Chapter 1

Initialization of Tropical Cyclones in Numerical Prediction Systems

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Additional information is available at the end of the chapter

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1. Introduction

Tropical cyclones (here after TCs) are intense atmospheric vortices that form over warm ocean waters. Strong TCs (called hurricanes in the North Atlantic basin, or typhoons in the western north Pacific basin) can cause significant loss of lives and property when making landfall due to destructive winds, torrential rainfall, and powerful storm surges. In order to warn people of hazards from incoming TCs, forecasters must make predictions of the future position and intensity of the TC. In order to make these forecasts, a forecaster uses a wide suite of tools ranging from his or her subjective assessment of the situation based on experience, the climatology and persistence characteristics of the storm, and most importantly, *models*, which make a prediction of the future state of the atmosphere given the current state. In this chapter, the focus is on dynamical models. A dynamical model is based on the governing laws of the system, which for the atmosphere are the conservation of momentum, mass, and energy. Since the system of partial differential equations that govern the atmosphere is highly nonlinear, a numerical approximation must be made in order to obtain a solution to these equations. Short term (less than 7 days) numerical weather prediction is largely an initial value problem. Therefore it is critical to accurately specify the initial condition. The accuracy of the initial condition depends on the forecast model itself, the quality and density of observations, and how to distribute the information from the observations to the model grid points (data assimilation). Since most TCs exist in the open oceans, most observations come from satellites, and often intensity and structure characteristics are inferred from the remotely sensed data [10]. Therefore a key problem that remains for TC initialization is the lack of observations, especially in the inner-core (less than 150 km from the TC center).

TCs are predicted using both global and regional numerical prediction models. Global models simulate the atmospheric state variables on the sphere, while regional model simulate the variables in a specific region, and thus have lateral boundaries. Due to smaller domains of interest, regional models can generally be run at much higher horizontal resolution than global models, and thus they are more useful for predicting tropical cyclone intensity and structure. As an example of how well TC track and intensity has historically been predicted, Fig. 1 shows the average track and intensity errors from official forecasts from the National Hurricane Center from 1990-2009. While there has been a steady improvement in the ability to predict track (left panel), there has been little to no improvement in this time period in the prediction of TC intensity (right panel). Currently there is a large effort to improve intensity forecasts: the National Oceanic and Atmospheric Administration (NOAA) Hurricane Forecast Improvement Project (HFIP).

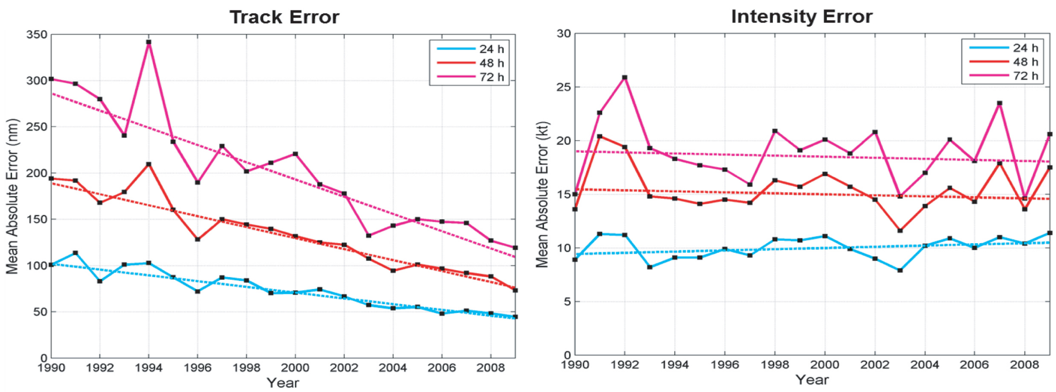

Figure. 1. Average mean absolute errors for official TC track (left panel) and intensity (right panel) predictions at various lead times in the North Atlantic basin from 1990-2009. Data is courtesy of the National Hurricane Center in Miami, FL, and plot is courtesy of Jon Moskaitis, Naval Research Laboratory, Monterey, CA.

Errors in the future prediction of TC track, intensity and structure in numerical prediction systems arise from imperfect initial conditions, the numerical discretization and approximation to the continuous equations, model physical parameterizations (radiation, cumulus, microphysics, boundary layer, and mixing), and limits of predictability. While improvements in numerical models should be directed at all of these aspects, in this chapter we are focused on the initial condition. The purpose of TC initialization is to give the numerical prediction system the best estimate of the observed TC structure and intensity while ensuring both vortex dynamic and thermodynamic balances. In this chapter, a review of different types of TC initialization methods for numerical prediction systems is presented. An overview of the general TC structure and challenges of initialization is given in the next section. In section 3, the direct vortex insertion schemes are discussed. In section 4, TC initialization methods using variational and ensemble data assimilation systems are discussed. In section 5, initialization schemes that are designed for improved initial balance are discussed. A summary is provided in section 6.

2. Overview of the TC structure

Tropical cyclones come in a wide variety of different structures and intensities. Intensity is a measure of the strength of the TC, and is usually given in terms of a maximum sustained surface wind or the minimum central pressure. Structure is a measure of various axisymmetric and asymmetric features of the TC in three dimensions. Structure encompasses the outer wind structure (such as the radius of 34 kt wind), inner core structure (such as the radius of maximum winds, eyewall width and eye width), as well as various asymmetric features (inner and outer spiral rain bands, asymmetries in the eyewall, asymmetric deep convection, and asymmetries due to storm motion and vertical wind shear). Additionally, structure would encompass vertical variations in the TC (such as the location of the warm core and how fast the tangential winds decay with height). While there are some observations (particularly for horizontal aspects of the structure from remote satellite imagery), there are never enough observations to know the complete three-dimensional flow and mass field in the TC.

In this section we outline some important structural aspects of the TC, including the basic axisymmetric and asymmetric structures that should be incorporated into the numerical model initial condition. An atmospheric state variable ψ, which may be temperature or velocity, may be interpolated to a polar coordinate system about the TC center and decomposed as $\psi(r, \phi, p, t) = \overline{\psi}(r, p, t) + \psi'(r, \phi, p, t)$, where $\overline{\psi}(r, p, t)$ is the axisymmetric component of the variable (where the overbar denotes as azimuthal mean), and $\psi'(r, \phi, p, t)$ is the asymmetric component of the variable. Here r is the radius from the vortex center, ϕ is the azimuthal angle, p is the pressure height, and t is the time. Often TCs are observed to be mostly axisymmetric (but with lower azimuthal wavenumber asymmetries due to storm motion and vertical shear), however in certain instances, and in certain regions of the TC, there can be large amplitude asymmetric components.

2.1. Axisymmetric structure

Fig. 2 shows the basic axisymmetric structure of a TC from a real case, Hurricane Bill (2009), obtained from the initial condition of (COAMPS®) numerical prediciton system [1] shown. In the Fig. 2a, the azimuthal mean tangential velocity is shown, in Fig. 2b the radial velocity is shown, and in Fig. 2c the perturbation temperature is shown. There are three important regimes in Fig. 2: (i) the boundary layer, (ii) the quasi-balance layer, and (iii) the outflow layer. The boundary layer is the region of strong radial inflow near the surface in Fig. 2b. Above the boundary layer, the winds are mostly tangential in the quasi-balance layer, and then at upper levels (Fig. 2b) the outflow layer with strong divergence and radial outflow is evident. In Fig. 2a, it can be seen that the strongest tangential winds are near the surface and decay with height, and in Fig. 2c a mid to upper level warm core is evident. While this is just one case, it illustrates the basic axisymmetric structure of a TC. While the vertical velocity is not shown in this figure, there exists upward motion in

1 COAMPS® is a registered trademark of the Naval Research Laboratory

the eyewall region, and this combined with the low to mid-level radial inflow and upper level outflow constitute the hurricane's secondary (or transverse) circulation. Changes in the secondary circulation are largely responsible for TC intensity change.

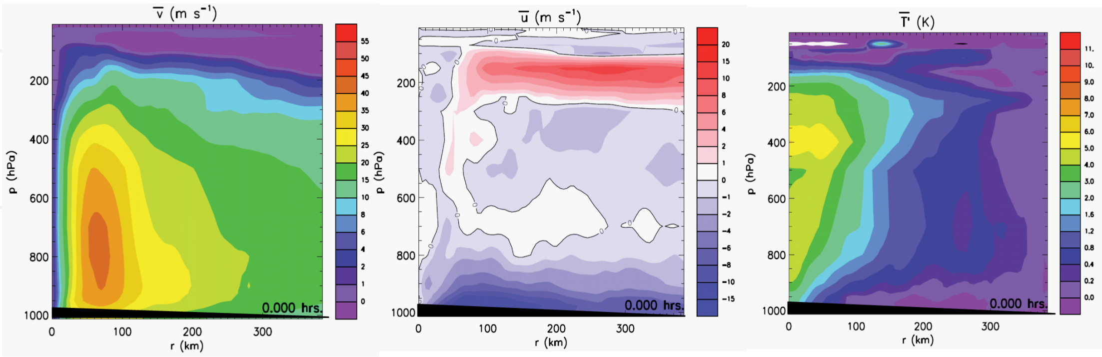

Figure. 2. Azimuthal mean structure of the initial condition of Hurricane Bill (2009) in the Naval Research Laboratory's Coupled Ocean/Atmosphere Mesoscale Prediction System COAMPS®. Panels: a) tangential velocity (m s^{-1}), b) radial velocity (m s^{-1}), and c) perturbation temperature (K). Reproduced from [18].© Copyright 2011 AMS (http://www.ametsoc.org/pubs/crnotice.html).

Using the quasi-balance approximation, where the vorticity is much larger than the divergence, the *f*-plane radial momentum equation can be approximated by

$$\frac{\partial \Phi}{\partial r} = \frac{v^2}{r} + fv, \tag{1}$$

where $\Phi = gz$ is the geopotential, v is the tangential velocity, f is the Coriolis parameter, and r is the radius from the TC center. Outside of deep convective regions, the hydrostatic approximation (in pressure coordinates) is also largely valid,

$$\frac{\partial \Phi}{\partial p} = -\frac{RT}{p}, \tag{2}$$

where p is the pressure, R is the gas constant, and T is the air temperature. Taking $\partial/\partial p$ (1) and $\partial/\partial r$ (2) while eliminating the mixed derivative term, the vortex thermal wind relation is obtained

$$\frac{\partial v}{\partial p}\left(\frac{2v}{r} + f\right) = -\frac{R}{p}\frac{\partial T}{\partial r}. \tag{3}$$

This equation states that a vortex in which v decreases with decreasing p must have warm core, i.e., T must decrease with increasing radius. This is evident in Fig. 2b, where the warm core begins at upper levels, where v is rapidly decreasing.

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In the outflow and boundary layers, there exists significant divergent and convergence, respectively, such that the quasi-balance approximation is no longer valid. Therefore an appropriate initialization scheme for TCs should not only capture the primary axisymmetric tangential (azimuthal) circulation, but also the secondary circulation, including the boundary and outflow layers. Additionally, there must be a thermodynamic balance between the boundary layer inflow, rising air in deep and shallow convection, and upper level outflow.

2.2. Asymmetric structure

In order to illustrate some asymmetric features in TCs, Fig. 3 shows two hurricanes: Hurricanes Dolly (2008) and Alex (2010). Hurricane Dolly was very asymmetric in the inner-core region. Note the azimuthal wavenumber-4 pattern in the eyewall radar reflectivity. Hurricane Alex (2010) was also very asymmetric, and had a large spiral rainband emanating from the core, and no visible eye. The point illustrated here is that TCs come in a wide variety of shapes and sizes, and often have prominent asymmetric features. While there is some structure dependence on intensity (i.e., stronger TCs in general are more axisymmetric than weaker TCs), at any initial time a given TC may have very different structure, and the goal of the initialization system is to capture its true state. Remote satellite measurements generally give a decent estimate of the horizontal structure. In fact, microwave data has allowed the ability to “see through” visible and infrared cloud shields, giving improved estimates of the deep convection and precipitation. However, typically there is much less data about the vertical structure. For example, the boundary layer structure or convective and stratiform heating profiles of Alex's rainband would not generally be known. Due to the lack of observations in TCs, in TC initialization systems, aspects of the structure are often specified using estimated information from satellite images.

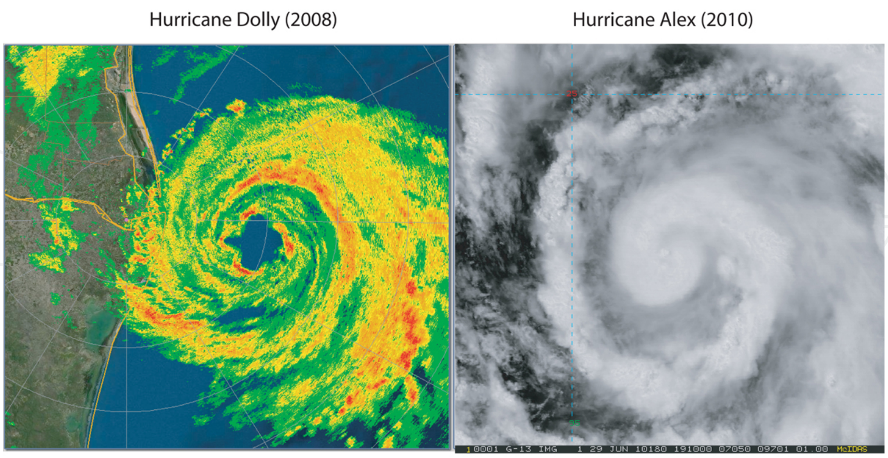

Figure. 3. Radar and visible satellite imagery depicting asymmetric features in TCs. Hurricane Dolly (2008) (left panel) had asymmetries in the eyewall and rain bands. Hurricane Alex (2010) (right panel) had a large azimuthal wavenumber-1 spiral rain band propagating outward from the vortex center. The left panel is courtesy of the NOAA National Weather Service and the right panel is courtesy of the NOAA/NESDIS in Fort Collins, CO.

3. Direct insertion schemes

As discussed in the previous section, TCs are poorly observed, particularly in the inner-core region. The North Atlantic basin is the only basin that routinely has aircraft reconnaissance missions into storms when they are close to the U.S. southeast coastal regions. The aircraft reconnaissance missions can provide important inner-core structural data using airborne Doppler radar and dropwindsondes, as well as direct or remote measurements of surface wind speed and minimum central pressure. Due to the lack of observations of the inner-core structure of TCs, vortex "bogussing" has been used to improve the representation of the TC in numerical prediction systems. Generally speaking, vortex bogussing is the creation of a TC-like vortex that can be inserted into the initial fields of numerical models [28]. The direct insertion methods take a bogus vortex and insert it directly into the numerical model initial conditions. The bogus vortex can be generated in different ways, which are described below. The main strength of these methods is that the vortex is usually self-consistent. However, some weaknesses exist. First, there can be imbalances that may exist when blending the inserted vortex with the environments in the model analysis. Secondly, for weak TCs and TCs experiencing vertical shear, it is not desirable to insert a vertically stacked vortex into the initial conditions (which is often the case with bogus vortices). Additionally previous studies have shown strong sensitivity to the vertical structure of the bogus vortex, which is often not well observed [46].

After a bogus vortex is created, there needs to be a method to properly insert this vortex into the initial fields of the forecast model. The first guess fields (or the previous model forecast which is valid at the analysis time), usually will already contain a TC-like vortex from the previous forecast. However this vortex may have an incorrect position, intensity, and structure, and therefore it should be removed from model fields. Vortex removal and insertion methods require a number of steps. The common method, discussed by [26] is as follows. First, the total field (e.g., surface pressure) is decomposed into a basic field and disturbance field using filtering. Next, the vortex with specified length scale is removed from the disturbance field. Then, the environmental field is constructed by adding the non-hurricane disturbance with the basic field. Finally, the specified vortex can then simply be added to the environmental field. Schemes of this nature are widely used in operational tropical cyclone prediction models in order to improve the TC representation from the global analysis [27, 34, 50].

3.1. Static vortex insertion

Since TCs are observed to largely be in gradient and hydrostatic balance above the boundary layer [49], one method is to insert a balanced vortex. Routine warning messages are generated by TC warning centers that include estimates of the maximum sustained surface wind, central pressure, and size characteristics (such as the radii of 34 kt winds). Using a function fit to the observed radial wind profile (e.g., a modified Rankine vortex or more sophisticated methods [19, 20]) along with a vertical decay assumption, one can obtain an axisymmetric tangential wind field in the radius-height plane. Following this, the mass field (temperature and pressure) may be obtained by solving the nonlinear balance equation in conjunction with the hydrostatic equation. Then this balanced vortex may be directly inserted into the model initial conditions, as a representation of the actual observed TC vortex. While this method is relatively straightforward, there are a few potential problems: (i) TC vortices are not balanced in the boundary and outflow layers, where strong divergence exists, and (ii) in convectively active regions of the vortex the hydrostatic balance assumption is not valid. It is possible to relax the strict balance assumptions above by building in the boundary layer and outflow structure diagnostically. The addition of boundary and outflow layers should reduce the amount of initial adjustment after insertion.

3.2. Insertion of a dynamically initialized vortex

Instead of specifying a vortex (usually analytically) to represent a TC, another method is to spin-up a TC-like vortex in a numerical model in an environment with no mean flow, and then insert this vortex into the model initial conditions. This method is called a TC dynamic initialization method because the TC vortex is developed from numerical simulation of a nonlinear atmospheric prediction model with full physics that requires prior model integration. The benefits of such a procedure are that the numerical model will generate a more realistic structure for the boundary layer and the outflow layer, and the moisture variables can also be included. The TC dynamic initialization is usually accomplished through Newtonian relaxation. A Newtonian relaxation term is added to the right hand side of a desired prognostic variable (e.g., the tangential velocity or surface pressure) in order to anchor the vortex to the desired structure and/or intensity. The Geophysical Fluid Dynamics Laboratory hurricane prediction model uses an axisymmetric version of its primitive equation to perform the dynamic initialization to a prescribed structure [3, 26, 27]. Recent work has also shown encouraging results with the TC dynamic initialization method using an independent three-dimensional primitive equation model in conjunction with a three-dimensional variational (3DVAR) data assimilation scheme [18, 61]. In Fig. 4, a flow diagram is shown depicting a TC dynamic initialization method applied after three-dimensional variational (3DVAR) data assimilation, where TCs are spun up using Newtonian relaxation to the observed surface pressure. This procedure showed a positive improvement in TC intensity prediction, as average errors in maximum sustained surface wind and minimum central pressure were reduced at all forecast lead times.

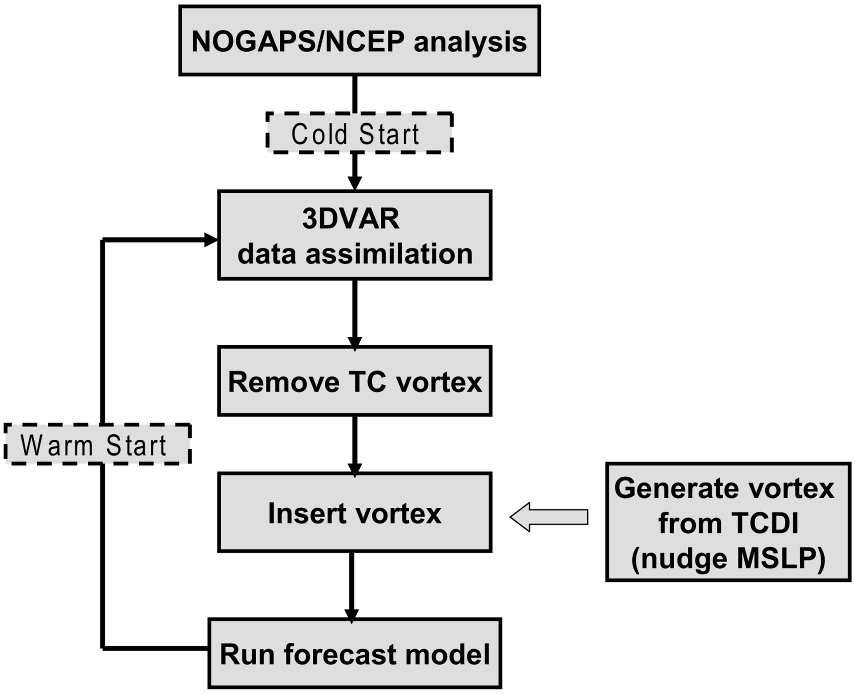

Figure. 4. Application of a TC dynamic initialization scheme to a 3DVAR system, reproduced from [18]. A TC is nudged to observed central mean sea level pressure (MSLP) in a nonlinear full-physics model, and then inserted into the forecast model initial conditions after 3DVAR. © Copyright 2011 AMS (http://www.ametsoc.org/pubs/crnotice.html)

4. Data assimilation systems for TC initialization

The purpose of data assimilation is to produce initial states (analyses) for numerical prediction that maximizes the use of information contained in observations and prior model forecasts to produce the best possible predictions of future states. Most data assimilation methods use observations (e.g., in-situ and remote measurements) to correct short-term model forecasts (the first guess), and therefore the accuracy of the resulting analysis is not just a function of the data assimilation methodology, but the fidelity of the forecast model itself. This analysis is then used as the initial condition for the forecast model. In this section, we discuss the data assimilation strategies that incorporate observational data into the model for proper representation of TCs at the initial time.

In the variational method, a cost function is minimized to produce an analysis that takes into account both the model and observation (including instrument and representativeness) errors. 3DVAR systems (or three-dimensional variational methods) solve this cost function in the three spatial dimensions, while 4DVAR (four-dimensional) systems add the temporal component in a set window. Generally speaking, most atmospheric observations are more applicable to the synoptic scale flow pattern, and often there are few (if any) observations of the inner-core of TCs or other mesoscale or small scale phenomena, aside from infrequent field campaigns. Yet even if these observations exist, it is not trivial to assimilate them while ensuring the proper vortex dynamic and thermodynamic balances.

4.1. 3DVAR systems

The replacement of optimal interpolation (OI) data assimilation scheme by the variational (VAR) method significantly improved the forecast skill of numerical weather prediction systems. The motivation originated from the difficulties associated with the assimilation of satellite data such as TOVS (TIROS-N Operational Vertical Sounders) radiances. It was shown by [31] that the statistical estimation problem could be cast in a variational form (3DVAR) which is a different way of solving the problem than the OI scheme which solves directly. The first implementation of 3DVAR was done at the National Centers for environmental Prediction (NCEP) [36] and later on at the European Center for Medium Range Weather Forecasting (ECMWF) [4]. Other centers like the Canadian Meteorological Centre [13], the Met Office [30], and Naval Research Laboratory [6] also implemented a 3DVAR scheme operationally.

The common method for TC vortex initialization in 3DVAR systems is through the use of adding synthetic observations [15, 17, 29, 55, 65]. Synthetic observations are observations that are created from the estimates of the TC structure and intensity that come from tropical cyclone warning centers (such as the National Hurricane Center in Miami, FL, and the Joint Typhoon Warning Center in Pearl Harbor, HI), and give the best estimate of the storm position, intensity and structure. The synthetic observations are used to enhance the TC representation in the numerical model initial conditions, which generally cannot be adequately captured using the conventional observations. The synthetic observations themselves may be created by sampling a function that matches the observed vortex, and these observations are treated as radiosonde data with assigned proper position information and are included with all other observations and blended with the model first guess using the 3DVAR system. Generally speaking, the observation error is set very low with the TC synthetic observations in the assimilation process, so that the analysis process will largely retain these characteristics of the synthetic observations near the TC. A number of TC synthetic observations are shown for Typhoon Morakot (2009) in Fig. 5, which are ingested into the Naval Research Laboratory's 3DVAR scheme [6], reproduced from [29].

One strength of 3DVAR systems is that synthetic or other TC observations from reconnaissance missions can be assimilated easily into the system. The main problem with using 3DVAR systems for TC initialization is that they generally do not have the proper balance constraints for mesoscale phenomena. Most 3DVAR systems have a geostrophic balance condition to relate the mass and wind fields, which is not valid for tropical cyclones and other strongly rotating mesoscale systems, where there exists a nonlinear balance between the mass and wind fields. The improper balance constraint for TCs in 3DVAR systems can result in rapid adjustment during the first few hours of model integration, causing the model vortex to deviate to a state that is very different from the initially ingested synthetic observations. This discrepancy will most likely be carried throughout the forecast period and can cause a large bias for intensity prediction. It has been recently demonstrated how quickly a 3DVAR system can lose the desired TC characteristics [61]. Additionally, it is very hard to use a 3DVAR data assimilation system to adequately capture the secondary circulation correctly, so as to have consistency between the boundary-layer inflow, vertical motion and heating, and outflow.

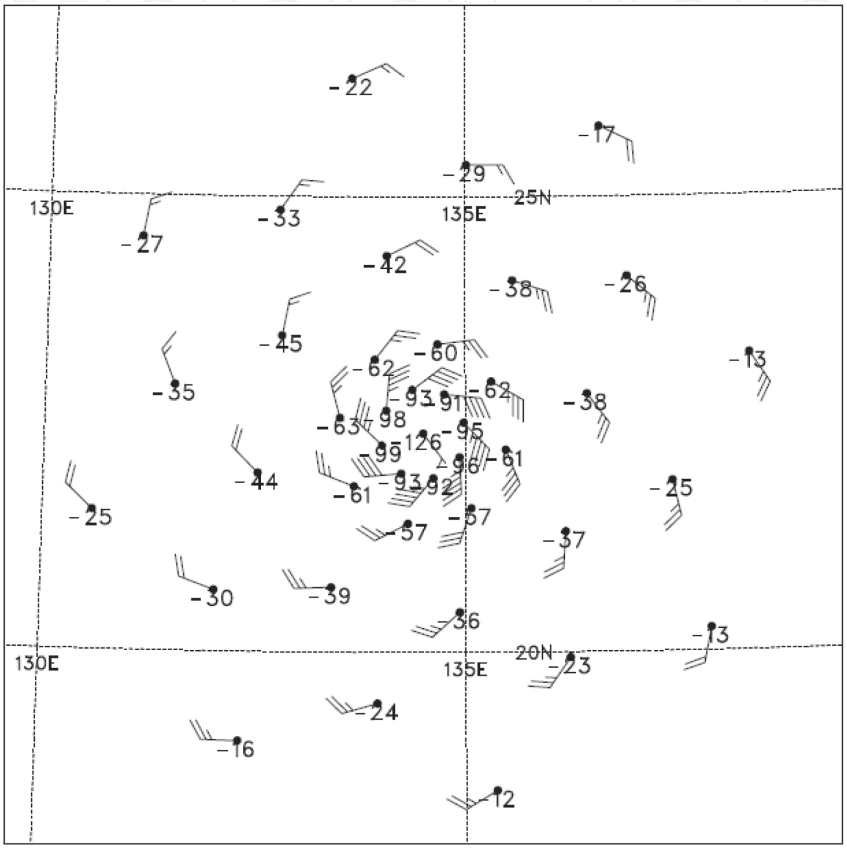

Figure. 5. Depiction of near-surface TC synthetic observations for Typhoon Morakot (2009), reproduced from [29]. The synthetic TC observations are blended with all other observations in the 3DVAR data assimilation.

In addition to the synthetic data, dropwindsonde data from aircraft reconnaissance missions may also be included in variational data assimilation systems. Dropwindsondes measure a quasi-vertical profile of the troposphere from where they are launched. A number of studies have shown a positive impact of assimilating dropwindsonde data on TC track [47, 51]. However there can be significant variability on the impact on a case by case basis.

4.2. 4DVAR systems

The 4DVAR data assimilation system is a generalization of 3DVAR for assimilating observations that are distributed within a specified time window. The goal of 4DVAR is to significantly improve the 3DVAR deficiencies, especially in properly initializing a multi-scale weather system. Compared to 3DVAR, the 4DVAR analyses do not typically show a significant imbalance in the first hours of the forecast. This spin-up process is often associated with the presence of spurious gravity waves that need to be removed by an initialization process (discussed in the next section). A 4DVAR data assimilation system usually requires the development of the tangent linear model and corresponding adjoint system for the forecast model, which are not trivial, in order to iteratively minimize the difference between the first guess fields and the observation. 4DVAR data assimilation systems have been developed for major operation centers for their global prediction system and have led to improvements in forecast skill: ECMWF [40], the Canadian Meterological Centre [14], the U.K. Met Office [41], the Naval Research Laboratory [56], and the Australian Bureau of Meteorology. In some of the 4DVAR systems, synthetic observations are also ingested to improve the TC vortex representation, similar to 3DVAR systems.

An example of an operational TC prediction model that uses a 4DVAR scheme for initialization is ACCESS-TC (Australian Community Climate and Earth System Simulator system for Tropical Cyclones), and a number of other studies have also employed 4DVAR systems for TC initialization [35, 52, 54, 63, 64]. For example, the utility of 4DVAR data assimilation in assimilating irregularly distributed observations in both space and time (such as AMSU-A retrieved temperature and wind fields, as well as the mean sea level pressure (MSLP) information) has been shown by [63]. Using a 72-hour simulation of a land-falling typhoon, they concluded that both the satellite data and the MSLP information could improve the typhoon track forecast, especially for the recurving of the track and landing point. The MM5-4DVAR data assimilation system developed by the Air Force Weather Agency (AFWA) [42] has been employed [62] with a comprehensive satellite products to construct a continuous-coverage, high-resolution TC dataset. Twelve typhoons that occurred over the western Pacific region from May to October 2004 were selected for this reanalysis. The resulting analysis fields show very similar structure of TCs in comparison with satellite observations, demonstrating the capability of 4DVAR in retaining the final structure of the data.

4.3. Ensemble Kalman filter systems

Another four-dimensional data assimilation system, the ensemble Kalman filter (EnKF), has also been adopted for geophysical models [11, 21]. The Kalman filter, is an algorithm which uses a series of measurements observed over time (thus four-dimensional), produces estimates of unknown variables. More formally, the Kalman filter operates recursively on streams of noisy input data to produce a statistically optimal estimate of the underlying system state. The original Kalman Filter assumes that all probability density functions are Gaussian and provides algebraic formulas for the change of the mean and the covariance matrix by the Bayesian update, as well as a formula for advancing the covariance matrix in time provided the system is linear. However, maintaining the covariance matrix is not computationally feasible for high-dimensional systems. For this reason, EnKFs were developed that replace the covariance matrix by the sample covariance computed from the ensemble forecast. The EnKF is now an important data assimilation component of ensemble forecasting. An overview of the work done with the EnKF in the oceanographic and atmospheric sciences can be found in [12].

An intercomparison of an EnKF data assimilation method with the 3D and 4D Variational methods was made using the Weather Research and Forecasting (WRF) model over the contiguous United States during June of 2003 [60]. It is found that 4DVAR has consistently smaller errors than that of 3DVAR for winds and temperature at all forecast lead times except at 60 and 72 h when their forecast errors become comparable in amplitude. The forecast error of the EnKF is comparable to that of the 4DVAR at the 12-36 h lead times, both of which are substantially smaller than that of the 3DVAR, despite the fact that 3DVAR fits the sounding observations much more closely at the analysis time. The advantage of the EnKF becomes even more evident at the 48-72 h lead times.

The EnKF has recently been applied to the TC initialization problem [1, 9, 16, 44, 45, 48, 53, 58, 59]. The EnKF assimilation of inner-core data, such as airborne Doppler radar winds has shown some promising results with improving the vortex structure and intensity forecasts [1, 57]. In Fig. 6, the performance of an EnKF system for predicting TC intensity is shown for a sample of cases in which airborne Doppler radar data was assimilated, reproduced from [57]. As shown in the figure, average intensity errors were reduced by the EnKF assimilation of radar data. [53] used an ensemble Kalman filter (EnKF) to assimilate center position, velocity of storm motion, and surface axisymmetric wind structure in a high-resolution mesoscale model during the 24-h initialization period to develop a dynamically balanced TC vortex without employing any extra bogus schemes. The surface radial wind profile is constructed by fitting the combined information from both the best-track and the dropwindsonde data available from aircraft surveillance observations, such as the Dropwindsonde Observations for Typhoon Surveillance near the Taiwan Region (DOTSTAR). The subsequent numerical integration shows minor adjustments during early periods, indicating that the analysis fields obtained from this method are dynamically balanced. While the EnKF methods are appealing, due to its ensemble nature, it can be significantly more costly (in a computational sense) than the variational methods.

5. Initialization Schemes

While the direct insertion and data assimilation techniques can produce estimates of the observed TC, inevitably imbalances will exist after interpolation and analyses procedures. As discussed earlier, the imbalances will typically be greater for the 3DVAR schemes than 4D schemes. The primary purpose of the initialization schemes is to improve the initial dynamic and thermodynamic balances of the TC, so that spurious gravity waves are filtered from the initial condition [5]. In this section, we discuss three widely used initialization schemes: nonlinear normal mode initialization, digital filters, and dynamic initialization.

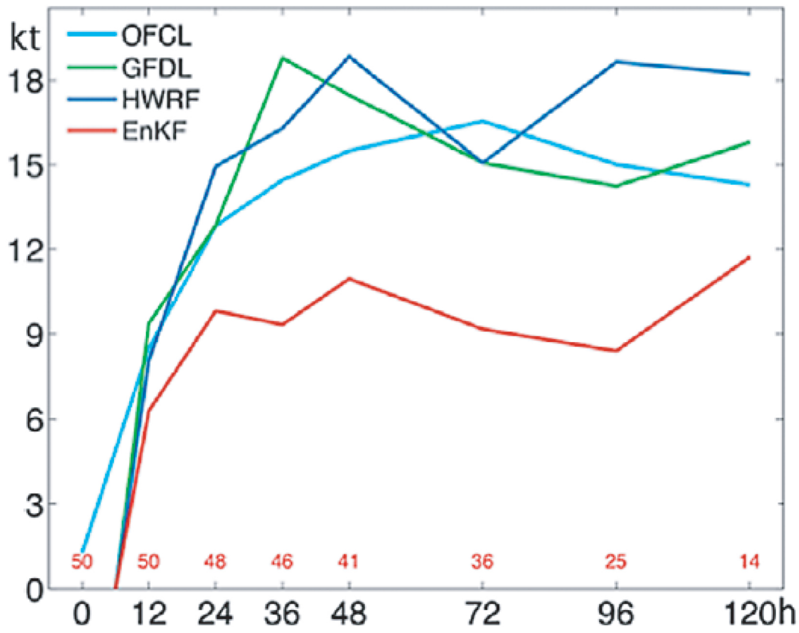

Figure. 6. Mean absolute error (ordinate) in the maximum sustained surface wind versus forecast lead time (abscissa) in a homonegeous sample of cases with airborne Doppler radar data during 2008-2010. As shown the EnKF system which assimilates the radar data had a lower average intensity error than the offical National Hurricane Center forecast (OFCL) and other operational hurricane prediction models (GFDL and HWRF). Figure is courtesy of Fuqing Zhang, reproduced from [57] by permission of American Geophysical Union.

5.1 Nonlinear normal mode initialization

Since an important goal of initialization to provide a balanced initial state from which minimum spurious gravity activity remains [5], methods have been specifically developed to remove such gravity waves from the initial conditions. An early strategy for removal of high frequency oscillations is the nonlinear normal mode method [2, 33, 43]. The eigenvalues of the linearized version of the nonlinear forecast model are the normal modes of the system. For a three-dimensional atmospheric model, these normal modes will encompass higher frequency sound and gravity waves, as well as lower frequency Rossby waves. The idea with the normal mode initialization is to project the analysis vector on to the slower modes in order to reduce gravity waves in the initialization.

5.2 Digital filters

Another method to remove high frequency variability is the digital filter. Similar to the electronic analogue, the digital filter performs a mathematical operation on a time signal to reduce or enhance certain aspects of that signal. For atmospheric applications, this is usually accomplished using a filter that has a cutoff frequency, so that waves of a desired frequency can be removed from the analysis [32]. The benefits of the digital filter is that it is a straightforward way to remove waves of a certain frequency without changing the initial condition significantly [22]. The digital filter can be used in both adiabatic and diabatic modes.

5.3 Dynamic initialization

Dynamic initialization (DI) is a short-term integration of the full model before it actually starts the forecast integration to allow the forecast model to handle the spin-up issue. It usually includes two steps: adiabatic backward integration (i.e., to −6 hour) and diabatic forward integration to the initial time. During adiabatic backward integration, the model physics does not contribute to the tendency of the variables so that this process is quasi-reversible (except the effect of numerical diffusion). In the forward integration (i.e., from −6 hour to the actual initial time at zero hour), the model incurs diabatic process with Newtonian relaxation to some chosen variables so that the initial fields are close to the analysis without introducing small model error during the extra integration time. The idea here is, taking TC prediction as an example, that the 3DVAR procedure produced a reasonably accurate initial state, however, imbalances for TCs with their multiple scales will exist and they should be removed prior to the start of model integration. This process also allows for the build up of the boundary layer and secondary circulation of the TC. The forward DI can be accomplished by relaxation to any or a combination of the model prognostic variables at the analysis time. Of course, much care should be taken in choosing the proper combination. One commonly adopted DI procedure is to relax to the analysis horizontal momentum during the initialization period. DI can also be enhanced by separately relaxing to the nondivergent and divergent wind components, with different relaxation coefficients [7]. This is useful because the nondivergent winds are better captured by the 3DVAR analysis than the divergent winds, and allows for direct way of including relaxation to the heating profiles (which affect the divergent circulation). Various methods have used to incorporate the diabatic effects into the dynamic initialization procedure. These methods include modifying the humidity vertical profiles due to rain rate assimilation, physical initialization, and dynamic nudging to the satellite observed heating profiles [7, 23, 24, 25, 37, 38, 39]. As an example of an operational system, the Australian Bureau of Meteorology used a diabatic dynamic initialization scheme in their earlier tropical cyclone prediction system (TC-LAPS). The diabatic, dynamic initialization was used after a high-resolution objective analysis to improve the mass-wind balance of the vortex while building in the heating asymmetries [8].

6. Conclusions

This chapter reviewed different methods for initializing TCs in numerical prediction systems. The methods range from simpler direct insertion techniques to more advanced dynamic initialization, and from three-dimensional to four-dimensional data assimilation techniques. The strengths and weaknesses of the different schemes were discussed. The direct insertion techniques take either an analytically specified vortex or a dynamically initialized vortex and insert it into the numerical model analysis. These schemes require removal of the TC vortex in the numerical model first guess or analyzed fields, which is often not at the right location or does not match the observations. The direct insertion schemes are appealing because a vortex can be constructed to match the observations, however, there is no guarantee that when inserting this vortex into the analysis that dynamic and thermodynamic balance will exist. In the data assimilation techniques for TC initialization, synthetic observations matching the observed TC structure and intensity are created, and a data assimilation system blends these observations with all other observations to generate the analysis. 3DVAR systems are not as well suited for the TC initialization due to its inability to produce a nonlinear balance between the mass and wind fields. 4DVAR and ensemble Kalman filter schemes show some promising results for TC initialization, in particular, in obtaining a better dynamic and thermodynamic balance, and in the case of the EnKF also providing probabilistic information by running an ensemble. Finally, full domain dynamic initialization (adiabatic and diabatic) techniques were discussed. These schemes are advantageous because they are relatively straightforward to implement, and they are able to produce better dynamic and thermodynamically balanced vortices without the development of the four-dimensional data assimilation.

There are a number of significant challenges that remain for TC initialization. First, most TCs lack of observations needed to construct accurate structure for the storms. Only a handful of TCs in the North Atlantic Ocean basin have routine reconnaissance missions. No matter how advanced the initialization system is, it will always be limited by lack or uncertainty in the observations. Secondly, TCs span multiple scales of motion, ranging from turbulence to deep convective updrafts to vortex scale waves (e.g. vortex Rossby waves), to its interaction with the environments and synoptic scale features. While the synoptic scale is largely responsible for TC track, many of these smaller-scale features are important for intensity. These features are transient and unbalanced, leading to initialization challenges. Third, it is difficult to initialize TCs properly in different environments, such as a TC in shear or with dry air wrapping into its core. Finally, if TC intensity largely depends on deep convective evolution, there are inherent limits to predictability.

In spite of these challenges, much progress has been made of the TC initialization front, and there are promising results from the EnKF, 4DVAR and dynamic initialization schemes. The recent trend in data assimilation is to combine the advantages of 4DVAR and the Kalman filter techniques. Considering the threat that TCs will continue to play, efforts must continue to develop enhanced initialization schemes along with the new technologies for data assimilation to better predict track and intensity.

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