HRRR Time-Lagged Ensemble Guidance
2016 WPC Winter Weather Experiment

Web: http://rapidrefresh.noaa.gov/hrrrtle/
GRIB-2 output grids also available via FTP and LDM

Trevor Alcott, Isidora Jankov, Curtis Alexander
ESRL/GSD/EMB
Contact: trevor.alcott@noaa.gov

HRRR Time-Lagged Ensemble (HRRR-TLE)

Time-lagged ensembles are a computationally inexpensive substitute for full ensembles, using the "free" uncertainty information provided by a single, rapidly-cycled deterministic model (or a small set of deterministic models). Rather than running a large number of simultaneous simulations where initial conditions are perturbed based on uncertainty information from a data assimilation routine, time-lagging simply combines forecasts from deterministic model runs initialized at different times. Differences in the initial conditions from one run to the next are used in lieu of uncertainty estimates of the initial atmospheric state.

The HRRR-TLE combines forecasts from multiple deterministic HRRR runs, *initialized* at different times but *valid* at the same time. The current version, frozen for the duration of WWE 2016, uses the 3 most recent runs of the experimental ESRL "HRRRx". The HRRRx operates with a ~2-h latency, and we chose to set hour zero of the HRRR-TLE forecast to the current time. For example, the **12z HRRR-TLE utilizes forecasts from HRRRx runs initialized at 8z, 9z and 10z.**

Why only 3 runs? Additional time-lagged members *in theory* provide greater spread. However, in practice the spread increase is small beyond 3-4 members, and spread is not necessarily useful if older runs are producing poor forecasts. There are in fact few situations where an older run could possibly produce a better forecast, unless the model is "cold started" and requires substantial time to spin up, or long-latency observations have a large impact. Increasing the membership also decreases the maximum lead time of the ensemble. Combining these factors, we find an optimal membership of 3 HRRRx runs, forgoing a small increase in spread in favor of achieving longer lead times.

Most time-lagged ensembles are underdispersive. The differences in initial conditions from one run to the next, especially for an hourly-cycled model, are typically not as large as the actual analysis errors. Hence integrating forward in time from those underdispersive initial conditions leads to forecasts that do not come close to capturing the full range of possible future states. To address this issue, we employ the statistical post-processing methods described below to artificially increase the spread and achieve more reliable probabilistic forecasts.

Probabilistic QPF

HRRR-TLE PQPF provides 0-6 and 6-12-h probabilities of exceeding various precipitation thresholds. **These forecasts benefit from two post-processing steps. First, forecasts from each member are bias corrected based on verification of past forecasts at the same lead time.** The bias correction technique is a quantile-mapping approach, where a regression equation is calculated to adjust quantiles (e.g., 99^{th} percentile) of HRRR QPF toward quantiles of Stage-IV QPE. Based on a series of experiments, we chose to use a calibration dataset of 50 past forecasts and a linear curve fit from QPF to QPE. For example, if the slope of the linear fit is 0.9 and intercept is zero, forecasts of 1.0 in / 6 h are adjusted to 0.9 in / 6 h. Given the simplicity of this technique, the results are surprisingly good, but skill decreases beyond thresholds of 3.0 in / 6 h. Calibration coefficients are recalculated daily based on the most up-to-date set of 50 forecast-analysis pairs.

In the second step, our algorithm uses a spatial filter of varying size to increase the ensemble spread at a given point. Through several experiments, we find that an 80-km filter achieves the best reliability over the CONUS. This means that forecasts at all grid points in an 80-km radius around a given point are considered ensemble "members". Physically speaking, this is an attempt to incorporate larger spatial forecast errors than the raw 3-member ensemble is able to provide. **HRRR-TLE output is not a "neighborhood probability" – the probability of > 1.0 in QPF at a point is just that – the probability of receiving 1.0 inches at that point.** We are only *using* forecasts from surrounding areas to *calculate* a more reliable probability *at that point*.

It's not hard to imagine where a constant spatial filter size might cause problems: complex terrain. When precipitation processes are dominated by orographic forcing, forecasts 80 km away from a mountain range do not add value to the probabilistic forecast over the range itself. Over high terrain and low valleys we find a spatial filter size of only 12 km is much more appropriate. HRRR-TLE output therefore weights the probabilistic QPF and snowfall forecasts more toward a 12-km radius over complex terrain, and more toward an 80-km radius over flat terrain. "Complex terrain" points are those where the elevation is significantly higher or lower (by 250 m) than the average elevation of the surrounding area (~80-100-km radius). The resulting forecasts both appear more physically realistic and verify better than those achieved with a constant filter size across the CONUS.

Probabilistic Snowfall

HRRR-TLE probabilistic snowfall forecasts provide 0-6 and 6-12-h probabilities of exceeding various snowfall accumulation thresholds. The output is actual snowfall depth, not a snow-water equivalent. **Our algorithm uses a varying spatial filter identical to that for PQPF, and leverages snowfall forecasts derived directly from the HRRRx microphysics scheme.** This recent (Dec 2015) addition to the microphysics scheme calculates a variable-density accumulation of all frozen precipitation types, including contributions from snow, graupel and cloud ice with a temperature dependency. There is no use of a fixed or climatological snow-to-liquid ratio.

Bias-correction is not employed for snowfall, since we lack a universally accepted snowfall dataset. Snowfall is also subject to a large variety of forecast errors, including the precipitation forecast, the column temperature profile *and* any potential false assumptions in the microphysics-based snowfall algorithm. A correction appropriate for one scenario might be entirely inappropriate for another—to a much greater degree than for QPF. Hence bias correction is much more complex, and we have tabled this topic for future development.

<u>Snowfall Rate</u>

HRRR-TLE snowfall rate forecasts are the instantaneous probability of exceeding various rate thresholds at a point, at each forecast hour from 0 to 12. Our algorithm employs a varying spatial filter similar to that for PQPF and snowfall, but also uses the 1-h snowfall forecasts for the hour before, and hour after the valid time as ensemble "members". Owing to the additional spread provided by this temporal filtering, and the larger run-to-run differences noted for hourly snowfall forecasts, the flat-terrain spatial filter size for snowfall rate is reduced to 40 km. **As for the 6-h snowfall accumulation guidance, the instantaneous snowfall rate guidance uses snow accumulation forecasts directly from the HRRRx microphysics scheme.** This algorithm does *not* combine QPF with a snow-to-liquid ratio, and also does *not* employ an initial bias correction step for the same reasons described above in Probabilistic Snowfall.

<u>Future</u>

Following WWE 2016, the development focus will shift to severe weather and flash flooding. Additional products will debut at the SPC Hazardous Weather Testbed and the Flash Flooding and Intense Rainfall experiment. There are plans to expand the HRRR-TLE winter weather output for testing in WWE 2017, with improved calibration and filter algorithms, and possibly including additional fields such as freezing rain probabilities.

ESRL/GSD
2015-16 HRRRX (experimental HRRR a.k.a. HRRRv2)
Deterministic Winter Precipitation Fields

Water Equivalent of Accumulated Snow Depth (kg/m^2 or mm)

Discipline 0, Category 1, Parameter 13, "WEASD"

- Snow-only water-equivalent accumulation at surface from microphysics
- Ignores contributions from graupel or ice
- Reported as "accumulation" and starts with zero value
- Provided in both one-hour and run-total forecast buckets
- Can use traditional 10:1 ratios to estimate accumulated snow depth
- Hourly bucket values used as the input to the HRRR-TLE probabilities of all snowfall rates

Accumulated Snow Depth (m)

Discipline 0, Category 1, Parameter 29, “ASNOW”

- Variable-density accumulation of all frozen precipitation types from the microphysics, minus snow melt, is computed inside the land surface model (RUC)
- Includes contributions from snow, graupel and ice with temperature-dependent density
- Reported as “accumulation” and starts with zero value
- Provided only as run-total forecast
- Can be evaluated against the traditional 10:1 estimate
- Used as the input to the HRRR-TLE probabilities of snow accumulation > 1, 3 or 6 inches in 6 hrs

Water Equivalent Snow Depth (kg/m^2 or mm)

Discipline 0, Category 1, Parameter 13, “WEASD”

- Water equivalent of “snow pack” as reported by the land-surface model
- All frozen precipitation included (snow, graupel, ice)
- Cycled from previous forecasts and can have non-zero starting value
- Includes effects of new frozen precipitation, melting and sublimation
- Provided as an instantaneous surface value at the top of each hour

Snow Depth (m)

Discipline 0, Category 1, Parameter 11, “SNOD”

- Depth of “snow pack” as reported by the land-surface model
- All frozen precipitation included (snow, graupel, ice)
- Cycled from previous forecasts and can have non-zero starting value
- Includes effects of new frozen precipitation, melting and sublimation
- Provided as an instantaneous surface value at the top of each hour

Percent of Frozen Precipitation (%)

Discipline 0, Category 1, Parameter 39, “CPOFP”

- Ratio of frozen precipitation (snow + graupel + ice) to total precipitation (snow + graupel + ice + rain)
- Provided as an instantaneous surface value at the top of each hour

Categorical Snow Precipitation Type (0 = no or 1 = yes)

Discipline 0, Category 1, Parameter 36, “CSNOW”

- Identification of snow precipitation type at surface based on explicit microphysics, precipitation intensity and surface temperature
- Identification of precipitation for very small rates < 0.01”/hr

- Can exist with one or more other precipitation types
- Provided as an instantaneous surface value every 15 min into forecast

Categorical Graupel Precipitation Type (0 or 1)

Discipline 0, Category 1, Parameter 35, “CICEP”

- Identification of graupel (sleet or ice-pellets) precipitation type at surface based on explicit microphysics, precipitation intensity and surface temperature
- Identification of precipitation for very small rates < 0.01”/hr
- Can exist with one or more other precipitation types
- Provided as an instantaneous surface value every 15 min into forecast

Categorical Freezing Rain Precipitation Type (0 or 1)

Discipline 0, Category 1, Parameter 34, “CFRZR”

- Identification of freezing rain precipitation type at surface based on explicit microphysics, precipitation intensity and surface temperature
- Identification of precipitation for very small rates < 0.01”/hr...i.e. freezing drizzle
- Can exist with one or more other precipitation types
- Provided as an instantaneous surface value every 15 min into forecast

Categorical Rain Precipitation Type (0 or 1)

Discipline 0, Category 1, Parameter 33, “CRAIN”

- Identification of rain precipitation type at surface based on explicit microphysics, precipitation intensity and surface temperature
- Identification of precipitation for very small rates < 0.01”/hr
- Can exist with one or more other precipitation types
- Provided as an instantaneous surface value every 15 min into forecast