# Journal of Hydrometeorology

## Impact of Moisture Flux and Freezing Level on Simulated Orographic Precipitation Errors over the Pacific Northwest

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Impact of Moisture Flux and Freezing Level on Simulated Orographic Precipitation Errors over the Pacific Northwest

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Abstract

The 12-24 h predictions at 1.33-km grid spacing from the Pennsylvania State University–National Center for Atmospheric Research Mesoscale Model (MM5) using the Thompson bulk microphysical scheme from the Weather Research and Forecasting model are compared with data from a radiosonde site at Salem, OR (SLE), just upstream (west) of the Oregon Cascades, precipitation gauges over a portion of the Pacific Northwest, and a National Weather Service WSR-88D radar in Portland, OR. Comparison of model output with observations of warm storms with high freezing level (SLE observed temperature at 1.5 ASL > -1°C) and cold storms with low freezing level (SLE observed temperature at 1.5 ASL < -1°C) shows some distinct differences. Model precipitation is better correlated with the upstream relative humidity weighted integrated moisture transport for warm storms ($r^2=0.81$) as compared to cold storms ($r^2=0.54$). For storms with relatively small wind, temperature, and moisture flux errors at the Salem, OR rawinsonde site just upstream of the Cascades, the MM5 tends to overpredict precipitation for cold storms. Comparison of model ice water content (IWC) with that derived from a WSR-88D radar indicates that surface precipitation overprediction for cold storms is associated with too much IWC in the layer between -13 and -5 °C over the Cascade windward slopes. A favorable overlap of the snow depositional growth region within the mountain wave ascent and insufficient fallout likely contribute to the precipitation over-prediction. This study also highlights the benefit of using an operational radar to complement conventional surface precipitation gauges for model precipitation evaluation over mountainous terrain.
1. Introduction

Several studies have investigated the impacts of horizontal resolution and different microphysical parameterizations on simulated orographic precipitation (Colle et al. 1999; Colle and Mass 2000; Grubisic et al. 2005; Mass et al. 2002; Garvert et al. 2005a,b; Lin and Colle 2009; among others). At relatively high resolution (1-2 km grid spacing), the horizontal flow, vertical motion, and precipitation distributions are realistically represented over terrain (Garvert et al. 2005b; Colle et al. 2005); however, numerous precipitation biases over terrain at high resolution have been noted. These biases have been attributed in part to deficiencies in the model bulk microphysical parameterizations (BMPs) (Colle and Mass 2000; Garvert et al. 2005b; Milbrandt et al. 2008, 2010; among others). In addition to the model BMPs, errors from synoptic and mesoscale kinematic and thermodynamic fields also impact model quantitative precipitation forecast (QPF) (Richard et al. 2007; Roebber et al. 2008; Minder et al. 2008; Schlemmer et al. 2010).

Low-level moisture flux is an important ingredient for orographic precipitation (Smith 1979). The strong correlation between upstream water vapor transport and orographic precipitation has been documented in many locations, such as along the California coast (Neiman et al. 2002; Smith et al. 2010), the European Alps (Smith et al. 2003; James et al. 2004; Muller and Kaspar 2011), and the Andes (Smith and Evans 2007; Falvey and Garreaud 2007. Colle et al. (2008) and Hahn and Mass (2009) used a case study approach to show that the accuracy of the predicted precipitation over the Pacific Northwest is dependent on the upstream moisture flux errors. The drying ratio (Smith et al. 2005) is a metric of the relative amount of water vapor removed (by precipitation)
compared to the inflow water vapor. It follows that the larger the observed drying ratio, the stronger the dependence of model precipitation errors on upstream moisture flux errors. Smith et al. (2005) estimated an annual drying ratio of 0.43 for Oregon.

Analysis of a large sample of storms from two cool seasons allows us to take previous work a step further. In this paper, we examine how variations in freezing level height can modify both the observed relationship between inflow moisture flux and precipitation as well as the relationship between model errors in moisture flux and errors in predicted precipitation. Operational radar observes precipitation-sized particles in a three-dimensional volume and thus provides a way to complement surface precipitation evaluation. Ground-based radars have been used to evaluate the model precipitation and wind structures over a barrier for specific case studies, but operational radars have not been used previously over multiple seasons to evaluate the model predictions over mountainous terrain. We utilize gauge, radiosonde, and three-dimensional radar data sets to deduce potential sources of surface precipitation error within the model.

After describing the experiment setup and observational datasets in section 2, the model precipitation performance and its connection to upstream moisture flux and freezing level height are presented in section 3. Section 4 summarizes the main results with a brief discussion.

2. Model setup and observational datasets

a. Model setup

The Penn-State/NCAR Mesoscale Model (MM5 Version 3.7) was used with 1.33,
4, and 12 km domains nested within a 36-km domain covering a wide region of the eastern Pacific and Pacific Northwest (not shown). The 4-km domain covers a portion of Washington and Oregon (Fig. 1), while the 1.33-km domain is centered over parts of southwest Washington and northwest Oregon. The MM5 was used in this study rather than the Weather Research and Forecasting (WRF; Skamarock et al. 2005) since (1) many orographic precipitation case studies in this region have used MM5 (Colle and Mass 2000; Grubisic et al. 2005; Mass et al. 2000; Garvert et al. 2005a,b; among others) and (2) the goal of this study is not to verify the latest model and parameterizations, but rather to generalize some of the previous case study results and to illustrate the influences of moisture flux and freezing level on the precipitation errors, which can occur for any modeling system. The Thompson et al. (2004) BMP in MM5 was replaced with the Thompson et al. (2008) version, which was available in version 2 of WRF, so that these results can be related to other WRF studies using this scheme (Thompson et al. 2008; Colle et al. 2008; Lin et al. 2009).

For the 2005-2006 and 2006–2007 cool seasons (November to March), the MM5 was run twice daily to 24 h starting at 0000 and 1200 UTC, with initial and lateral boundary conditions derived from the 6-h NCEP Global forecast system (GFS) model analyses at 1-degree spacing. The snow cover for each WRF run was initialized using the Rapid Update Cycle (RUC) analysis (20-km horizontal spacing), while the SST, soil temperature, and soil moisture were obtained from the GFS analysis. The 4- and 1.33-km domains were initialized at 0600 and 1800 UTC using the 6-h forecast from the 12-km domain. Four dimensional data assimilation (analysis nudging; Stauffer and Seaman 1990)
was used during the first 12 hours of the 36 and 12-km domains. The goal of nudging the outer domains and the use of GFS analysis boundary conditions was to reduce the large-scale errors in order to investigate the short-term performance within the inner nests. The last 12 hours of the 18-h simulation (6-18 h) from the 4- and 1.33-km domains were used for verification.

The model physics include the ETA PBL (Janjic 1994), Thompson microphysics (Thompson et al. 2008), Dudhia (1989) short and long wave radiative transfer, and MM5 simple slab land surface model. The modified Kain Fritsch cumulus scheme (Kain and Fritsch 1993; Kain 2004) was used in the 36 and 12-km domains. A positive definite moisture advection (PDA) scheme (Skamarock 2006) was not available in MM5. Hahn and Mass (2009) showed a PDA moisture scheme in WRF can reduce the surface precipitation by 3-17% over the Pacific Northwest for a particular case study. Lin and Colle (2009) noted ~10% reduction of surface precipitation by using PDA for another case study over the Oregon Cascades. The interpretation of the precipitation verification results in this study includes an expectation of model surface precipitation over-prediction of up to 20%, since PDA was not used.

b. Observational datasets

1) Precipitation gauge network

Daily liquid-equivalent precipitation data from the National Weather Service (NWS) Cooperative stations (COOP) and the National Resources Conservation Services (NRCS) snowpack telemetry (SNOTEL) sites (Fig. 1) were synthesized to evaluate the
model surface precipitation performance. Previous studies by Garvert et al. (2005b) and Colle et al. (2008) have suggested that 1.33-km grid spacing better resolves the vertical motions over the Cascade Mountains than 4-km grid spacing; thus, the precipitation verification in this paper will focus on the 1.33-km domain. The twice-daily precipitation forecasts (6-18 h) from the 1.33-km MM5 domain were interpolated to the gauge locations using an inverse distance Cressman (1959) approach as in Colle et al. (1999), and summed to get the model 24-h precipitation. We define model precipitation bias score for a storm as the ratio between the mean forecast precipitation for all stations within the 1.33-km domain and the observed mean precipitation at these same stations. The over- and under-prediction days in the analysis are defined as bias scores greater than 1.3 and less than 1.0, respectively to account for some precipitation gauge undercatchment and not using PDA for moist variables.

2) Radiosonde

Radiosonde observations of wind, pressure, temperature, and moisture are made twice daily (0000 and 1200 UTC) at Salem, OR (SLE in Fig. 1). Both the 4-km MM5 and observed meteorological variables were linearly interpolated to a vertical grid spacing of 200-m between 100 and 7900 m ASL. To relate the 12 hourly SLE soundings to the daily precipitation, daily profiles of moisture, winds, and temperature were computed following Falvey and Garreaud (2007),

\[
X = (X_{-12h} + 2X_0 + X_{12h}) / 4, \quad (1)
\]

where \(X_{-12h}\) and \(X_{12h}\) are moisture, winds, and temperature observations 12 h before and 12 h after the radiosonde observations at 1200 UTC (\(X_0\)).
A dry bias has been noted for the Vaisala radiosonde (e.g., Turner et al. 2003), and we found a similar dry bias during saturated conditions in the SLE sounding (not shown). Therefore, following Turner et al. (2003), we apply a 5% increase of relative humidity (RH) to the SLE sounding, with the caveat that RH cannot exceed 100% with respect to water. The 4-km MM5 forecasts every 12-h at forecast hour 6 (0000 and 1200 UTC) were interpolated to the Salem site, and the same daily average method given in Eq. 1 was used to get the model daily sounding. The model and observed column-integrated RH weighted moisture flux (for simplicity, called as moisture flux hereafter) was computed from the sounding. Wind and temperature near the crest level (1.5 km ASL) are used for later storm categorization.

3) WSR-88D radar

The National Weather Service (NWS) Weather Surveillance Radar-1988 Doppler (WSR-88D) radar at Portland, OR (RTX in Fig. 1) provided information on the three-dimensional precipitation structures within ~150 km range of the radar. The Level II data were interpolated to a grid with 2-km spacing in the horizontal and 1 km in the vertical at ~6 minute time intervals following Yuter et al. (2011). The 1.33-km MM5 outputs at 15-minute intervals are interpolated horizontally and vertically to the corresponding radar grid points.

To compare the model cloud and precipitation with radar directly, both model derived radar reflectivity and radar-retrieved ice water content above the freezing level are used. Model reflectivity is calculated in the Rayleigh scattering regime using the microphysical assumptions in Thompson et al. (2008), including particle size distribution
and mass-dimension relationship. IWC retrieval from cm-band radar has not been extensively explored. We follow Hogan et al. (2006, Eq. 14) to retrieve IWC using radar reflectivity and temperature. As in Hogan et al. (2006), only measurements with an observed column maximum reflectivity larger than 12 dB are used, which includes primarily precipitation conditions. Correspondingly, only model grid columns with non-zero surface rainfall are considered in the analysis. We also limit the comparison of IWC to those levels in the vertical with temperatures less than -5 °C to minimize the bright band effect.

The comparison focuses on a 40x30 km box over the windward slope of Cascades (the small black box in Fig. 1) within the 1.33-km domain and RTX radar range. The box is ~90 km from the radar site to minimize the influence of the radar’s cone of silence and excludes regions with severe radar beam blocking. We also compare model output and radar data for a west-east cross section from the Willamette Valley to the Cascade crest (the dashed box in Fig. 1).

c. Storm screening and categorization

In this study, a heavy precipitation event is defined as a day on which either observed or model mean rain gauge precipitation within the 1.33-km domain is over 12.7 mm (0.5 inch) over a 24-h period starting at 0000 UTC. This threshold was chosen to focus on larger, longer lasting storms. The resulting 90 events were modeled as described above. We first screened out those poorly simulated events (5 days) based on a comparison of the SLE sounding at 1.5 ASL km (near the crest level of Cascades) with the model. Storms
with an absolute value of model daily averaged temperature error > 4 K or wind direction error > 25 degrees azimuth were removed from the study data set. A failure to reproduce these basic conditions in the model is likely related to a poor initialization. We further restricted the analysis to events (77 days) with predicted or observed southwesterly (180-270 degree) winds at 1.5 km ASL so that the radiosonde at Salem, OR is reasonably representative of the inflow air going over the Cascades in our comparison box. Finally, we categorize the 77 storms based on freezing level height and integrated moisture flux relative bias in Table 1. The 77 storms are subdivided into warm storms (observed temperatures at 1.5 km ASL at SLE greater than -1 °C) and cold storms (observed temperatures at 1.5 km ASL at SLE less than -1 °C). We then categorize storms within the cold and warm categories based on the integrated moisture flux relative bias (> 0.2 “over-prediction”, < -0.2 “under-prediction”, and “good” or “well-predicted” otherwise). To better isolate differences in forecasts as a function of freezing level, we also examine 38 well-simulated storms, those days with biases of wind speed and integrated moisture flux less than 0.2 and temperature bias less than 1 K (Table 2).

3. Results

a. Seasonal relationships between moisture flux and downstream precipitation

The heaviest precipitation accumulations within the 1.33-km domain, based on the sum of two cool seasons, are situated over some of the narrow ridges (500-700 mm) that are exposed to southerly or southwesterly low-level flow as well as the isolated volcanic peaks (Fig. 2a). Precipitation minima (180-330 mm) are located within the Cascade valleys and the lee of high volcanic peaks. There are also two widespread precipitation minima in
the low land areas of the Columbia River (150-240 mm) and the lee of the Cascades (30-90 mm). The 1.33-km MM5 simulated the seasonal precipitation within 30% of observed at many of the precipitation gauge sites (orange diamonds in Fig. 2b). Precipitation over-prediction (bias > 130%) is preferentially occurring just upstream (southwest) of the Cascade foothills and in the immediate lee of Cascades.

The average wind speed, wind direction, and moisture and moisture flux profiles of all 77 storms are shown in Fig. 3. The MM5 overestimates the winds at SLE by 1-1.5 m s$^{-1}$ in a layer between 0.5 and 1 km ASL, while it under-predicts the flow by ~2 m s$^{-1}$ above 2.5 km ASL. This overestimated wind in the boundary layer has been noted by Garvert et al. (2007) in the simulation of an orographic precipitation storm over the same region. The MM5 wind direction is generally 10 degrees more subgeostrophic than observed above 2.5 km ASL. The combination of overestimated moisture (~8%) below 1.2 km ASL and the over-predicted winds at low levels, yields a mean moisture flux error of ~20 g m$^2$s$^{-1}$ (~25%) around 0.8 km ASL. This average moisture error (~8%) is larger than that at the model initialization time (~2%, not shown) and suggests that the moisture error is either advected from over the Pacific Ocean or developed during the model integration.

Despite the errors in the average vertical profiles of wind and moisture, the integrated moisture fluxes at SLE and downstream orographic precipitation for the set of 77 storms are positively correlated, both within the MM5 ($r^2=0.75$) and the observations ($r^2=0.80$) (Fig. 4a).

b. Impact of freezing level on model precipitation bias
The subdivision of the 77 storms into warm and cold subsets yields a slight improvement in the correlation coefficient for the warm storms ($r^2=0.81$ for both MM5 and observed) and a decrease in correlation for cold storms (MM5 $r^2=0.54$, observed $r^2=0.77$). Unlike warm storms, for cold storms there is a large difference in the magnitude of correlation between moisture flux and precipitation in the MM5 versus observed. This discrepancy between model and observed is a clue that some kind of model bias is occurring in the cold storms (lower freezing level) more frequently than the warm storms (higher freezing level).

An alternate way of describing the relationship between inflow moisture flux and precipitation is in terms of drying ratio (Smith et al. 2005). Drying ratio is defined here as the ratio of the water vapor flux approaching the barrier divided by the precipitation fallout over the 1.33-km domain. In general, drying ratio increases with decreasing temperature at 1.5 km ASL. Examination of the scatter in Fig. 4b indicates a tendency for the model to over-predict drying ratio compared to observed, particularly for cold storms (observed temperatures at 1.5 km ASL smaller than -1 °C). These cold storm drying ratio overestimates of ~30-50% in the model indicate that too much water vapor is being removed as precipitation by the ice microphysics portion of the BMP. The average drying ratio for cold storms is 0.31 for MM5 and 0.19 for observed (Table 2). Among the 38 well-simulated forecasts, MM5 always overestimates precipitation for cold storms with 12 days falling into our over-prediction category with biases $>1.3$ and 4 days with bias scores near 1.2 (blue crosses in Fig. 4d). This over-prediction for cold storms is larger than that can be explained if a PDA scheme had been applied.
The spatial distribution of precipitation biases (Fig. 5a) also provides supporting evidence that the over-prediction bias for cold storms is systematic across the model domain. The mean precipitation bias scores at gauge locations for cold storms show that the 1.33-km MM5 over-predicts precipitation by > 50% over a large area of the domain including valley, windward slope, and mountain lee locations (Fig. 5a) resulting in an average bias score of 1.57 (Table 2). Over-prediction over such a wide range of topography is consistent with some kind of systematic error in ice microphysics. Warm storms, in contrast, show a spatial pattern of biases with a more even mix of over-predicted, under-predicted and well-predicted gauge locations (Fig. 5b) resulting in an average bias score of 1.16 (Table 2).

c. Comparisons of IWC

Using the Portland, OR WSR-88D radar, we examine the 1.33-km prediction precipitation biases at the surface for the 38 well-simulated storms in the context of the model’s IWC predictions and radar estimated IWC for levels with temperatures < -5 °C. Profiles of MM5 and radar-estimated IWC averaged as a function of temperature are shown in Fig. 6 for the volume over the small box in Fig. 1. The MM5 predicts larger IWC for cold days than warm days at altitudes lower than -35 °C with differences as large as 40% near -5 °C. Observed IWC is similar for warm and cold storms at temperatures lower than -13 °C. For warm storms, IWC is underestimated by the model for the entire layer between -40 and – 5 °C. In contrast, for the layer between -13 °C and -5 °C within cold storms, the model IWC (black dashed line in Fig. 6) is increasingly overestimated with
increasing temperature compared to observed IWC (black solid line in Fig. 6). Such distinct differences in model versus observed IWC fields for temperatures higher than -13 °C suggests that the BMP tends to produce too much snow or it underestimates the riming and fallout at these temperatures for cold storms.

The average radar reflectivity for a west-east cross section across the Cascades (the dashed box in Fig. 1) for the 1.33-km MM5 and Portland, OR radar provides additional information on the IWC verification differences for cold versus warm storms shown in Fig. 6. Over the Cascade windward slope, the observed radar reflectivities are several dB higher at a given altitude in the warm storms as compared to the cold storms. When compared within the same temperature zone (-20 to -5 °C, Fig. 7a,b), the observed reflectivities are similar for warm and cold storms.

The contours of the MM5 IWC field for cold storms (Fig. 7d) show a large region of values > 0.15 g m\(^{-3}\) extending from the Cascades westward across the domain. In comparison, IWC > 0.15 g m\(^{-3}\) for warm storms is present only over the Cascades. This difference in the spatial distribution of IWC translates into model estimated reflectivity values for the cold storms (Fig. 7d) of 10-20 dB within the -15 °C to 0 °C layer, which are ~5 dB larger than the estimated reflectivities for warm storms in the same temperature zone (Fig. 7c).

For both warm and cold storms, MM5 has maximum ascent near 2 km ASL over the windward slopes of the Cascades (Figs. 7c,d). For the warm events with a freezing level near 2 km ASL (Fig. 7c), the maximum upward motion is at temperatures near 0 °C. This will increase the concentration of super-cooled droplets favorable for riming growth and
graupel production. Cloud water is as high as 0.2 g m$^{-3}$ in the updraft regions of warm storms. The larger fall speed of graupel compared to snow results in more efficient IWC fallout where riming is active. As a result, less IWC remains aloft where abundant super-cooled cloud water exists.

For cold events (freezing level near 1 km ASL), the maximum snow depositional growth region (~-15°C) overlaps with the maximum ascent near 2 km ASL (Fig. 7d) and the model generates large amount of snow (up to 0.25 g m$^{-3}$) in this region. In addition, cloud water production is reduced (cloud water is only 0.1 g m$^{-3}$ near -5 °C) and riming growth is not as efficient compared to warm storms. Both favorable snow depositional growth and inefficient riming growth contribute to the larger IWC aloft in cold storms. Snow over-prediction has been noted in several orographic precipitation case studies using different BMPs (Garvert et al. 2005b; Lin and Colle 2009; Milbrandt et al. 2010). The results from this study suggest that the overestimated IWC aloft for cold storms is occurring over many events and it is likely from some systematic biases associated with ice microphysical processes within the BMP.

4. Discussion and summary

The surface precipitation from two cool seasons of high-resolution MM5 simulations over the Pacific Northwest were evaluated using precipitation gauge data, an upstream sounding and a WSR-88D radar. The model could realistically simulate the seasonal precipitation distribution over the Oregon Cascades. The 1.33-km MM5 seasonal precipitation is generally within 90-130% of observed over most of the rain gauge sites (Fig. 2b). In concurrence with previous studies, for the seasonal set of 77 storms, there is a
high correlation between moisture flux and surface precipitation in both the observed ($r^2=0.80$) and modeled storms ($r^2=0.75$). As a result, model precipitation error typically increases with increasing moisture flux error.

The observed air temperature at 1.5 km ASL at the SLE radiosonde site was used to subdivide the 77 seasonal storm days into warm storm ($T > -1^\circ C$) and cold storm ($T < -1^\circ C$) categories. Drying ratios were ~30-50% higher for the model compared to observations for cold storms. These systematically higher drying ratios for the MM5 indicate that too much water vapor is being removed as precipitation in the cold storms. The simulated precipitation for cold storms was less correlated with the moisture flux ($r^2=0.54$) than observed ($r^2=0.77$), which is likely the result of the surface precipitation overprediction in the model for cold storms. In contrast, both the model and observed had a good correlation between precipitation and moisture flux for warm storms ($r^2=0.81$ for both MM5 and observed), and there was less widespread precipitation overprediction in the model for warm storms.

For a well-simulated subset of storms (38 cases), those with errors less than 20% in wind speed and moisture flux and a temperature bias < 1 K, were also separated into warm and cold storm categories in order to better understand the underlying physics. Unlike the 22 well-simulated warm storms, the 16 well-simulated cold storms overestimated precipitation at gauge locations across the Willamette Valley and the windward and lee slopes of the Cascades within the model domain. At altitudes with temperatures below -15 °C, the model generally underestimated IWC compared to radar estimated IWC. An exception to this tendency is the region at altitudes between -13 °C and -5 °C where the
model IWC for cold storms became increasingly larger than observed with decreasing altitude. Based on the juxtapositions of the locations of mean upward motions and air temperature within the model, it is likely that both a favorable snow depositional growth region overlaid with mountain wave lifting and inefficient riming growth and fallout over the windward slopes within cold storms contribute to both the -13°C to -5°C layer IWC over-prediction and surface precipitation over-prediction.

Snow depositional growth parametrization in BMPs has large uncertainties associated with particle capacitance, particle size distribution, and particle mass and fall velocity characteristics. For example, Lin and Colle (2009) found snow aloft in the depositional growth zone for an orographic storm was reduced by 60% when the capacitance for aggregates instead of spheres was used. The abrupt transition from snow to graupel in some BMPs neglects the abundance of partially rimed particles in mixed-phase clouds. Lin and Colle (2011) proposed a new BMP that includes the gradual change from snow to graupel and thus represents the partially rimed particles. A reduced snow depositional growth rate appropriate for aggregates and inclusion of partially rimed particles might help improve the noted systematic over-prediction bias for cold storms.

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## List of Tables

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<th>Cold days (31)</th>
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<td>5 (1.42)</td>
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<td>fqv good</td>
<td>33 (1.15)</td>
<td>23 (1.48)</td>
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<td>fqv under</td>
<td>1 (1.01)</td>
<td>3 (1.17)</td>
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<table>
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