Diagnosing systematic numerical weather prediction model bias over the Antarctic from short-term forecast tendencies

Steven M. Cavallo, University of Oklahoma School of Meteorology, Norman, OK

The Antarctic Mesoscale Prediction System (AMPS) is a derivative of the Advanced Research Weather Research and Forecasting (ARW-WRF) limited area model (LAM), with modifications in physics parameterizations aimed to improve polar prediction (Powers et al. 2003). AMPS forecasts are a single deterministic realization initialized using a 3DVAR method employed from a Global Forecasting System (GFS) analysis. Data assimilation is not continuously cycled and AMPS forecasts are initialized from a non-native analysis (a different model is used in the data assimilation and the forecast). During September-December 2010, the Concordiasi intensive observing period (IOP) occurred over the Antarctic and parts of the Southern Ocean, where unique vertical atmospheric profiles were collected from dropsondes that were deployed from driftsondes within the Southern Hemisphere polar vortex (Rabier et al. 2010). This provided an opportunity to examine systematic model bias in the AMPS LAM, where horizontal grid spacing was 45-km at the time of the IOP. This study uses short-term forecast tendencies to formally diagnose systematic model error for the period 21 September - 30 September 2010. The hypothesis of this study is that the sources of model bias can be diagnosed to the precise physical parameterization and locations using short-term forecast tendencies in a method referred to here as the mean initial tendency analysis (MITA) increment method (e.g., Klinker and Sardeshmukh 1992; Rodwell and Palmer 2007).

To minimize initial condition error so that it is statistically distinguishable from model error, it is best if the same identically configured model used to create the analysis is used for forecasts (e.g., Rodwell and Palmer 2007; Klocke and Rodwell 2014). In these cases, the analysis is referred to as a 'native' analysis since the same model is used in both the data assimilation and forecasts (e.g., Klocke and Rodwell 2014). The departure of the short-term forecasts from the observed atmospheric state in the early time steps allows for the potential identification of process-level errors, and this growth of errors is often referred to as model 'spin-up' (Rodwell and Palmer 2007). Thus, the AMPS numerical weather model and an Ensemble Adjustment Kalman Filter (EAKF) within the Data Assimilation Research Testbed (DART) framework (Anderson et al. 2009) are used here to create a fully cycled atmospheric ensemble data assimilation system, which is hereafter referred to as 'A-DART' for brevity.

A one-month control ensemble analysis is created for which DART is identically configured as in Cavallo et al. (2013) assimilating the following conventional observations: Radiosondes, marine buoys, geostationary satellite atmospheric motion vectors (AMVs), METAR, Aircraft Communications Addressing and Reporting System data (ACARS), Automatic Weather Stations (AWS), and Global Positioning System (GPS) data. Cavallo et al. (2016) previously implemented the MITA increment method over a domain in the tropical North Atlantic Ocean with 36-km horizontal grid spacing using the conventional observations listed above with the ARW-WRF LAM model. A systematic model bias was diagnosed from the planetary boundary layer parameterization scheme, and was found to originate from erroneously specified sea surface temperatures (SSTs) over the North Atlantic Ocean. In addition, a systematic warm temperature bias in the free-troposphere was found to originate from the convective parameterization.

A large-scale upper-level wind bias is immediately evident in the A-DART control. This bias is evident from the analysis increments of wind and is greatest in the 45°S-60°S latitude range. Comparison of 6-h forecasts to Antarctic radiosonde profiles reveal a strong warm temperature bias in upper-levels, everywhere above 300 hPa. In addition to A-DART, this bias is apparent in forecasts from both the stand-alone AMPS and the GFS models. Given that ARW-WRF and AMPS physical parameterizations do not use a time-varying ozone profile, and that this time period exactly coincides with the annual depletion of Antarctic ozone, it is first hypothesized that a large-scale upper-level circulation bias is present due to too much shortwave heating over the Antarctic continent as a result of erroneously high ozone concentrations. Two experiments are then devised to test this hypothesis: (1) Implement time-varying, latitude-dependent ozone profiles in the physics, and (2) assimilate AMV data from polar-orbiting satellites. Both experiments result in only modest reductions in model bias. Therefore, the MITA increment method is then applied to determine where additional model bias originates.

While the MITA increment method has been more commonly used in global models, Cavallo et al. (2016) is the only study where it has been applied to a limited area mesoscale numerical weather prediction model. They found that analyzing forecast tendencies over shorter time intervals can be successful as long as the forecast model has appropriately spun-up to represent the mean analysis increment over the 6-h data assimilation cycling period, which in their study was sufficient after about 30-minutes. In the present study, this was found to be sufficient for forecast tendencies beginning at 1 hour, or 25 model time steps.

Statistically significant cold temperature biases are found in the boundary layer from 0-4 km above ground level (AGL) (700-1000 hPa), and in upper-levels from 10-20 km AGL (20-300 hPa). This cold bias is in contrast to the warm bias seen from radiosonde comparisons, however, it is noted that radiosonde locations are predominantly located around 60°S latitude in the Antarctic. A decomposition of the forecast tendency components reveals that the upper-level bias derives from the dynamics and longwave radiation tendencies equatorward of 60°S latitude near the locations of geostationary satellite AMV observations. To test whether the geostationary AMV observations are biased, the case is re-cycled with Atmospheric Infrared Sounder (AIRS) satellite retrievals and results in substantially reduced bias. Given the number of AIRS retrievals is much greater than the number of AMV observations, it is concluded that the geostationary AMVs exhibit a possible wind bias, where the wind from AMVs is too strong. Regarding the boundary layer bias, A-DART is again re-cycled to test whether well-documented cloud-phase errors in polar regions (e.g., Sandvik et al. 2007) contribute to a cold mid-tropospheric temperature bias. Model bias is reduced approximately by half, and the reduction in bias occurs primarily in the storm-track region over the Southern Ocean and over sea ice areas.

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