Evaluation of MM5 Simulations With HTSVS With and Without Inclusion of Soil-Frost Parameterization

Anne D. Cherry  
Department of Physics, University of Iowa, Iowa City, IA 52242

Nicole Mölders  
Geophysical Institute, University of Alaska, 903 Koyukuk Drive, Fairbanks, AK 99775

Abstract

Permafrost and seasonally frozen ground are important surface features in high-latitudes. Because of this, a soil-frost parameterization was added to the Penn State University/NCAR mesoscale meteorological model MM5 in combination with the well validated hydro-thermodynamic soil vegetation scheme HTSVS, which takes into account among other things soil freezing and thawing. Reanalysis of temperature, wind vector, specific humidity and observations of precipitation were used to evaluate the importance of the soil-frost parameterization on the forecast for an episode in summer. R.m.s. errors for both forecasts are reasonable with the largest errors coming from the precipitation data. Improvements in r.m.s. error for the forecast with the soil-frost parameterization added are mostly in the atmospheric boundary layer. Just as for r.m.s. error, the mean error for the soil-frost forecast is closer to zero than the mean error for the forecast made without the soil-frost parameterization. The consistent negative bias of the mean error is also improved by the inclusion of soil-frost. For precipitation, the wind vector, and in the mid-troposphere for temperature, the improvement index of the forecasts decreases as time increases, meaning that the inclusion of soil-frost makes the model more accurate especially as it is projected farther into the future. However, for the atmospheric boundary layer temperatures and for specific humidity the improvement index actually increases with time, meaning that the addition of a soil-frost parameterization for these variables does not continue to improve the longer range forecast as much as it does for the other variables. Both the bias and threat scores decrease as the precipitation threshold increases and generally increase with time. In addition, according to the threat scores, inclusion of soil-frost processes improves the prediction of moderate precipitation. In general, it is shown that with the inclusion of a soil-frost parameter in the model, forecast errors are decreased.

1. Introduction

Permafrost occurs in small discontinuous areas over all but the southern coast of Alaska and is continuous in the far north of Alaska (Fig. 1). The coupling between soil moisture and thermal processes is fundamental to high-latitude soil process and must be parameterized appropriately in numerical models.

In the last few years, there have been some efforts to develop soil-frost parameterizations for use in mesoscale meteorological models (e.g., Koren et al. 1999, Boone et al. 2000, Warrach et al. 2001, Mölders and Walsh 2002). Koren et al. (1999) developed a soil-frost model for the NCEP-Eta model, and tested and evaluated it offline. Warrach et al. (2001) developed and evaluated a soil-frost parameterization for use in hydrological and atmospheric models. Viterbo et al. (1999) demonstrated that
introducing soil-frost into the European Centre for Medium-Range Weather Forecasts (ECMWF) model improved the simulation of annual temperature cycle in the soil and helped to reduce the systematic biases in 2 m temperatures in winter.

Figure 1. Permafrost distribution over Alaska (from the Groundwater Atlas of the United States)

Therefore, it is expected that the addition of a soil-frost parameterization to the Penn State University/National Center for Atmospheric Research (NCAR) mesoscale meteorological model MM5 (e.g., Dudhia 1993) will improve the accuracy of the forecasts. To test whether the added simulated processes improve the forecast of the model, several methods of error analysis are used. Here the addition of soil-frost to the model was tested by performing an evaluation of the results from simulations with and without inclusion of the soil-frost parameterization.

2. Data
a) Model set-up

The Penn State University/NCAR mesoscale meteorological model MM5 (e.g., Dudhia 1993) is applied in combination with the well validated hydro-thermodynamic soil vegetation scheme HTSVS (e.g., Kramm et al. 1996, Mölders et al. 2003a, b). The following model set up is used: The explicit moisture scheme of Reisner et al. (1998) is applied to clouds at the resolvable scale, and Grell's cumulus scheme (1993) for subgrid-scale clouds. Grell et al.'s (1994) simple radiation scheme is used. The treatment of boundary layer physics follows Hong and Pan (1996). The hydro-thermodynamic soil vegetation scheme is the land surface model used in our study. HTSVS calculates the exchange of momentum, heat, and moisture at the vegetation-soil-atmosphere interface, with special consideration of heterogeneity on the micro-scale by the mixture approach. It considers water uptake by plants, including a vertically variable root distribution, dependent on vegetation type, and the temporal variation of soil albedo. HTSVS takes
into account heat conduction, water vapor fluxes within the soil, water vapor fluxes, and water diffusion (including the Richards-equation) within the soil as well as cross-effects such as the Ludwig-Soret and Dufour effects, soil freezing and thawing, and the related release and consumption of latent heat energy (e.g., Kramm et al. 1996, Mölders et al. 2003a).

b) Model input data and initialization

The MM5 is a mesoscale short range weather forecast model that predicts, among other variables, temperature, wind, specific humidity, non-convective precipitation, and convective precipitation. Non-convective and convective precipitation output from the MM5 simulation were added to obtain a single value that could be compared to the observed values since observations do not distinguish the mechanism leading to precipitation. From this point on, frost will refer to the forecast made including the soil-frost parameterization and no frost will refer to the forecast made without this parameterization.

The model was run for the period from July 20, 0000 UT 2001 to July 23, 1200 UT 2001. Initial and boundary conditions are taken from the NCEP (National Center for Environmental Prediction) and NCAR Reanalysis Project (NNRP data). The vegetation fraction of each grid-cell is a weighted average of the July and August monthly five-year mean green vegetation cover data (0.15° resolution) derived from AVHRR data (Gutman and Ignatov 1998). The 1-km resolution USDA State Soil Geographic Database (Miller and White 1998) and 10-min resolution USGS-terrain and vegetation data provide the soil-texture, terrain elevation, and land-use type.

The model domain used here has 39 x 39 grid points with a grid increment of 45 km and is centered on Fairbanks, AK (64.49” N, 147.52” W). The large domain size allows for capturing the large-scale changes over the three day simulation. There are 23 vertical layers reaching to 100 hPa, five soil layers, and one canopy layer. The lower boundaries of the soil layers are at -0.01, -0.23, -0.54, -1.27, and -2.95 m with the centers at -0.07, -0.15, -0.36, -0.83, and -1.93m, respectively. In snow-covered areas, five equidistant snow layers are considered. Their thickness depends on snow height.

Interpolated total soil moisture and temperature data from the NCEP operational Eta forecasts served to initialize soil volumetric liquid water content, soil ice content and soil temperature. The consideration of soil-frost requires determining the fraction of the total soil water that is initially frozen at the given initial soil temperature. As freezing raises soil temperature, a diagnostic procedure serves to distribute the total soil-water between the liquid and solid phase (Mölders and Walsh 2003). This procedure ensures local equilibrium between soil temperature, soil volumetric liquid water and ice content at the given soil temperature. Soil temperature and total soil moisture (sum of soil liquid water and soil ice content) are constant throughout all simulations at the bottom of the soil model.

c) Precipitation observations

Precipitation observations were made at 126 Alaska locations within the large MM5 domain every 24 hours. In the following, we use the convention that the 24 hour accumulated precipitation predicted by the model corresponds to the observed precipitation accumulated from July 19 2400 UT 2001 to 20, 2400 UT 2001, and so on.
For grid points that contained multiple observations, the observations were averaged to produce one value for each point.

**d) Synoptic situation**

In the period simulated, severe thunderstorms occurred over Alaska. The weather situation is governed by a ridge extending from the Gulf of Alaska into the Interior leading to wind from south to southwest. Soil volumetric water content is low in areas of frozen ground and permafrost, while higher values occur along the coastal areas and the Yukon. In soil layer 4 and 5, soil volumetric liquid water content is strongly related to soil type, and it decreases with depth in areas of permafrost. The volumetric liquid soil water content is higher in lower elevated than in mountainous areas because higher amounts of the total soil volumetric water content are frozen in the latter regions. On July 20, air temperature increases from the west to the east over southern Alaska and the Interior. It decreases from south to north over the northern part of the state. The air is cooler and wetter in the maritime than the more continental areas. Air temperatures range from 8 to 22°C. In the atmospheric boundary layer (ABL), relative humidity exceeds 80% at 850 and 700hPa over western Alaska. Over northeastern Alaska and the Yukon Territory, it is less than 60% (30%) at 850 hPa (700hPa).

**3. Method**

Reanalysis of temperature, wind vector, specific humidity (all available every 12 hours) and observations of 24 hour accumulated precipitation were used to calculate the root mean square error, mean error, and s1 skill score for each forecast. The improvement index was computed using the r.m.s. error of both forecasts. The accuracy of the *frost* forecast and the *no frost* forecast were compared using all of these values. In addition, the bias and threat scores were calculated for each of the precipitation forecasts. These values for the *frost* and *no frost* forecasts were also compared to determine which model version is more accurate.

**a) Root Mean Square Error**

The root mean square error gives an overview of the accuracy of the data set. The r.m.s. error formula for comparing two data sets is defined as (e.g., Anthes 1989)

$$\text{r.m.s.} = \left[ \frac{1}{I \cdot J} \sum_{i=1}^{I} \sum_{j=1}^{J} (s_{i,j} - o_{i,j})^2 \right]^{1/2}$$

(1)

where I and J are the total number of verification grid points on the y and x axes and $s_{i,j}$ and $o_{i,j}$ are the model simulation and observed values for the grid point in question, respectively. Since the wind is given as a combination of wind speeds in two directions (u and v), the r.m.s. error formula must be changed slightly to transform these two speeds into one wind vector. The wind vector r.m.s. error is given by (e.g., Anthes 1989)

$$\text{Mean Vector Wind Error} = \frac{1}{I \cdot J} \left[ \sum_{i=1}^{I} \sum_{j=1}^{J} \left( (u_{s,i,j} - u_{o,i,j})^2 + (v_{s,i,j} - v_{o,i,j})^2 \right) \right]^{1/2}$$

(2)

where the u and v subscripts denote the data for the u and v wind directions. Again, I and J are the total numbers of verification grid points in y and x direction.
b) Improvement Index

The improvement index uses the r.m.s. errors of two data sets to determine whether the experimental result has improved the amount of error as compared to the result obtained from the control data. The improvement index is defined as

\[
\text{Improvement Index} = \frac{\text{RMS}_{\text{frost}}}{\text{RMS}_{\text{nofrost}}} = \frac{\left[ \sum_{i=1}^{I} \sum_{j=1}^{J} (s_{i,j}^{\text{frost}} - o_{i,j}^{\text{frost}})^2 \right]^{1/2}}{\left[ \sum_{i=1}^{I} \sum_{j=1}^{J} (s_{i,j}^{\text{nofrost}} - o_{i,j}^{\text{nofrost}})^2 \right]^{1/2}}
\]

where \(s_{i,j}^{\text{frost}}\) and \(s_{i,j}^{\text{nofrost}}\) are the values for the frost and no frost forecasts, respectively. Therefore, an improvement index greater than one signifies a degrade in forecast accuracy and an improvement index of less than one signifies an improvement over the no frost forecast.

c) Mean Error

To complement and expand on results obtained using the r.m.s. error formula, the mean error gives an error measurement that shows bias in the model. The formula for mean error (MER) is (e.g., Anthes 1989)

\[
\text{Mean Error} = \frac{1}{I \cdot J} \left[ \sum_{i=1}^{I} \sum_{j=1}^{J} (s_{i,j} - o_{i,j}) \right]
\]

where \(I\) and \(J\) are the total amount of verification grid points in the x and y direction, and \(s_{i,j}\) and \(o_{i,j}\) are again the values of the points in question for the simulation and the observed data.

d) S1 Skill Score

The \(S_1\) skill score is used to quantify the skill of a field according to the horizontal gradient of the field instead of only the value of the data at any given verification point. The formula used here for the \(S_1\) score is (e.g., Anthes 1989)

\[
S_1 = \frac{\sum_{\text{AdjacentPairs}} |\Delta s - \Delta o|}{\sum_{\text{AdjacentPairs}} \max(|\Delta s|,|\Delta o|)} \times 100 = \\
\frac{\sum_{i=1}^{I} \sum_{j=1}^{J} |s_{i,j} - s_{i,j-1}| - |o_{i,j} - o_{i,j-1}| + \sum_{i=2}^{I} \sum_{j=1}^{J} |s_{i,j} - s_{i-1,j}| - |o_{i,j} - o_{i-1,j}|}{\sum_{i=1}^{I} \sum_{j=2}^{J} \max(|s_{i,j} - s_{i,j-1}|,|o_{i,j} - o_{i,j-1}|) + \sum_{i=2}^{I} \sum_{j=1}^{J} \max(|s_{i,j} - s_{i-1,j}|,|o_{i,j} - o_{i-1,j}|)} \times 100
\]

Adjacent pairs are only considered in the horizontal direction, so for each pressure level a separate \(S_1\) skill score was calculated just as separate r.m.s. and mean errors were calculated for each pressure level.

e) Bias and Threat Scores

The final method used in quantifying the improvement of adding a soil-frost parameterization to the MM5 model is known as precipitation evaluation. The first
quantity is known as the bias score, which indicates whether the model over or under predicts precipitation for certain thresholds. The threat score is used to measure the skill in predicting the area of precipitation for a certain threshold. The bias score and threat score are defined as (e.g., Anthes 1989)

\[ \text{Bias Score} = \frac{F}{R} \]  
\[ \text{Threat Score} = \frac{C}{(F + R - C)} \]

where \( F \) is the number of grid points where the threshold amount of precipitation was forecasted, \( R \) is the number of grid points that the threshold amount was observed, and \( C \) is the number of grid points where threshold precipitation was both forecasted and observed. The threshold amounts used were 0.01, 0.025, 0.254, 0.64, 1.27, and 2.54 cm.

4. Results

a) Root Mean Square Error

In applying the r.m.s. error formula to the forecasts for frost and no frost, several general observations can be made. Over all, r.m.s. errors were reasonable with the largest errors coming from the precipitation data. As can be seen in Figure 2, there is a distinct daily fluctuation in r.m.s. error for the forecasts which disappears at pressures less than 850 hPa. This fluctuation is due to daily surface heating in mountainous regions and is observed for both the temperature and specific humidity. Daily fluctuations also appear when the mean error, \( s_1 \) skill scores, and improvement indices of the temperature and specific humidity are computed. R.m.s. errors (and mean error and \( s_1 \) scores as well) also tend to increase with time, as is expected in weather forecasting since small errors present in even the most precise initial conditions become larger over time as a simulation is run. In addition, errors decrease with altitude up to the tropopause for all three altitude dependent variables. At the tropopause errors often increase sharply and then decrease again in the stratosphere. This decrease with altitude is most obvious in specific humidity (Fig. 3), while the sharp increase at the tropopause is well illustrated by the mean vector wind error (Fig. 4).

Some r.m.s. error results, however, do not agree with the general results presented above. The wind r.m.s. errors, mean errors, and \( s_1 \) scores do not show any daily fluctuations. The precipitation r.m.s. error decreases with time up to 48 hours and then increases to 72 hours.

In comparing the r.m.s. error of the two forecasts, the error on the forecast with frost is smaller for all cases except specific humidity. The error difference is largest in the lower troposphere and virtually vanishes at the mid and upper troposphere (Fig. 3). In most cases, and especially at mid-troposphere, as time increases so does the difference between the error for frost and no frost (Fig. 5). While during the first two days of simulations both simulations have about the same accuracy, frost makes a better forecast toward the end of the period simulated (Fig. 5). In the case of the specific humidity in the lower troposphere, it can be seen that the r.m.s for frost has what is essentially a higher amplitude of daily fluctuation than the r.m.s. error for no frost (Fig. 2). This means that frost makes a better prediction at night than during the day.
Figure 2. Root mean square error of specific humidity for 1000 hPa.

Figure 3. Root mean square error for specific humidity at 72 hours.
Figure 4. Mean vector wind error at 72 hours.

Figure 5. Mean vector wind error for 700 hPa.
b) Improvement Index

The improvement index also shows some general trends. Because the difference in r.m.s. error for frost and no frost decreases as altitude increases, the improvement index necessarily approaches one in all variables as altitude increases (Fig. 6). This means that for the higher troposphere and stratosphere, whether or not soil-frost is included plays no role in the forecast accuracy. The index also shows daily fluctuations for temperature and specific humidity in the lower troposphere since the r.m.s. error values of these two variables also has daily fluctuations. The improvement index is lowest in the ABL. This fact reinforces the impression that improvements in r.m.s. error for frost were mostly in the ABL. For precipitation, the wind vector, and in the mid-troposphere for temperature, the improvement index also decreases as time increases, meaning that the inclusion of permafrost makes the model more accurate especially as it is projected farther into the future. However, for the ABL temperatures and for specific humidity the improvement index actually increases with time, meaning that the addition of a soil-frost parameterization to the model for these variables does not continue to improve the longer range forecast as much as it does for the other variables, especially precipitation.

![Image of Improvement Index Temperature @ 24 Hours](image_url)

Figure 6. The improvement index of temperature for 24 hours.

c) Mean Error

The mean errors show the same general trends as the r.m.s. errors. The errors and error differences for the mid-troposphere, the high-troposphere and the stratosphere are smaller than for the lower troposphere, the errors increase with time, there is clear daily fluctuation of error in the lower troposphere, and smaller mean error for the frost forecast over all. The specific humidity shows a higher mean error (higher amplitude of daily fluctuation) for the frost forecast in the lower troposphere, and just as it showed for the
r.m.s. error, the *frost* error is lower as it ascends to mid-troposphere. The larger mean errors in the ABL may result from differences between the model landscape and its natural equivalent.

According to the mean errors MM5 underestimates all variables in the lower and mid-troposphere (Fig. 7). At the tropopause and above, the mean error tends to be small and can be either slightly positive or slightly negative.

d) *S*₁ *Skill Score*

For weather forecasting, a *S*₁ skill score of 30 for ground level and 20 above 500 hPa is considered an excellent forecast and a score of 80 or above is very poor (e.g., Anthes 1989). By this standard, both the *frost* and *no frost* forecasts were poor with the temperature and specific humidity forecasts having the lowest skill scores and the precipitation forecast having the highest. Several of the trends of the skill score are similar to those of r.m.s. error and mean error. The skill score generally decreases as altitude increases with a sharp peak at the tropopause at about 200 hPa for specific humidity and temperature, but with a decrease there for wind. Again, the specific humidity and temperature skill scores showed daily fluctuations in the lower troposphere and the difference in the scores for *frost* and *no frost* is also largest in the lower troposphere.

![Mean Error Temperature @ 24 Hours](image)

Figure 7. Mean error for temperature at 24 hours.

As can be seen in Figure 8 the *frost* score is sometimes higher and sometimes lower than the *no frost* score, making a general pattern difficult to determine. For specific humidity the *S*₁ score for *frost* is generally lower, but for temperature the *frost* score is lower in the lower troposphere and becomes higher starting at around 800-850 hPa. For the wind values the *S*₁ scores are very similar, with the *frost* scores slightly
higher from 1000-800 hPa and then slightly lower from 800-700 hPa. This means that the gradient of the wind field is not improved by inclusion of frost. This is in substantial agreement with Mölders and Walsh (2003) who found that frost processes have only a slight impact on the wind prediction. For precipitation the $s_1$ score is higher for the frost forecast before 48 hours and lower after 48 hours.

![S1 Score Temperature Pressure=800 hPa](image)

**Figure 8.** $S_1$ Score for temperature at 800 hPa.

e) Precipitation Evaluation

Both the bias and threat scores decrease as the precipitation threshold increases and generally increase with time (the bias score decreases slightly with time for the two lowest thresholds). Below the 0.254 cm threshold, the bias and threat scores for frost are lower, but are higher above the 0.254 cm threshold (Fig. 9). The difference in the scores also increases with time, meaning that for higher thresholds the consideration of soil-frost processes improves the model for longer precipitation forecasts especially (Fig. 10).
5. Conclusion

Based on the evaluation of simulations with and without the inclusion of soil-frost, we conclude that if soil-frost is not included in mesoscale modeling, errors in forecasting
temperature, wind, specific humidity and precipitation are generally higher, especially in the lower troposphere. This means that soil-frost processes have to be included in mesoscale weather forecasts for high-latitudes. The difference in errors between frost and no frost tend to decrease as altitude increases and also to increase with time except in the case of specific humidity. The overall bias of the model, as shown in mean error calculations is to under predict all values, but the addition of soil-frost to the model corrects this bias somewhat. The bias and threat scores for precipitation improve with the addition of soil-frost processes to the model for thresholds above 0.254 cm. The difference between the scores increases with time for these thresholds.

To generalize the results, future investigations should be on the importance of soil-frost processes in winter when the soil is covered by a snow layer.

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