Operational Numerical Weather Prediction Models

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Operational Numerical Weather Prediction Models: Outline

- Model Development Summary
- Review of select parameterizations, data assimilation, and initialization
- Specific Global, Mesoscale, and Cloud-allowing NWP models
- Select parameterizations and NWP skill based on limited literature search; implications for operational NWP models
- What atmospheric phenomena can be resolved/simulated by a particular NWP model?
- Predictability
- Summary
NWP Model Development: Summary

- **Determinism**: Latter states evolve from earlier ones in accordance with physical laws. (Laplace, 1996; Lorenz 1993)

- **Primitive equations**: Based on Newton’s 2\textsuperscript{nd} law of motion, equation of state, conservation of mass, thermodynamic energy equation (Bjerkness 1904) (model dynamics)

- **Discretization**: Atmospheric fluid $\rightarrow$ finite grid elements. Continuity of time $\rightarrow$ finite time increment [finite difference equations]

- **Parameterizations**: Account for the implicit effects of (emulate) unresolved processes (model physics)

- **Initial value problem**: Initial values provided by data assimilation

- **Data Assimilation**: “Using all the available information to determine as accurately as possible the state of the atmospheric or oceanic flow” (Talagrand, 1997)
NWP Model Development: Summary

- **Initialization**: Balanced analysis (e.g. Glickman, 2000; Stull, 2015)
- Forward integration
- **Primary** \((t, u, v, \text{ etc.})\) and **Secondary variable/parameter** (CAPE, simulated reflectivity, etc.) **output**
Discretization: NWP Model Grid Cell Depiction Example (Stull, 2015)
Review of select parameterizations, data assimilation, and initialization
Select parameterizations

**Figure 4.1.1:** Physical processes in the atmosphere and their interactions. The dynamical processes for resolvable scales, in bold, are explicitly computed by the model “dynamics” (discussed in Chapters 2 and 3). The other subgrid-scale processes are parameterized in terms of the resolved-scale fields. (Adapted from Arakawa, 1997.)

Kalnay (2003)
Select Parameterizations: PBL/Turbulence

Motivation to account for PBL/Turbulence (Randall, et al., 1985; Stensrud, 2007)

- The PBL is the layer adjacent to the earth wherein turbulence is the dominate mechanism responsible for the vertical redistribution of sensible heat, moisture, and momentum
- Sensible/latent heat turbulence fluxes most important source for moist static energy for atmospheric circulations
- PBL friction the most prevalent atmospheric KE sink
- Potential for deep convection (via CAPE) and convective mode (via wind profile) related to PBL structure
Select Parameterizations: PBL/Turbulence

**Problem:**
Representation of turbulent flow in the primitive equations requires a grid spacing ≤ 50-m (Stensrud, 2007)

**Solution:**
Reynolds averaging to account for the statistical effects of subgrid scale eddies (Stensrud, 2007)

\[ u = \bar{u} + \hat{u} \]

- \( \bar{u} \rightarrow \) spatial average over a grid box
- \( \hat{u} \rightarrow \) subgrid scale perturbation
## Turbulence Closure Problem (Warner, 2011)

Table 4.1 Example of the prognostic equations for the first three statistical moments, indicating the number of equations and the number of unknowns.

<table>
<thead>
<tr>
<th>Example prognostic variable</th>
<th>Statistical moment</th>
<th>Equation</th>
<th>Variable parameterized</th>
<th>Number of equations</th>
<th>Number of unknowns</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\bar{u}_i$</td>
<td>First</td>
<td>$\frac{\partial \bar{u}_i}{\partial t} = ... - \frac{\partial}{\partial x_j} \bar{u}'_i u'_j$</td>
<td>$u'_i u'_j$</td>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td>$\bar{u}'_i u'_j$</td>
<td>Second</td>
<td>$\frac{\partial}{\partial t} \bar{u}'_i u'_j = ... - \frac{\partial}{\partial x_k} \bar{u}'_i u'_j u'_k$</td>
<td>$u'_i u'_j u'_k$</td>
<td>6</td>
<td>10</td>
</tr>
<tr>
<td>$u'_i u'_j u'_k$</td>
<td>Third</td>
<td>$\frac{\partial}{\partial t} \bar{u}'_i u'_j u'_k = ... - \frac{\partial}{\partial x_m} \bar{u}'_i u'_j u'_k u'_m$</td>
<td>$u'_i u'_j u'_k u'_m$</td>
<td>10</td>
<td>15</td>
</tr>
</tbody>
</table>
Select Parameterizations: PBL/Turbulence

Turbulence Closure Approaches (Warner, 2011)

Local Closure: Relate unknown variables (what must be parameterized) to known variables at nearby vertical grid points

Nonlocal Closure: Relate unknown variables (what must be parameterized) to known variables at any number of vertical grid points

Fig. 4.15 Schematic of the distinction between local closures and two different types of nonlocal closures. Panel (a) applies to local closures, and (b) and (c) pertain to nonlocal closures. See the text for details.
Select Parameterizations: PBL/Turbulence

Warner (2011); originally adapted from Stull (1991)

Local closure approximation of vertical heat flux near zero in center of PBL (unless correction $\gamma$ applied), yet studies reveal that heat transfer exist throughout the PBL

Example of problem with Local PBL scheme:

Local closure approximation of vertical heat flux:

$$\bar{\theta}'w' = -K_H \left( \frac{\partial \bar{\theta}}{\partial z} - \gamma \right)$$

Warner (2011); originally adapted from Stull (1991)
Select Parameterizations: Microphysics

Motivation to account for cloud microphysics

Microphysical processes govern formation, growth, and dissipation of cloud particles which influences development and evolution of moist convection (Stensrud, 2007)

Problem

Foregoing processes occur on molecular scales, thus unresolved by NWP models

Solution

Explicit microphysics parameterization $\rightarrow$ explicitly represent clouds and associated microphysical processes (Stensrud, 2007)
Select Parameterizations: Microphysics

Parameterize:
- Phase changes of water
- Various interactions between cloud and precipitation particles

Two classes of microphysical parameterizations based on how size distribution represented:

Bulk: Use analytical equation (gamma, exponential, log-normal, etc.) to parameterize particle size distribution for each species; size spectra evolution from predictive equations for the following moments (used in operational NWP models)
- Single moment $\rightarrow$ Predict only particle mixing ratio
- Double moment $\rightarrow$ Predict particle mixing ratio and number concentrations (more realistic particle size distribution and size sorting)
- Triple moment $\rightarrow$ Predict mixing ratio, number concentration, and reflectivity

Bin: Discretize particle size distribution into finite size/mass categories (“bins”); predictive equations for each size bin and species (computationally expensive; used in research)

Morrison (2010); Stensrud (2007); Warner (2011)
Select Parameterizations: Microphysics

Initialization of microphysical parameters/variables:

*Problem: Difficult to determine initial values*

- Existence of select atmospheric species only inferred by satellite imagery or surface observations
- Vertical and horizontal distribution of species unknown
- Must initialize with corresponding circulations

*Solutions*

- Assume zero number concentrations at NWP model initialization and assume that realistic values will spin up within 3-6 h of NWP model start.
- Use values from analysis background/first guess (output from short-term NWP prediction)
- Use output from Newtonian relaxation/nudging

Warner (2011)
Select Parameterizations: Convection

Motivation to Account for Convection

*Deep Moist convection*
- Important to the prediction of atmospheric circulations (Stensrud, 2007)
- Warms environment via compensating subsidence, and dries the atmosphere via removal of water vapor (Warner, 2011)

*Shallow convection*
- Modifies the surface radiation budget, and influences the turbulence/structure of the PBL (Randall et al. 1985)

Problem
NWP grid spacing of ≤ 100-m needed to resolve convective clouds (Bryan et al 2003; Petch 2006) → not feasible for state-of-the-art operational NWP models.

Solution
Parameterize the implicit effects of subgrid scale convection (e.g Molinari and Dudeck, 1986; Molinari and Dudeck, 1992)
Select Parameterizations: Convection

Convective Parameterization Overall Objective (Arakawa, 1993)

- Properly represent convective timing, location, evolution and intensity
- Properly define the environmental modification to convection in order to accurately predict subsequent convection

Fig. 4.4 Schematic of the interaction between large-scale processes and moist convection. Adapted from Arakawa (1993).
Select Parameterizations: Convection

Categorizing convective parameterization schemes (Warner, 2011)

A. **Deep Layer (Equilibrium) Control** (convection controlled by CAPE development) and **Low Level (Activation) Control** (convection controlled by removal of CIN)

B. **Represent only deep convection, shallow convection, or both**

C. **Classified in terms of atmospheric grid scale variables affected by convection**

D. **Define the final atmospheric state after convection effected the change (static scheme) or simulate the process by which the change takes place (dynamic scheme)**

**Trigger Function:** Set of criteria that prescribe time/location of the parameterized convection activation
Select Parameterizations: Convection

Relationship between parameterized sub-grid scale convection and resolved-scale convection (Warner, 2011)

A. Precipitation can be produced as a byproduct of the activation of moist convection by the convective parameterization scheme and by explicit prediction of grid-scale precipitation by microphysical parameterization.

B. Parameterized precipitation is generated within a sub-saturated grid box (since convection parameterized is of sub-grid scale), while resolved scale precipitation in the microphysics scheme requires grid box saturation.

C. Convective parameterization generally does not produce cloud water/ice on the grid-scale, thus no cloud radiative effects.

D. Parameterized and resolved scale precipitation may predominate at different regions of an event (e.g. MCS parameterize convection dominate convective region while microphysics scheme influences the stratiform rain region.)
Select Parameterizations: Convection

Relationship between parameterized sub-grid scale convection and resolved-scale convection (Warner, 2011)

Partitioning of parameterized and resolved scale precipitation a function of meteorological event and convective parameterization scheme

Fig. 4.7 Ratio (percentage) of subgrid-scale precipitation to total precipitation (sum of subgrid and resolved precipitation) for simulations of two meteorological cases, where four different convective parameterizations were used for each case. The horizontal grid increment was 36 km, and the ratios are based on totals for the computational area. Panel (a) pertains to simulations of a mesoscale convective system that occurred in May, and panel (b) pertains to simulations of an Arctic front in February, with some convection in the warm air mass. The four convective parameterizations were the Grell (GR; Grell 1993, Grell et al. 1994), Kain–Fritsch (KF; Kain and Fritsch 1993), Betts–Miller (BM; Betts and Miller 1986), and Anthes–Kuo (AK; Anthes 1977, Grell et al. 1994) schemes. Adapted from Wang and Seaman (1997).
Select Parameterizations: Convection

Important issues related to convective parameterization

1. $\geq 10$-km: fully explicit approach (no convective parameterization) cannot successfully simulate mesoscale organization of convection (Molinari and Dudeck, 1992)

$\leq 20$-km: Fundamental assumption of convective parameterization begins to break down (Molinari and Dudeck, 1992)

$\leq 20$-km: Inclusion of convective parameterization may result in simultaneous implicit effects of subgrid scale convection and explicit convection (Molinari and Dudeck, 1992)

2. Convective parameterization removes excess instability and rainfall occurs as a byproduct of the process. Thus, do not rely on the timing and position of convective precipitation in NWP models with convective parameterization (UCAR, 2002)
Select Parameterizations: Convection

*NWP Model skill when Convective Parameterization turned off (≤ 10-km)*

**5-10 km:** Convective overturning develops/evolves too slowly; updraft/downdraft mass fluxes and precipitation rates too strong during mature phase (Weisman et al. 1997)

**4-km:**
- Adequately resolve squall line mesoscale structures (Weisman et al. 1997)
- Exaggerates scale of individual convective cells contributing to a high QPF bias (e.g. Deng and Stauffer, 2006)
- Can accurately/skillfully predict convection occurrence and mode. Less skillful with regard to timing and position (Fowle and Roebber, 2003; Weisman et al. 2008)

**4-km → 2-km:** Miniscule improvement in prediction skill; added value likely not worth the factor of 10 increase in computational expense (Kain, 2008)

**2-km → 0.25 km:** Simulations of supercell very sensitive to grid spacing (2-km: steady state/unicellular ≤ 1-km: cyclic mesocyclogenesis (Adlerman and Droegemeier, 2002)
NWP Model skill when Convective Parameterization turned off (≤ 10-km)

0901 UTC 4/14/2015 WSR-88D
0900 UTC 4/14/2015 HIRESW ARW WARM START
0900 UTC 4/14/2015 NSSL COLD START

0900 UTC 4/14/2015 HRRR HOT START
NWP Model skill when Convective Parameterization turned off (≤ 10-km)

1000 UTC 4/14/2015 WSR-88D

1000 UTC 4/14/2015 HIRESW ARW

WARM START

4.2 km

1000 UTC 4/14/2015 HRRR HOT

START

3.0 km

1000 UTC 4/14/2015 NSSL COLD

START

4.0 km
NWP Model skill when Convective Parameterization turned off (≤ 10-km)

1100 UTC 4/14/2015 WSR-88D

1100 UTC 4/14/2015 HIRESW ARW WARM START

1100 UTC 4/14/2015 HRRR HOT START

1100 UTC 4/14/2015 NSSL COLD START

Legend: dBZ (Category)
-75 (-15)
-70 (-14)
-65 (-13)
-60 (-12)
-55 (-11)
-50 (-10)
-45 (-9)
-40 (-8)
-35 (-7)
-30 (-6)
-25 (-5)
-20 (-4)
-15 (-3)
-10 (-2)
-5 (-1)

1100 UTC 4/14/2015 HRRR HOT

1100 UTC 4/14/2015 NSSL COLD

4.2 km

3.0 km

4.0 km
Data Assimilation Methods: Continuous versus Sequential (Warner, 2011)

Fig. 6.6: Schematic showing the components of data-assimilation cycles for the intermittent and continuous methods. See the text for details.
Data Assimilation Methods: 3D-Variational (3D-Var) (Lorenc, 1986)

- Background $X_b$ (short-term NWP model prediction)
- Direct and indirect observations $Y_o$
- Background and observations error covariances ($B$, $R$)
- Minimize scalar cost function $J$ to determine an optimal analysis $X = X_a$:

$$2J(X) = (X - X_b)^T B^{-1} (X - X_b) + [Y_o - H(X)]^T R^{-1} [Y_o - H(X)]$$

- Iterative methods used to minimize $J$ (Conjugate gradient, Quasi-Newton, etc.)
Figure 11. Schematic representation of the variational cost-function minimization (here in a two-variable model space): the quadratic cost-function has the shape of a paraboloid, or bowl, with the minimum at the optimal analysis $x_a$. The minimization works by performing several line-searches to move the control variable $x$ to areas where the cost-function is smaller, usually by looking at the local slope (the gradient) of the cost-function.
Data Assimilation Methods: Ensemble Kalman Filtering (EnKF) (e.g. Houtekamer et al., 1996)

- Historically, $B$ computed via “NMC” method (Parrish and Derber, 1992):
  \[
  B \approx \alpha E \left\{ \left[ X_f(48 \ h) - X_f(24 \ h) \right] \left[ X_f(48 \ h) - X_f(24 \ h) \right]^T \right\}
  \]
- Major limitation: Isotropy of $B$.
- EnKF: $B$ replaced by anisotropic/flow-dependent error covariances generated by an ensemble of concurrent K data assimilation cycles (Kalnay 2003):
  \[
  P_l^f \approx \frac{1}{K - 2} \sum_{k \neq l} (X_k^f - \overline{X}_l^f)(X_k^f - \overline{X}_l^f)^T
  \]
- Hybrid EnKF: Hamill and Synder (2000) suggested a hybrid between 3D-Var and EnKF (Kalnay 2003):
  \[
P_l^{f(\text{hybrid})} = (1 - \alpha)P_l^f + \alpha B_{3D-Var}
  \]

In the text, $X_f$ denotes forecast states, $\overline{X}$ denotes analysis states, and $E$ denotes ensemble averaging.
Data Assimilation Methods: Advantage of EnKF over 3D-Var (Pu et al. 2013)

3D-Var

Fig. 3. The 3DVAR analysis increments of temperature (K; top row), u-component (m s\(^{-1}\); middle row) and v-component (m s\(^{-1}\); bottom row) of wind at the lowest model level with assimilation of 2-m temperature (left column), 10-m winds (middle column) and both 2-m temperature and 10-m winds (right column) from a single observation station over complex terrain. The shaded contours show the terrain heights (unit: m). '+' denotes the location of the observation station.
Data Assimilation Methods: Advantage of EnKF over 3D-Var (Pu et al. 2013)

EnKF

Fig. 7. Same as Fig. 3, except for the EnKF analysis increments. The half radius of the horizontal localization used in the experiments is 320 km. No vertical localization is applied.
The 00 (06,12,18) UTC cycle uses 9 h prediction from 18 (00,03,06) UTC GDAS cycle as the background. Assimilation window for the 00 (06,12,18) UTC cycle is from 21 (03,09,15) UTC to 03 (09,15,21) UTC.

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Data Assimilation Methods: Method used in the GFS v13.0.2 (11 May 2016)

80 member ensemble of 9 h Predictions for background error covariance

9 h GSM prediction used in Hybrid 4DEnVar
The 00 (12) UTC cycle uses 3 h prediction from 18 (06) UTC delayed cut-off analysis as the background. Assimilation window for the 00 (12) UTC cycle is from 21 (09) UTC to 09 (21) UTC.
The 00, 06, 12, 18 UTC cycle uses 6 h prediction from GDAS valid 12 h earlier as initial background. 12 h Assimilation window involving four 3 h NMMB predictions serving as background for subsequent GSI analysis and 3 h NMMB run (initialized with diabatic digital filter).
Data Assimilation Methods: Method used in the RAPv3 (Benjamin et al., 2015) (23 August 2016)

Fig. 2. Flow diagram for the Rapid Refresh. The maroon components are for the RAP model using WRF and DFI. Brown-like tilted boxes indicate observation types [reflectivity (refl), cloud (clld—nonprecipitating) and precipitating (from radar) hydrometeor observations, and all other observations, described in Table 4] for the three assimilation components. GSI data assimilation includes both hybrid EnKF-var assimilation (light blue) using the GFS 80-member ensemble (GFS Ens—red) to define the ensemble-based background error covariance and the cloud and hydrometeor (for both cloud and precipitation) component (green).
Data Initialization Methods

- **Nonlinear Normal Mode Initialization**
  Segregate high and low frequency components of initial input data via vertical and horizontal structure functions. High frequencies assumed to have no meteorological significance are removed (Daley, 1981)

- **Newtonian Relaxation (Nudging)**
  NWP model runs during a pre-forecast period and is relaxed toward/constrained by observations and/or series of analyses; approximate dynamic balance develops during pre-forecast period as inertia-gravity waves associated with mass/momentum imbalance propagate away from domain (Hoke and Anthes, 1976)

- **Digital Filter Initialization**
  Perform an adiabatic NWP model integration backward in time (short time period such as 3 h), then a diabatic integration forward in time (initialization time in center) and apply a digital filter to the resultant time series to remove high frequencies (Huang and Lynch, 1993)
Specific Global, Mesoscale, and Cloud-allowing NWP models
Select NWP Models to Support WFO Operations

GLOBAL
- ECMWF
- GFS
- GDPS

LIMITED AREA MODELS [MESOSCALE]
- 12-km NEMS-NMMB (NAM)
- 13-km Rapid Refresh (RAP)

LIMITED AREA MODELS [MESOSCALE AND CONVECTION ALLOWING/PERMITTING]
- 4-km CONUS NAM nest
- 3-km High Resolution Rapid Refresh (HRRR)
- 3-4 km HIRESW (WRF-ARW and NEMS-NMMB)
- 4-km NSSL Realtime
- 4-km Texas Tech WRF
The Mesoscale

- 2-20 km ($\gamma$) 20-200 km ($\beta$) 200-2000 km ($\alpha$) (Orlanski, 1975)
- “...horizontal spatial smaller than the conventional rawinsonde network, but significantly larger than individual cumulus clouds...” (Pielke, 2013)
- “..horizontal extent large enough for the hydrostatic approximation to the vertical pressure distribution to be valid, yet small enough for the geostrophic and gradient winds to be inappropriate as approximations to the actual wind circulation above the planetary boundary layer...” (Pielke, 2013)
“Convection-Allowing/Permitting” and “Convection-Resolving” NWP Models

CONVECTIVE ALLOWING/PERMITTING: Simulate deep convection without convective parameterization

- $\leq 4$ km grid spacing (Weisman et al. 1997)

CONVECTIVE RESOLVING: Resolving convective clouds without convective parameterization

- $\leq 0.1$ km grid spacing (Bryan et al. 2003; Petch 2006)
- $\leq 0.5$ km grid spacing (Jascourt S. 2010)
## NWP Model Configurations: RAPv2 versus RAPv3 (Scheduled for 23 August 2016)

<table>
<thead>
<tr>
<th>Model</th>
<th>Domain</th>
<th>Grid spacing</th>
<th>Vertical levels</th>
<th>Boundary condition</th>
<th>Initialization Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>RAPv3</td>
<td>North American</td>
<td>13-km</td>
<td>50</td>
<td>GFS</td>
<td>Hourly (cycled)</td>
</tr>
<tr>
<td>RAPv2</td>
<td>North American</td>
<td>13-km</td>
<td>50</td>
<td>GFS</td>
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</tbody>
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<table>
<thead>
<tr>
<th>Model</th>
<th>Dynamic Core</th>
<th>Assimilation</th>
<th>Radar DA</th>
<th>Radiation LW/SW</th>
<th>Microphysics</th>
</tr>
</thead>
<tbody>
<tr>
<td>RAPv3</td>
<td>ARW v3.6+</td>
<td>GSI Hybrid 3D-VAR/Ensemble (0.75/0.25)</td>
<td>13-km DFI + low reflect</td>
<td>RRTMG v3.6</td>
<td>Thompson-aerosol v3.6.1</td>
</tr>
<tr>
<td>RAPv2</td>
<td>ARW v3.4.1</td>
<td>GSI Hybrid 3D-VAR/Ensemble (0.50/0.50)</td>
<td>13-km DFI</td>
<td>RRTM</td>
<td>Thompson v3.4.1</td>
</tr>
</tbody>
</table>
## NWP Model Configurations: RAPv2 versus RAPv3

<table>
<thead>
<tr>
<th>Model</th>
<th>Cumulus Parameterization</th>
<th>Planetary Boundary Layer</th>
<th>Land Surface Model</th>
<th>Initialization (Balancing)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RAPv3</td>
<td>Deep: Grell and Freitas (2014)</td>
<td>MYNN v3.6+</td>
<td>RUC v3.6+</td>
<td>Digital Filter Initialization (DFI)</td>
</tr>
<tr>
<td></td>
<td>(Grell and Devenyi, 2002)</td>
<td></td>
<td></td>
<td>(Weygandt and Benjamin, 2007)</td>
</tr>
</tbody>
</table>
NWP Model Configurations: RAPv2 versus RAPv3

RAPv2 bias → insufficient cloud coverage → excessive downward solar radiation

RAPv3 limits warm bias in RAPv2 (Benjamin et al. 2016) via shortwave radiation attenuation

1. Microphysics updated to include predictions for IN and CNN → increase clear-sky albedo
2. MYNN PBL scheme → improved sub-grid cloud representation (RH-based cloud fraction) and coupling to radiation scheme
3. Accounting for shallow cumulus clouds in the Grell-Freitas convective parameterization scheme

Fig. 10. Conceptual model of positive feedback model bias associated with RAPv2 warm and dry bias.
## NWP Model Configurations: RAPv3 versus HRRRv2

<table>
<thead>
<tr>
<th>Model</th>
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<tr>
<td>HRRR</td>
<td>CONUS</td>
<td>3-km</td>
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<td>RAP</td>
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<tr>
<td>HRRR</td>
<td>ARW V3.6.1</td>
<td>GSI Hybrid 3D-VAR/ Ensemble (0.75/0.75)</td>
<td>3-km 15 min LH+ low reflect (Weygandt and Benjamin, 2007)</td>
<td>RRTMG v3.6 (Iacono et al. 2008)</td>
<td>Thompson-aerosol v3.6.1 (Thompson and Eidhammer, 2014)</td>
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## NWP Model Configurations: RAPv3 versus HRRRv2

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</tr>
</thead>
</table>
| RAPv3  | **Deep:** Grell and Freitas (2014)  
**Shallow:** Grell-Freitas-Olson | MYNN v3.6+ (Nakanishi and Niino, 2004, 2009) | RUC v3.6+ (Smirnova et al. 2008) | Digital Filter Initialization (DFI) (Weygandt and Benjamin, 2007) |
| HRRR   | **Deep:** NONE  
**Shallow:** MYNN PBL Clouds     | MYNN v3.6+ (Nakanishi and Niino, 2004, 2009) | RUC v3.6+ (Smirnova et al. 2008) | Digital Filter Initialization (DFI) (Weygandt and Benjamin, 2007) |
Evolution of The North American Mesoscale Forecast System (NAM)

8 June 1993 – 19 June 2006
(Hydrostatic) *Eta Model*

20 June 2006 – 30 September 2011
*Weather Research and Forecasting Non-hydrostatic Mesoscale Model: WRF-NMM*

WRF ➔ Modeling framework, NMM ➔ dynamic core

1 October 2011 – Present
*NOAA Environmental Modeling System Non-hydrostatic Multiscale Model on the Arakawa B-grid: NEMS-NMMB*

NEMS ➔ Modeling framework, NMMB ➔ dynamic core
WRF Modeling Framework
NEMS Modeling Framework
## NWP Model Configurations: RAPv3 versus NEMS-NMMB (NAM)

<table>
<thead>
<tr>
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<tbody>
<tr>
<td>NEMS-NMMB</td>
<td>North American</td>
<td>12-km (Parent)</td>
<td>60 (27 in 0-3km layer)</td>
<td>GFS</td>
<td>3-hr (cycled)</td>
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<td>13-km</td>
<td>50</td>
<td>GFS</td>
<td>Hourly (cycled)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model</th>
<th>Dynamic Core</th>
<th>Assimilation</th>
<th>Radar DA</th>
<th>Radiation LW/SW</th>
<th>Microphysics</th>
</tr>
</thead>
<tbody>
<tr>
<td>RAPv3</td>
<td>ARW v3.6+</td>
<td>GSI Hybrid 3D-Var/ Ensemble (0.75/0.25)</td>
<td>13-km DFI + low reflect (Weygandt and Benjamin, 2007)</td>
<td>RRTMG v3.6 (Iacono et al. 2008)</td>
<td>Thompson-aerosol v3.6.1 (Thompson and Eidhammer, 2014)</td>
</tr>
</tbody>
</table>
# NWP Model Configurations: RAPv3 versus NEMS-NMMB (NAM)

<table>
<thead>
<tr>
<th>Model</th>
<th>Cumulus Parameterization</th>
<th>Planetary Boundary Layer</th>
<th>Land Surface Model</th>
<th>Initialization (Balancing)</th>
</tr>
</thead>
</table>
| RAPv3          | **Deep:** Grell and Freitas (2014)  
**Shallow:** Grell-Freitas-Olson | MYNN v3.6+ (Nakanishi and Niino, 2004, 2009) | RUC v3.6+ (Smirnova et al. 2008)                                                   | Digital Filter Initialization (DFI)  
(Weygandt and Benjamin, 2007)                     |
<table>
<thead>
<tr>
<th>Model</th>
<th>Domain</th>
<th>Grid spacing</th>
<th>Vertical levels</th>
<th>Boundary condition</th>
<th>Initialization Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>HIRESW(CONUS): (1) NEMS-NMMB (2) WRF-ARW</td>
<td>CONUS</td>
<td>(1) 3.6-km</td>
<td>50 (16 in lowest 120 hPa)</td>
<td>RAP (IC) GFS (BC)</td>
<td>3-hr (cycled)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2) 4.2-km</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NAMCONUSNEST: NEMS-NMMB</td>
<td>CONUS</td>
<td>4-km</td>
<td>60 (27 in 0-3km layer)</td>
<td>NAM</td>
<td>3-hr (cycled)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model</th>
<th>Dynamic Core</th>
<th>Assimilation</th>
<th>Radar DA</th>
<th>Radiation LW/SW</th>
<th>Microphysics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(2) ARW v3.6.1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
## NWP Model Configurations: HIRESWINDOW v6.1.5 (CONUS) versus NAMCONUSNEST

<table>
<thead>
<tr>
<th>Model</th>
<th>Cumulus Parameterization</th>
<th>Planetary Boundary Layer</th>
<th>Land Surface Model</th>
<th>Initialization (Balancing)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) NEMS-NMNM</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2) WRF-ARW</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NEMS-NMNB</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
NAM INTEGRATION DOMAINS
RAP: expand domain, extend to 30 h
## NWP Model Configurations: NSSL Realtime WRF versus Texas Tech WRF

<table>
<thead>
<tr>
<th>Model</th>
<th>Domain</th>
<th>Grid spacing</th>
<th>Vertical levels</th>
<th>Boundary condition</th>
<th>Initialization Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>NSSL Realtime WRF</td>
<td>CONUS</td>
<td>4-km</td>
<td>35</td>
<td>NAM</td>
<td>12 h</td>
</tr>
<tr>
<td>Texas Tech WRF</td>
<td>South Central CONUS</td>
<td>3-km</td>
<td>38</td>
<td>GFS</td>
<td>6 h</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model</th>
<th>Dynamic Core</th>
<th>Assimilation</th>
<th>Radar DA</th>
<th>Radiation LW/SW</th>
<th>Microphysics</th>
</tr>
</thead>
<tbody>
<tr>
<td>NSSL Realtime WRF</td>
<td>ARW</td>
<td>NAM Analysis (40-km) only</td>
<td>No</td>
<td>LW: RRTM (Mlawer, et al. 1997) SW: Dudhia</td>
<td>WSM6 (Hong and Lim 2006)</td>
</tr>
<tr>
<td>Texas Tech WRF</td>
<td>ARW v3.5.1</td>
<td>GFS Analysis only</td>
<td>No</td>
<td>LW: RRTM (Mlawer, et al. 1997) SW: Dudhia</td>
<td>Thompson (Thompson et al. 2008)</td>
</tr>
</tbody>
</table>
# NWP Model Configurations: NSSL Realtime WRF versus Texas Tech WRF

<table>
<thead>
<tr>
<th>Model</th>
<th>Cumulus Parameterization</th>
<th>Planetary Boundary Layer</th>
<th>Land Surface Model</th>
<th>Initialization (Balancing)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NSSL Realtime WRF</td>
<td>NONE</td>
<td>MYJ (local) (Janjic 1994, 2001)</td>
<td>Noah (Ek et al. 2013)</td>
<td>NONE</td>
</tr>
<tr>
<td>Texas Tech WRF</td>
<td>NONE</td>
<td>YSU (nonlocal) (Hong et al. 2006)</td>
<td>Noah (Ek et al. 2013)</td>
<td>NONE</td>
</tr>
<tr>
<td>Model</td>
<td>Domain</td>
<td>Grid spacing</td>
<td>Vertical levels</td>
<td>Boundary condition</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>-------------------------</td>
<td>-----------------------</td>
<td>-----------------</td>
<td>--------------------</td>
</tr>
<tr>
<td>GFS</td>
<td>Global</td>
<td>~13-km (Equator; days 0-10)</td>
<td>64 layers</td>
<td>N/A</td>
</tr>
<tr>
<td>ECMWF IFS HRES 5/2016</td>
<td>Global</td>
<td>9-km</td>
<td>137</td>
<td>N/A</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model</th>
<th>Dynamic Core</th>
<th>Assimilation</th>
<th>Radar DA</th>
<th>Radiation LW/SW</th>
<th>Microphysics</th>
</tr>
</thead>
</table>
## NWP Model Configurations: GFS versus European Centre for Medium-Range Weather Forecasts (ECMWF)

<table>
<thead>
<tr>
<th>Model</th>
<th>Cumulus Parameterization</th>
<th>Planetary Boundary Layer</th>
<th>Land Surface Model</th>
<th>Initialization (Balancing)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GFS</td>
<td><strong>Deep:</strong> Simplified Arakawa-Schubert (SAS)</td>
<td><strong>Strongly unstable PBL</strong> Hybrid Eddy Diffusivity Mass Flux (EDMF)</td>
<td>Noah LSM (Ek et al. 2003)</td>
<td>Digital Filter Initialization (DFI)</td>
</tr>
<tr>
<td></td>
<td><strong>Shallow:</strong> Mass Flux (cloud depth (\leq 150) hPa)</td>
<td><strong>Weakly unstable PBL</strong> EDCG</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ECMWF IFS</td>
<td>Bulk mass flux (Tiedtke, 1989; Bechtold et al. 2008, 2014)</td>
<td><strong>Surface layer</strong> 1st order K-diffusion Above Surface layer Stable PBL: 1st order K-diffusion Unstable PBL: EDMF (Köhler et al., 2011)</td>
<td>HTESSLE</td>
<td>4DVar (12-hr window)</td>
</tr>
<tr>
<td>5/2016</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
## NWP Model Configurations: GFS versus Global Deterministic Prediction System (GDPS)

<table>
<thead>
<tr>
<th>Model</th>
<th>Domain</th>
<th>Grid spacing</th>
<th>Vertical levels</th>
<th>Boundary condition</th>
<th>Initialization Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>GFS</td>
<td>Global</td>
<td>~13-km (Equator; days 0-10)</td>
<td>64 layers</td>
<td>N/A</td>
<td>6 h (cycled)</td>
</tr>
<tr>
<td>GDPS</td>
<td>Global</td>
<td>17.2 – 25 km</td>
<td>80</td>
<td>N/A</td>
<td>6 h (cycled)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model</th>
<th>Dynamic Core</th>
<th>Assimilation</th>
<th>Radar DA</th>
<th>Radiation LW/SW</th>
<th>Microphysics</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDPS v5.0.0 12/15/2015</td>
<td>GEM v4.7.2 (Hydrostatic)</td>
<td>Hybrid 4DEnVar 6 h window</td>
<td>No</td>
<td>Correlated-k distribution (Li &amp; Barker, 2005)</td>
<td>Sundquist scheme</td>
</tr>
</tbody>
</table>
## NWP Model Configurations: GFS versus Global Deterministic Prediction System (GDPS)

<table>
<thead>
<tr>
<th>Model</th>
<th>Cumulus Parameterization</th>
<th>Planetary Boundary Layer</th>
<th>Land Surface Model</th>
<th>Initialization (Balancing)</th>
</tr>
</thead>
</table>
| GFS   | **Deep:** Simplified Arakawa-Schubert (SAS)  
**Shallow:** Mass Flux (cloud depth $\leq 150$ hPa) | **Strongly unstable PBL**  
Hybrid EDMF  
**Weakly unstable PBL**  
EDCG | Noah LSM (Ek et al. 2003) | Digital Filter Initialization (DFI) |
| GDPS  | **Deep:** Kain & Fritsch (Kain and Fritsch, 1990; 1993)  
**Shallow:** Kuo Transient Scheme (Bélair et al., 2005) | Based on TKE (McTaggart-Cowan & Zadra, 2015) | Mosaic (Bélair et al 2003) | 4D-IAU (Incremental Analysis Update) |
## NWP Model Configurations: GFS versus Navy Global Environmental Model (NAVGEM)

<table>
<thead>
<tr>
<th>Model</th>
<th>Domain</th>
<th>Grid spacing</th>
<th>Vertical levels</th>
<th>Boundary condition</th>
<th>Initialization Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>GFS</td>
<td>Global</td>
<td>~13-km (Equator; days 0-10)</td>
<td>64 layers</td>
<td>N/A</td>
<td>6 h (cycled)</td>
</tr>
<tr>
<td>NAVGEM v1.2</td>
<td>Global</td>
<td>~37 km</td>
<td>50 layers</td>
<td>N/A</td>
<td>6 h (cycled)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model</th>
<th>Dynamic Core</th>
<th>Assimilation</th>
<th>Radar DA</th>
<th>Radiation LW/SW</th>
<th>Microphysics</th>
</tr>
</thead>
<tbody>
<tr>
<td>NAVGEM v1.2</td>
<td>Hydrostatic SI/SL</td>
<td>NAVDAS-AR (4DVAR) (Xu et al., 2005; Rosmond and Xu, 2006; Chua et al., 2009)</td>
<td>No</td>
<td>RRTMGM (Clough et al. 2005)</td>
<td>Prognostic cloud and ice scheme (Zhao and Carr, 1997; Sundqvist et al. 1989)</td>
</tr>
</tbody>
</table>
## NWP Model Configurations: GFS versus Navy Global Environmental Model (NAVGEM)

<table>
<thead>
<tr>
<th>Model</th>
<th>Cumulus Parameterization</th>
<th>Planetary Boundary Layer</th>
<th>Land Surface Model</th>
<th>Initialization (Balancing)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GFS</td>
<td><strong>Deep:</strong> Simplified Arakawa-Schubert (SAS)</td>
<td><strong>Strongly unstable PBL</strong> Hybrid EDMF EDCG</td>
<td>Noah LSM (Ek et al. 2003)</td>
<td>Digital Filter Initialization (DFI)</td>
</tr>
<tr>
<td></td>
<td><strong>Shallow:</strong> Mass Flux (cloud depth ≤ 150 hPa)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NAVGEM v1.2</td>
<td><strong>Deep:</strong> Simplified Arakawa-Schubert (SAS)</td>
<td>Eddy Diffusion (local) / Mass Flux (nonlocal)</td>
<td>Hogan (2007)</td>
<td>NAVDAS-AR (4DVAR) (Xu et al., 2005; Rosmond and Xu, 2006; Chua et al., 2009)</td>
</tr>
<tr>
<td>11/6/2013</td>
<td><strong>Shallow:</strong> Han and Pan (2011)</td>
<td>(Louis et al., 1982)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Select parameterizations and NWP skill based on limited literature search; implications for operational NWP models
Select Parameterizations and NWP model predictive skill: PBL/Turbulence

Hu et al (2010)
- The MYJ—a local PBL scheme—produced colder and more moist biases than nonlocal YSU and ACM2 schemes (Texas)

- Nonlocal mixing necessary to more accurately predict 0-3 km lapse rates
- Nonlocal mixing did not unrealistically smooth the strong vertical wind shear, thus retaining large low-level SRH (although less than from local scheme)
- Both local and nonlocal schemes overestimate MLCAPE
Select Parameterizations and NWP model predictive skill: Microphysics

Wheatley et al 2014: Sensitivity of a bowing MCS to microphysics parameterizations

- Thompson and double-moment NSSL produces greater rainwater mixing ratio aloft resulting in a stronger cold pool (lower surface temperature bias) relative to single moment
- Thompson greater snow production likely explains ability to produce more realistic stratiform precipitation regions, consistent with Yang and Houze (1995) who attribute stratiform rain to melting of snow
- Thompson and double-moment NSSL more realistic rear-to-front flow owing to stronger magnitude of horizontal buoyancy gradients produced along back edge of rearward-tilted MCS
Select Parameterizations: Microphysics

Wheatley et al 2014: Sensitivity of a bowing MCS to microphysics parameterizations: Implications for NWP models used at WFO CRP

- Relative to single moment microphysical schemes, double moment schemes more likely to accurately depict severe MCS
- The NSSL Realtime uses WSM6, a single moment scheme
Select Parameterizations and NWP model predictive skill: Convection

Deng and Stauffer (2006): Adjusting Convection parameterization, PBL, and data assimilation/initialization schemes to improve 4-km simulations

- Use of explicit convection (no convective parameterization) on a 4-km grid likely generates updrafts larger (4-km x 4-km) than observed in nature (~2-km) resulting in spurious high QPF values
- Use of a convective parameterization scheme on a 4-km grid improved precipitation and low-level wind (violation of CP assumption notwithstanding.)
- Combining observational-nudging FDDA with a convective parameterization scheme produced the best results
Select Parameterizations and NWP model predictive skill: Convection

Deng and Stauffer (2006): Adjusting Convection parameterization, PBL, and data assimilation/initialization schemes to improve 4-km simulations:

Implications for NWP models used at WFO CRP:

- HIRESW (3.6-km, 4.2-km), NAM CONUS NEST (4-km), NSSL Realtime and Texas Tech WRF (3-km) do not use convective parameterization, which may result in overestimate of precipitation.
- However, NSSL Realtime uses positive definite advection of moisture to limit high QPF bias (Skamarock and Weisman 2009)
Select Parameterizations and NWP model predictive skill: Convection

Pimonsree et al 2016: Sensitivity of QPF to convective parameterizations (BMJ, KF, GD, no CP, Ensembles) at 3-km resolution in complex terrain

- All schemes have capability to reasonably reproduce main character of spatial distribution of precipitation
- Grell-Devenyi schemes and ensemble of the 3 schemes yield better performance of simulated precipitation pattern
- Simulating precipitation at grey-zone resolutions (2-10 km grid spacing) should account for convective precipitation scheme for better simulated precipitation in high resolution grid scales over complex terrain
Select Parameterizations and NWP model predictive skill: Convection

Pimonsree et al 2016: Sensitivity of QPF to convective parameterizations (BMJ, KF, GD, no CP, Ensembles) at 3-km resolution in complex terrain: Implications for NWP models used at WFO CRP:

• NSSL Realtime and Texas Tech WRF do not have CP, thus less than optimal with regard to pattern of convection over Sierra Madre Oriental in Mexico.
Data Assimilation and NWP model predictive skill: Incorporation of radar data to improve QPF

- Assimilation of reflectivity via diabatic digital filter (DFI) within the RAP improves QPF (Weygandt, 2008; Benjamin et al. 2016)
- Assimilation of Doppler radial velocities (3D-Var) improved 6 h QPF of heavy rainfall event (10-km NWP model grid spacing) (Xiao et al., 2015)
- Indirect assimilation of radar reflectivity (retrieved rain water and estimated in-cloud water vapor) (3D-Var) improved short-term QPF skill up to 7 h during four summertime convective events (3-km NWP model grid spacing.) (Wang et al., 2013)
Data Assimilation and NWP model predictive skill: The issue of Spin up

**Spin-up:** “…Post-initialization development of realistic three-dimensional features during the model integration…” (Warner, 2011)

- **Cold Start:** No spin up processes in initial condition: no vertical motions/ageostrophic circulations. Model initialized with an analysis from another model (static initialization)
- **Warm Start:** Partially spun-up processes: vertical motions/ageostrophic circulations. Model initialized from an NWP model prediction (dynamic initialization)
- **Hot Start:** Completely spun-up processes/spin up eliminated: vertical motions/ageostrophic circulations. *Initial values for all microphysical species/variables and latent heat.* Model initialized from NWP model prediction (dynamic initialization)
Data Assimilation and NWP model predictive skill: The issue of Spin up

- **0003 UTC 4/14/2015 WSR-88D**
- **0000 UTC 4/14/2015 HIRESW ARW WARM START**
- **0000 UTC 4/14/2015 HRRR HOT START**
- **0000 UTC 4/14/2015 NSSL COLD START**
Data Assimilation and NWP model predictive skill: The issue of Spin up

0100 UTC 4/14/2015 WSR-88D

0100 UTC 4/14/2015 HIRESW ARW WARM START

0100 UTC 4/14/2015 HRRR HOT START

0100 UTC 4/14/2015 NSSL COLD START

Legend: dBZ (Category)
- 70 (15)
- 65 (14)
- 60 (12)
- 55 (11)
- 50 (10)
- 45 (9)
- 40 (8)
- 35 (7)
- 30 (6)
- 25 (5)
- 20 (4)
- 15 (3)
- 10 (2)
- 5 (1)

Artificial high frequency waves??
Data Assimilation and NWP model predictive skill: The issue of Spin up

0200 UTC, 4/14/2015 WSR-88D

0200 UTC, 4/14/2015 HIRESW ARW WARM START
4.2 km

0200 UTC, 4/14/2015 HRRR HOT START
3.0 km

0200 UTC, 4/14/2015 NSSL COLD START
4.0 km
Data Assimilation and NWP model predictive skill: The issue of Spin up

0300 UTC 4/14/2015 WSR-88D

0300 UTC 4/14/2015 HIRESW ARW WARM START
4.2 km

0300 UTC 4/14/2015 HRRR HOT START
3.0 km

0300 UTC 4/14/2015 NSSL COLD START
4.0 km
Data Assimilation and NWP model predictive skill: The issue of Spin up

**0400 UTC 4/14/2015 WSR-88D**

**0400 UTC 4/14/2015 HIRESW ARW WARM START**

**0400 UTC 4/14/2015 HRRR HOT START**

**0400 UTC 4/14/2015 NSSL COLD START**

Legend: dBZ (Category):
- 75 (15)
- 70 (14)
- 65 (13)
- 60 (12)
- 55 (11)
- 50 (10)
- 45 (9)
- 40 (8)
- 35 (7)
- 30 (6)
- 25 (5)
- 20 (4)
- 15 (3)
- 10 (2)
- 5 (1)
Data Initialization and NWP model predictive skill: Mass/Momentum Imbalances (Stull, 2015)

Figure 20.13
Demonstration of a dynamic system becoming balanced. (a) Balanced initial state of a pond of water (shaded grey), with no waves and no currents. (b) Extra water added in center of pond, causing the water-mass distribution to no longer be in equilibrium with the waves and currents. (c) Wave generation as the pond adjusts itself toward a new balanced state. (d) Final balanced state with slightly higher water everywhere, but no waves and no currents.
Data Initialization and NWP model predictive skill: Mass/Momentum Imbalances

4-km NSSL exhibits unbalanced MSLP pattern during 0-7 h period

NWP Models: MSLP @ KALI Location (4/14/2016)

Warner (2011)

Example of the model-simulated surface pressure at a grid point during the first 12 h of a LAM simulation, based on well-balanced and poorly balanced initial conditions (a). Also shown (b) is the computational-domain average of the absolute value of the second time derivative of the surface pressure, a measure of the intensity of inertia–gravity wave activity, for two LAM initializations with different degrees of initial imbalances. Part (b) is adapted from Tabet et al. (1981).
What phenomena can be simulated/resolved by a particular NWP Model?
What phenomena can be simulated/resolved by a particular NWP Model?

Grid point models: 8-10 grid points are needed to adequately **resolve and maintain** a feature during model integration (Lewis and Toth, 2011)

**Example: 20-km Thunderstorm.** Can the HRRR resolve it?
HRRR: 3-km grid spacing
3-km X 8 = 24 km. Cannot resolve and maintain phenomena smaller than 24 km
Thus, the HRRR **cannot** resolve and maintain the 20-km Thunderstorm
Predictability
Practical and Intrinsic Predictability

Practical Predictability

• Ability to predict based on procedures currently available (Lorenz, 1969)

• Can improve predictability by decreasing errors in initial conditions via better data assimilation methods and higher quality observations, or improve the NWP model parameterizations (e.g. Zhang et al. 2006)
Practical and Intrinsic Predictability

Intrinsic Predictability

- “Extent to which prediction is possible if an optimum procedure is used” (Lorenz, 1969)
- Predictability given both nearly perfect knowledge of the initial atmospheric state and a nearly perfect NWP model (Lorenz, 1969)
- Small amplitude errors such as undetectable random noise can rapidly grow and contaminate deterministic prediction
Practical and Intrinsic Predictability

Fig. 18. Idealized schematic illustrating the reduction of initial-condition error by reducing the ensemble spread highlighting the (a) practical predictability representative of the 9–10 Jun 2003 squall line and bow echo and (b) intrinsic predictability representative of a theoretical ensemble forecast with the ensemble forecast having equally favorable solutions. Solid shading—flow regime 1; striped pattern—flow regime 2; black dots—ensemble members; white dots—ensemble mean; white cross—forecast truth.

(Melhauser and Zhang, 2012)
NWP Models: Predictability of Convection

Intrinsic Predictability: Specific studies

- Small, undetectable perturbations grew rapidly and contaminated a mesoscale prediction of a heavy rainfall event, resulting in intrinsic predictability to $\leq 36$ h (Zhang et al. 2006)

- Small, undetectable perturbations too small to modify the initial mesoscale environmental moisture and instability fields, grew rapidly and contaminated a storm scale prediction of a tornadic thunderstorm, reducing intrinsic predictability to $\leq 3-6$ h (Zhang et al. 2013)
NWP Models: Predictability of Convection

Intrinsic Predictability:
Specific studies
- Similar NWP model Skew-T structure (differences approximately undetectable) produced divergence storm lifetimes (Elmore et al. 2002)
Predictability of Convective Storms

(Sun et al. 2014)

Fig. 9. Scale dependence of wavelet bandpass lifetime of fields of reflectivity (dBZ). The average over 1,424 h of warm season radar rainfall data and the 10th and 90th percentiles are shown.
1. Understand specific parameterization schemes and data assimilation methods used in NWP models

2. Planetary Boundary Layer (PBL) parameterization
   - Local (nonlocal) turbulence closure: Relate unknown variables to known variables at nearby (any number of) vertical grid points
   - Majority of turbulent energy found in largest eddies with depth characteristic of PBL depth → more consistent with nonlocal closure
   - Local schemes tend not to match heat flux observations
   - Local (Nonlocal) schemes tend to predict too shallow/moist (deep/dry) deep of a PBL
Summary: Issues Relevant to WFO CRP Forecast Operations

2. Planetary Boundary Layer (PBL) parameterization continued

- Local scheme examples: YSU, MRF, ACM2
- Nonlocal scheme examples: MYJ, QNSE, MYNN

3. Cloud Microphysics Parameterization

- Parameterize phase changes and interactions between particle species
- Single moment $\rightarrow$ Predict only particle mixing ratio
- Double moment $\rightarrow$ Predict particle mixing ratio and number concentration (more realistic particle size distribution/size sorting)
- Triple moment $\rightarrow$ Predict mixing ratio, number concentration, and reflectivity
Summary: Issues Relevant to WFO CRP Forecast Operations

3. Cloud Microphysics Parameterization continued

Thompson-aerosol (Thompson and Eidhammer, 2014)
1-moment predictions of snow, graupel
2-moment predictions of cloud ice, rain, CCN, IN, cloud water
(owing to 2-moment prediction of CCN and IN)

Thompson (Thompson et al. 2008)
1-moment predictions of cloud water, snow, graupel
2-moment predictions of cloud ice, rain

Ferrier and Aligo (Aligo et al. 2014)
1-moment predictions of cloud water, rain, snow

WSM6 (Hong and Lim, 2006)
1-moment predictions of cloud water, cloud ice, graupel, rain, snow, water vapor
Summary: Issues Relevant to WFO CRP Forecast Operations

3. Cloud Microphysics continued

**Modified WSM6 (Grasso et al. 2014)**
Adjustment to WSM6 (Hong and Lim, 2006) to reduce excessive graupel production to increase ice cloud mass to more reasonable quantities

**Prognostic Cloud scheme (Zhao and Carr, 1997)**
1-moment predictions of cloud water, cloud ice, rain, snow, water vapor

**Prognostic Cloud and ice scheme (Zhao and Carr, 1997; Sundqvist et al. 1989)**
1-moment predictions of cloud water, cloud ice, rain, snow, water vapor

**Sundqvist et al. (1989)**
1-moment prediction of cloud water
Summary: Issues Relevant to WFO CRP Forecast Operations

4. Convective Parameterization

- Parameterize sub-grid scale convection and remove excessive instability. Convective component of total precipitation is simply a byproduct of the activated convective scheme.
- Precipitation can be simultaneously produced as a byproduct of the activation of moist convection by the convective parameterization scheme and by explicit prediction of grid-scale precipitation by cloud microphysical parameterization.
- Parameterized precipitation is generated within a sub-saturated grid box (since convection parameterized is of sub-grid scale), while resolved scale precipitation in the microphysics scheme requires grid box saturation.
Summary: Issues Relevant to WFO CRP Forecast Operations

5. When Convective Parameterization (CP) Turned Off

[As of 1 September 2016, CP turned off in the 3-km HRRR, 4-km NSSL Realtime WRF, 3-km Texas TechWRF, 4-km NAM CONUS Nest, 4.2-km HIRES CONUSWRF-ARW, 3.6-km CONUS NEMS-NMNB]

- Precipitation can only occur due to grid scale microphysics and only after grid box is saturated; sub-grid scale convection not accounted for
- For NWP model grid spacing $\geq$ 4-km, subsequent exaggerated scale of individual convective cells likely will contribute to a high QPF bias (NSSL Realtime WRF uses positive definite advection of moisture to limit high QPF bias.)
- Adequate resolution of squall line mesoscale mesoscale structures require NWP model grid spacing $\leq$ 4-km
- For grid spacing range 0.25-km to 4-km, NWP models can skillfully predict convective initiation (CI) and mode (supercell, MCS, multi-cells, etc.), yet less skillful with regard to timing and position. **During convective forecast operations, use NWP models for CI and convective mode, not for timing and position**
6. **Data Assimilation**

3D-Variational (3D-Var) with use of background error covariances calculated from NWP model ensembles (EnKF) are flow-dependent/anisotropic and result in more realistic analysis increments over complex topography than those developed via the “NMC” method. 3D-Var/EnKF data assimilation resulted in more accurate 6 h predictions.

7. **Data Initialization**

NWP model initial condition with mass/momentum imbalances [4-km NSSL Realtime WRF, 3-km Texas Tech WRF] will generate artificial inertia-gravity waves which can adversely affect 0-6 h (or more) of the simulation; MSLP especially vulnerable since gravity waves adjust mass field to the wind field on the mesoscale.
8. RAPv2 versus RAPv3

RAPv3 decreased the warm bias in RAPv2 by reducing excessive downward solar radiation.

9. Select Parameterizations and NWP model predictive skill

- Local PBL/turbulence closure schemes tend to produce cooler/lower/moister PBL than nonlocal schemes.
- Nonlocal mixing necessary to more accurately predict 0-3 km lapse rates.
- 2-moment microphysics more accurately depict structure of bowing MCS (rear-to-front flow, cold pool strength) than 1-moment schemes.
- Use of a convective parameterization scheme on a 4-km grid (and on a 3-km in complex terrain) improved QPF.
10. Data Assimilation and NWP model predictive skill

- Assimilation (via 3D-Var) of radar reflectivity and Doppler radial velocities improves QPF skill during the 0-6 h period of the simulation.
- NWP models with a cold start [4-km NSSL Realtime WRF; 3-km Texas Tech WRF] will take awhile to spin up vertical velocities and ageostrophic circulations. Thus, the evolution of atmospheric processes will be delay relative to nature.

11. To adequately resolve and maintain a feature during model integration, the feature must span 8-10 grid points.
12. **Predictability**

*Practical Predictability*

- “Ability to predict based on what is currently available”
- Can increase Practical Predictability by improving data assimilation techniques, incorporating higher quality observations, or improving NWP model parameterizations

*Intrinsic Predictability*

- “Extent to which prediction is possible if an optimum procedure is used”
- Predictability given both nearly perfect knowledge of initial atmospheric state and nearly perfect NWP model
Summary: Issues Relevant to WFO CRP Forecast Operations

12. Predictability continued

Intrinsic Predictability continued

- Small undetectable perturbations can rapidly grow and contaminate deterministic prediction
- Cannot improve intrinsic predictability given chaotic atmosphere
THE END


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References Continued


References Continued


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