulated atmospheric observations near the TC inner-core region are meaningfully correlated with the oceanic state variables underneath and behind the TC (Figs. 6–9). Considering the large forecast uncertainties of atmospheric fields near the TC center (Figs. 3 and 4), and the large forecast uncertainties of oceanic state variables underneath the TC center and along the wake (Figs. 3g–i and 5), the flow-dependent error covariance should be able to effectively spread information from the inner-core atmospheric observations to the oceanic state variables based on Eq. (3). The resulting EnKF increments will be highly anisotropic, but appear able to correct the magnitude and structure of ocean fields. The results indicate that SCDA can potentially improve the oceanic initialization of coupled TC prediction by assimilating the inner-core atmospheric observations.

To also highlight the potential influence of ocean observations on the analysis of the atmospheric state, the cross-domain correlations between simulated oceanic observations and atmospheric state variables are also examined. Figure 10 shows the ensemble correlations between a simulated sea surface meridional current observation behind the TC center (shown by the green squares in Figs. 3g–i) and different atmospheric variables. The ocean current near TCs can be observed by aircraft-deployed profiling instruments (e.g., Meyers et al. 2016), gliders (e.g., Rudnick 2016), satellite (e.g., Dohan and Maximenko 2010), and high-frequency radars (e.g., Paduan and Washburn 2013). The sea surface meridional current behind the TC center is meaningfully and negatively correlated with the surface pressure near the TC center (Figs. 10a–c). This correlation suggests that a stronger sea surface current along the cold wake is associated with stronger a storm. The sea surface meridional current is also positively correlated with the surface pressure on the east of the TC, related to differences in the TC environment. This is because ensemble members with a northward track bias tend to have stronger intensities and are closer to the Azores High. Overall, the magnitude of the correlation increases with the TC intensity from 0000 UTC 10 September to 0000 UTC 11 September (Figs. 10a,b). The correlation is weaker at 0000 UTC 12 September (Fig. 10c) because the simulated sea surface meridional current observation is farther from the TC center than at 0000 UTC 10 September or 0000 UTC 11 September (Figs. 3g–i). Consistent with Fig. 10a–c, the surface wind speed around TC center is meaningfully and positively correlated with the sea surface meridional current behind the TC center (Figs. 10d–f). This simply indicates that the TC surface wind speed likely controls the intensity of the TC-generated near-inertial current. One interesting aspect is the correlation structure becomes more asymmetric at 0000 UTC 11 September and 0000 UTC 12 September, with the region of strongest correlation shifting from being centered near the TC center to the north of the TC center (Figs. 10e,f). This structural change is closely related to the acceleration of the TC translation speed, which induces a more pronounced rightward bias of the near-inertial current and SST cooling at 0000 UTC 11 September and 0000 UTC 12 September (Fig. 3). As a result, the sea surface meridional current behind the TC is more closely related to surface wind speed on the north side of the TC center. These results further validate the importance of using flow-dependent error covariance for adequate initialization of coupled TC prediction.

In addition to atmospheric surface variables, the sea surface meridional current observations also show meaningfully correlations with oceanic variables throughout the troposphere. With stronger sea surface meridional current behind the TC center, the wind speed within and outside the RMW tends to be stronger (Figs. 10g–i). The upper-level temperature near the TC center also increases with the sea surface meridional current, which implies a positive relationship between the temperature within the eye and the induced sea surface current. The correlation between the sea surface meridional
Fig. 7. As in Fig. 6, but for a simulated surface wind speed observation at the location marked by the red squares in Figs. 3d–f.
Fig. 8. As in Fig. 6, but for a simulated temperature observation at the location marked by the blue squares at 2 km altitude in Figs. 4d–f.
Fig. 9. As in Fig. 6, but for a simulated temperature observation at the location marked by the blue squares at 9 km altitude in Figs. 4d–f.
FIG. 10. Cross-domain correlations between a simulated sea surface meridional current observation at the location marked by the green squares in Figs. 3g–i and (a)–(c) surface pressure (SP), (d)–(f) surface wind speed (SWS), (g)–(i) wind speed (WS), (j)–(l) temperature (T), and (m)–(o) water vapor mixing ratio (Qv) along vertical cross sections through the storm center [dashed lines in (d)–(f)], same as the dashed lines in Figs. 3a–c] at (left) 0000 UTC 10 Sep, (center) 0000 UTC 11 Sep, and (right) 0000 UTC 12 Sep. Black dots show regions where the cross-domain correlations are significant at the 95% level.
FIG. 11. As in Fig. 10, but for a simulated oceanic temperature observation at −25 m depth, marked by the red squares in Figs. 5g–i.
current and the atmospheric moisture is weaker than the other correlations shown in Figs. 10g–l. Overall, the correlation between water vapor mixing ratio and sea surface current is still dynamically consistent, positive within the eyewall and negative within the eye (Figs. 10m–o). This pattern is associated with increased upward transport of moisture in the eyewall and dry subsidence in the eye with increased sea surface current.

The ensemble correlations between simulated temperature observations within the OML behind the TC center (shown by the red squares in Figs. 3g–i) and atmospheric state variables are shown in Fig. 11. The ocean temperature in the OML near TC can be observed by underwater gliders, and aircraft-deployed profiling instruments like airborne expendable conductivity temperature and depth (AXCTDs), airborne expendables bathythermographs (AXBTs), and airborne expendable current profilers (AXCPs). The ensemble correlations of the OML temperature observations (Fig. 11) are similar with that of the sea surface meridional current observations (Fig. 11), but the signs are reversed because the oceanic temperature in the TC wake is negatively correlated with the TC intensity. Considering the large forecast uncertainties of atmospheric variables near the TC center, and the large forecast uncertainties of oceanic variables in the TC wake, the meaningfully correlations suggest that SCDA can make dynamically and thermodynamically consistent corrections to the atmospheric initial conditions of coupled TC prediction. Similar with the assimilation of atmospheric observations, the resulting EnKF increments will be highly anisotropic, and ultimately determined by the dynamics of TC air–sea interactions.

5. Sensitivity to ensemble size

The forecast error covariance is sensitive to sampling errors (Houtekamer and Mitchell 1998; Anderson 2012; Miyoshi et al. 2014). However, the extensive computational cost of high-dimensional models imposes restrictions on the ensemble size. A small ensemble size can cause the forecast error covariance to be rank deficient, and overestimate the correlations between observations and model state variables at great spatial and vertical distances. Poterjoy et al. (2014) indicated that around 60 ensemble members are needed to accurately estimate the anisotropic ensemble correlations between state variables for convection-permitting TC prediction in an atmosphere-only model. In this section, we will evaluate the sensitivity of the cross-domain ensemble correlations to ensemble size. The cross-domain ensemble correlations reveal the fundamental dynamics associated with TC air–sea interactions and the potential impacts of SCDA. One should note that, in practical DA, not only the ensemble correlation component, but also the ensemble spread component of the forecast error covariance is influenced by sampling errors. One open question we want to investigate here is, with the current model configurations, how many ensemble members are needed to represent the physically consistent cross-domain relationships associated with TC dynamics.

Figure 12 shows the cross-domain ensemble correlation between a simulated surface wind speed observation and the
SST at 0000 UTC 11 September, as estimated using different ensemble sizes (160 to 20 ensemble members). The members are randomly chosen from the 200-member ensemble. We repeat the random sampling 20 times. Additional sampling does not significantly change the results (not shown here). The black contours demonstrate differences between the correlation calculated with smaller ensemble size and that calculated using the 200-member ensemble. Overall, the correlation structures in Fig. 12 are similar with that in Fig. 7e. The root-mean-square error (RMSE) calculated from the differences between two correlation fields increases with the reduction of ensemble size, which demonstrates an increase in sampling errors. From 160 to 80 members, the increase in RMSE is mainly from differences at smaller scales (<100 km), with maximum absolute differences below 0.25 (Figs. 12a–c). However, from 60 to 20 ensemble members the RMSE increases rapidly with decreasing ensemble size. Additionally, more organized structures, which considerably overestimate the correlations between surface wind speed observations and SST, are found as the horizontal distance from the simulated observation is increased (Figs. 12d–f). The erroneously strong long-distance correlations represent sampling errors rather than meaningful underlying dynamics. The maximum absolute difference in Figs. 12e and 12f are 0.50 and 0.72, respectively.

The potential impact of sampling error on SCDA is examined here. Taking an ocean model grid point far from the observation location (shown by the green square in Fig. 12), the ensemble correlations between the simulated surface wind speed observation and the SST at this model grid point are 0.11, 0.14, 0.15, 0.16, 0.26, and 0.44 in Figs. 12a–f. The correlation calculated using the 200-member ensemble is 0.10. To simplify the estimation, here we assume the ensemble spread component of the forecast error covariance is not influenced by sampling error (in practice, the ensemble spread component will also change with the ensemble size). The standard deviation of the forecasted surface wind speed at the observation location and the forecasted SST at the model grid point are 5.68 m s$^{-1}$ and 0.16°C, respectively (calculated from the 200-member ensemble). If the innovation (observation-forecast departure) is 10 m s$^{-1}$ and the observational error variance is 1 m$^2$ s$^{-2}$, the EnKF increments to the SST field at this model grid point will be 0.83°C, 0.91°C, 1.12°C, 1.20°C, 1.27°C, 1.91°C, and 2.86°C by using 200, 160, 120, 80, 60, 40, and 20 ensemble members, respectively [Eqs. (1) and (2)]. Statistically, the sampling variance increases when sample size decreases. Hence, the differences of the EnKF increment between different ensemble-size groups may be even bigger in the practical SCDA. In practice, tuned inflations of ensemble variance and observation errors are usually needed in order to obtain robust and reliable DA increments (e.g., Anderson 2009; Minamide and Zhang 2017).

Similar results are also found in the vertical direction (Fig. 13). As the ensemble size decreases below 60, erroneously strong correlations between surface wind speed and oceanic temperature below the OML are found (Figs. 13e–f). The maximum absolute differences is 0.29 when the ensemble size is bigger than 60 (Figs. 13a–d), while the values of the
maximum absolute differences grow to 0.46 and 0.67 when the ensemble size decreases to 40 and 20 (Figs. 13e–f).

The sensitivity of the cross-domain correlations between simulated oceanic observations and atmospheric state variables to ensemble size are also studied. Figures 14 and 15 show the cross-domain correlations between a simulated sea surface meridional current observation and near-surface wind speed at 0000 UTC 11 September calculated using different ensemble sizes. Similar with Figs. 12 and 13, the RMSE increases with decreasing ensemble size. More organized sampling errors can be found when the ensemble size is smaller than 60 (Figs. 14e–f and 15e–f), which overestimates the correlation at great horizontal and vertical distances from the simulated sea surface meridional current observation. These results suggest that, with the current model configurations, at least 60–80 ensemble members are required to minimize sampling errors in the cross-domain error covariance of Florence.

These results may be sensitive the model configurations (grid spacing, dynamical core, and physical schemes), model errors, nonlinearity and other factors. Future studies to systematically evaluate the effects of sampling errors on the SCDA in coupled models under different model configurations are warranted.

6. Conclusions

To reveal the potential influences of SCDA on TC initialization in coupled models, the flow-dependent cross-domain forecast error covariance is analyzed from a 200-member convection-permitting coupled ensemble forecasts of Hurricane Florence during its rapid intensification. The variance (standard deviation) and correlation components of forecast error covariance are each systematically examined.

In Eulerian coordinates, the forecast uncertainties of atmospheric and oceanic fields increase rapidly with forecast lead time. The error growth in this context is mainly from TC displacement errors. However, in the storm-relative framework, the biggest ensemble spread of atmospheric wind and mass fields can be found over the TC inner-core region, each of which are closely related to the TC intensity forecast uncertainty. The greatest atmospheric moisture ensemble spread is located outside the TC inner-core region, largely determined by uncertainty in TC size and structure. The largest forecast uncertainties with respect to oceanic variables are found along the TC wake with rightward biases. The largest forecast uncertainties of oceanic currents, vertical velocity, and temperature fields are located in the OML, at the thermocline, and near the bottom of the OML, respectively.

To reveal the potential impacts of SCDA, the cross-domain ensemble correlations associated with different simulated atmospheric and oceanic observations are examined. Both simulated TC inner-core atmospheric observations near the surface and within upper levels show meaningfully correlations with oceanic state variables from the sea surface to the thermocline, which indicate that SCDA can potentially improve the oceanic initialization of coupled TC prediction by assimilating inner-core atmospheric observations. The simulated oceanic observations also have meaningfully
correlations with atmospheric wind and mass variables from the surface to the upper troposphere. The dynamical structures of ensemble standard deviations and correlations are highly anisotropic and variable-dependent, which are ultimately driven by the underlying TC dynamics. Sensitivity experiments indicate that, with the current model configurations, at least 60–80 ensemble members are needed to represent adequate cross-domain linear multivariate relationships between different model variables.

Our results highlight the potential advantages of ensemble-based SCDA. The flow-dependent forecast error covariance, assuming an accurate modeling framework, can provide useful cross-domain information in the presence of highly anisotropic processes associated with TC air–sea interactions. Nevertheless, future research to study how different model configurations, including dynamical cores, horizontal and vertical resolutions, physical parameterizations, and coupling strategies, influence the dynamics and structures of the flow-dependent forecast error covariance are warranted. For example, the current uncertainties in boundary layer processes such as turbulence and the surface momentum and enthalpy exchange coefficients can influence the error growth dynamics in TC prediction (e.g., Bryan 2012; Nystrom et al. 2020), which can further influence the quality of error correlation statistics derived from the models. Also, because the dynamics of TC air–sea interactions can be considerably influenced by TC intensity, translation speed, and ocean stratifications, the detailed dynamical structures of the cross-domain error covariance can vary between different TC cases and during different stages of TC development. Ensemble initialization for TC prediction in atmosphere–ocean coupled models is also a challenging question deserving future investigation. Due to slower dynamics and sparser observations, ocean DA generally requires much longer periods for initialization. A short spinup period (several days) is used in this study to initialize the ensemble, which is similar with the setup of operational numerical models (e.g., Kim et al. 2014; Yablonsky et al. 2015). How the initial error covariance changes with the spinup length is still an open question that deserves further exploration. In addition, the forecast uncertainties of the ocean ahead of the TC may be underestimated in the current study because of the relative short spinup and the initialization of the ocean ensemble with identical initial conditions.

The advantage of SCDA for TC prediction still needs further investigations using real data experiments. Furthermore, an operational DA system is assimilating a large number of observations and the impact of additional cross-domain observations might or might not lead to consistent improvements in forecast skill. Another open question for the TC SCDA is how to properly perform covariance localization and inflation. Comprehensive localization and inflation methods considering the different dynamical and thermodynamical characteristics of the atmosphere and ocean need to be developed. These differences between the two domains include their different inertias, stratifications, and degrees of freedom, which all contribute to different model error growth dynamics.

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Fig. 15. As in Fig. 10h, but the cross-domain correlations are calculated using (a) 160, (b) 120, (c) 80, (d) 60, (e) 40, and (f) 20 ensemble members. The black contours show the differences between the correlations estimated using smaller ensemble size and the correlations calculated using 200 ensemble members (contoured every 0.15 starting from 0.15). The RMSE is shown in the upper-right-hand corner of each panel.
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REFERENCES