Comparison of the WRF dynamic downscaling using continuous and daily simulations for the year 2014

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Introduction

Climate models are invaluable tools for understanding the potential impacts of climate change on the atmosphere. While General Circulation Models (GCMs) are particularly effective for providing future climate projections, their high computational demands result in coarse spatial resolution, limiting their use for regional studies. To bridge this gap, dynamical downscaling employs Regional Climate Models (RCMs) driven by GCM data to produce finer-scale simulations for specific areas. Validating these models is essential to ensure they accurately replicate atmospheric trends in a region. This process involves comparing historical model outputs with observational data. Models closely aligned with observations are deemed reliable for predicting future trends. Dynamical downscaling often uses continuous simulations, but these can accumulate errors over time as models diverge from their initial input data. Techniques like spectral nudging help address this drift by selectively adjusting large-scale features to align with reference data. Alternatively, a series of independent, short simulations can be conducted, preventing error accumulation and reducing modelling time through parallel processing. However, this approach may limit the development of long-term processes, such as surface hydrological cycles, due to frequent resets of the model's memory. **This study aims to evaluate the performance of dynamical downscaling using the WRF model with ERA5 forcing, comparing continuous simulations with spectral nudging against daily reinitialized runs. The goal is to assess which approach better represents meteorological variables such as wind speed, temperature, humidity, precipitation, atmospheric pressure, and solar radiation**.

Data & Methods

WRF model setup

The WRF-ARW v4.3.3 model was used for dynamical downscaling, with initial and boundary conditions provided by the ERA5 reanalysis dataset. While ERA5 offers 0.25º spatial resolution, input data were selected to achieve a 1º resolution by sampling one out of every four grid points. Similarly, only data at 00:00, 06:00, 12:00, and 18:00 UTC (6-hour intervals) were used for model initialization. The model was configured with a single domain of 20-km spatial resolution, covering -115ºW to 40ºE in longitude and 60ºN to 20ºS in latitude, although only data above 20ºN was analysed. This focus aligns with the WRF parametrization's effectiveness in subtropical and extratropical regions. The study considered the year 2014, a typical year without extreme regional variability patterns like the North Atlantic Oscillation or El Niño–Southern Oscillation.

Dynamical downscaling methods

Two dynamical downscaling methods were applied. First, a continuous simulation for 2014 was conducted, employing spectral nudging for waves longer than 1000 km to reduce disruptions to large-scale circulation caused by interactions between the model solution and lateral boundary conditions. This simulation included a one-month spin-up period starting on 2013-12-01 at 00:00 UTC and was run on a single core. Second, the year was simulated as 365 independent daily runs, each preceded by a 12-hour spin-up period to allow the model to reach equilibrium. Each simulation spanned 36 hours, starting at 12:00 UTC on the preceding day, with the first 12 hours discarded. **These daily runs were executed in parallel** using 40 cores, **significantly reducing computational time compared to the continuous method**.

Validation

The simulations were fed with data from ERA5 with a 1º spatial resolution, then dynamically downscaled to a 20-km spatial resolution and lastly compared with data from ERA5 with a 0.25º spatial resolution. **Using the same dataset - with different spatial resolutions for input and comparison - allowed for an assessment of the reinitialized and continuous simulation techniques' ability to perform dynamical downscaling**. To facilitate this validation, the WRF model's 20-km output grid was bilinearly interpolated onto the 0.25º grid of the ERA5 data. This ensured that the variables from both datasets could be directly compared at the same grid points. Additionally, only the 6-hourly ERA5 data for 2014 were utilized to match the temporal resolution of the WRF outputs. To evaluate both simulation methods, several metrics were applied.

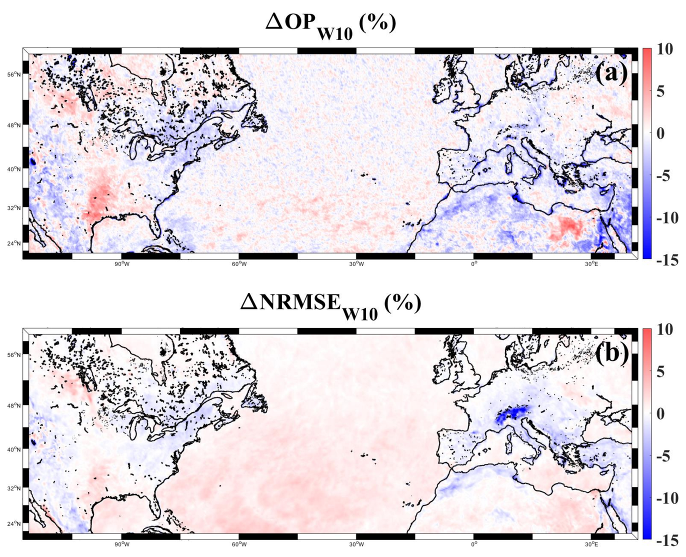
One essential metric was the Overlapping Percentage (OP), calculated at each grid point by comparing the WRF outputs with ERA5 data. The process involves generating the probability density function for each dataset using a specified number of bins and increments. The OP is then computed at each grid point using formula (1), where n is the number of bins, and Z_i is the frequency of occurrence of the variable's value corresponding to the bin (i), from the WRF or ERA5 dataset. This metric allows for a comparison of the overall distribution of simulated values with the reference dataset. A higher value indicates a greater similarity between the two datasets. Next, the Normalized Root Mean Square Error (NRMSE) was employed to validate the dynamical downscaling results at each grid point. It is calculated using formula (2), where T is the number of time steps (1460 for the year 2014 with a 6-hour temporal resolution), x_t is the value of the variable at time step (t), from the WRF or ERA5 dataset, and x_{min}^{ERA} and x_{max}^{ERA} are the minimal and maximal values from the ERA data, considering all time steps, at the specific grid points. This metric normalizes the RMSE by the range of the ERA5 signal, capturing the instantaneous differences between the simulated and reference values. Lower NRMSE values indicate smaller discrepancies between datasets. To compare the performance of the reinitialized and continuous dynamical downscaling methods, the difference in metrics (OP and NRMSE) was computed using formulas (3) and (4). **Positive Δ values for both metrics indicate that the reinitialized method produces more accurate results, while negative values favour the continuous method.**

Variables under study

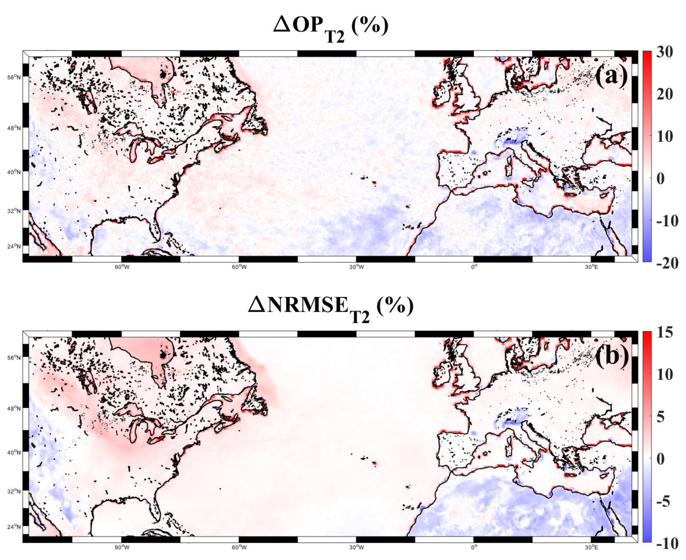
Various variables were analysed to assess the performance of both simulation methods. Instantaneous variables, recorded every 6 hours, included wind speed at 10 meters above the surface (W10), air temperature at 2 meters above the surface (T2), dew point temperature at 2 meters above the surface (DPT2), and surface atmospheric pressure (PSFC). Accumulated variables, such as precipitation (RAIN) and surface shortwave solar flux downwards (RSDS, referred to as solar radiation), represented the total accumulation over the 6 hours preceding each timestamp. These variables were direct outputs from the WRF simulations. Additionally, the integrated moisture vertical transport (IVT) was post-processed using the eastward and northward wind components and specific humidity for the atmospheric column between 1000 and 300 hPa. Lastly, the results were averaged across the study area based on soil type. "Ocean" refers to grid cells entirely over sea, while "Coast" includes cells with both land and sea. Grid cells below 1000 m altitude are labelled "Land," and those above 1000 m are categorized as "Mountain."

Results

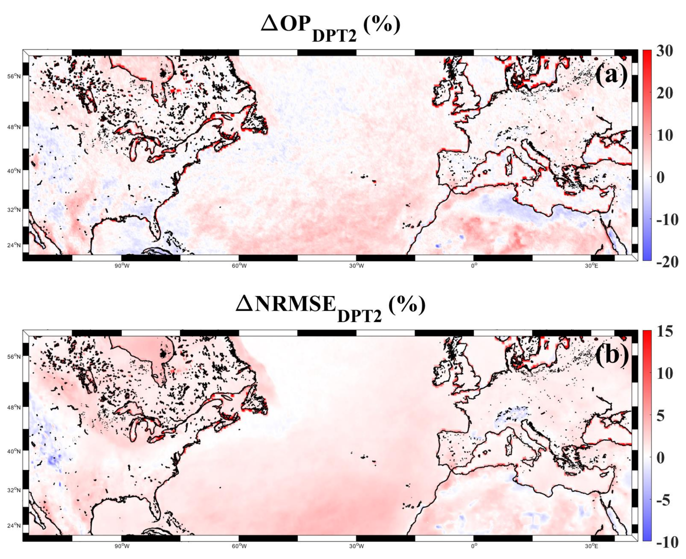
W10	OP (%)		NRMSE (%)	
	Reinitialized	Continuous	Reinitialized	Continuous
Ocean	93.7 ± 2.6	93.8 ± 2.0	6.5 ± 2.2	7.5 ± 2.2
Coast	82.8 ± 11.1	85.5 ± 9.9	13.2 ± 7.3	12.6 ± 6.3
Land	83.1 ± 12.0	83.5 ± 11.7	13.9 ± 8.5	13.8 ± 7.9
Mountain	62.6 ± 18.9	64.2 ± 19.1	29.5 ± 23.1	28.2 ± 21.8



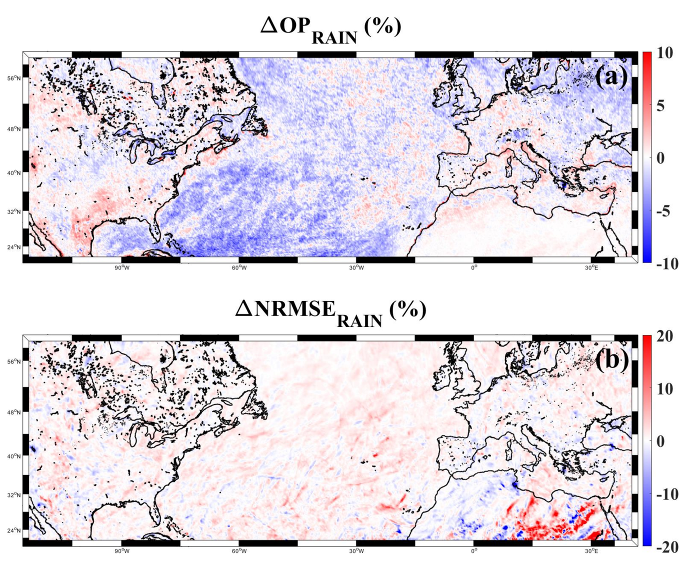
T2	OP (%)		NRMSE (%)	
	Reinitialized	Continuous	Reinitialized	Continuous
Ocean	93.0 ± 2.7	92.3 ± 5.3	4.1 ± 1.5	4.8 ± 2.2
Coast	87.6 ± 3.7	79.3 ± 10.7	5.5 ± 2.2	8.7 ± 3.9
Land	88.0 ± 2.7	87.9 ± 2.5	5.2 ± 2.0	5.3 ± 1.4
Mountain	87.0 ± 3.0	87.6 ± 2.8	6.3 ± 2.1	5.6 ± 1.6



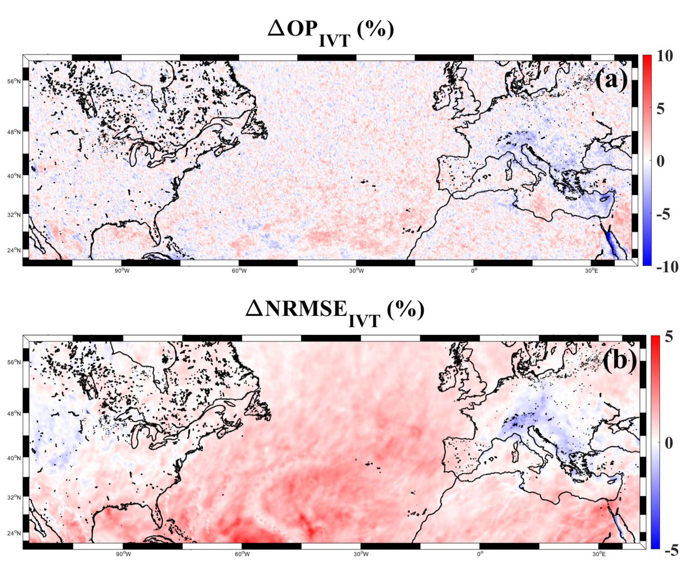
DPT2	OP (%)		NRMSE (%)	
	Reinitialized	Continuous	Reinitialized	Continuous
Ocean	89.9 ± 3.0	87.6 ± 5.7	5.4 ± 1.2	7.0 ± 2.3
Coast	88.1 ± 4.2	76.0 ± 15.5	6.0 ± 2.8	9.9 ± 4.7
Land	88.3 ± 3.9	86.8 ± 4.5	6.2 ± 2.8	7.3 ± 2.9
Mountain	87.7 ± 3.8	86.9 ± 4.6	8.3 ± 2.7	8.5 ± 2.8



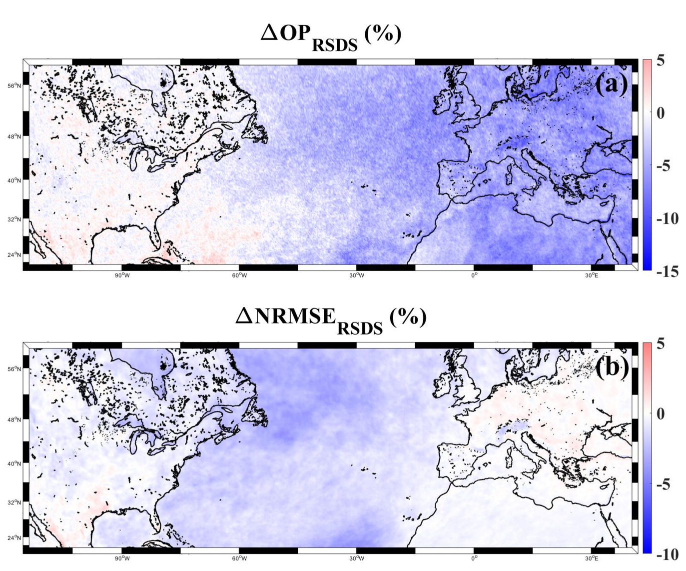
RAIN	OP (%)		NRMSE (%)	
	Reinitialized	Continuous	Reinitialized	Continuous
Ocean	84.4 ± 6.7	85.5 ± 6.2	7.0 ± 2.8	7.7 ± 2.8
Coast	89.8 ± 4.4	89.5 ± 4.8	7.7 ± 3.6	7.7 ± 3.2
Land	92.9 ± 4.5	92.9 ± 4.4	8.0 ± 5.2	8.8 ± 9.8
Mountain	91.9 ± 4.7	92.0 ± 4.5	8.8 ± 4.8	9.4 ± 4.6



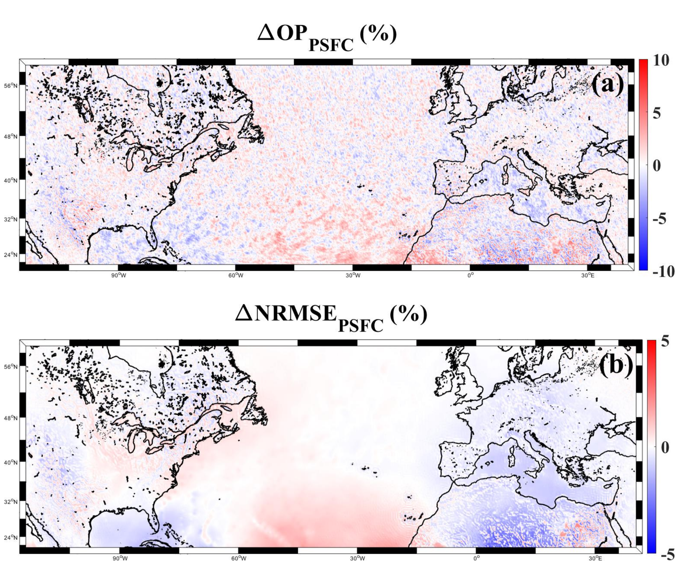
IVT	OP (%)		NRMSE (%)	
	Reinitialized	Continuous	Reinitialized	Continuous
Ocean	88.6 ± 1.9	88.3 ± 2.0	3.6 ± 1.3	4.7 ± 1.6
Coast	90.3 ± 2.4	90.5 ± 2.1	4.0 ± 1.7	4.3 ± 1.7
Land	91.3 ± 2.0	91.2 ± 1.9	4.2 ± 1.4	4.6 ± 1.4
Mountain	90.7 ± 3.0	90.6 ± 3.1	6.4 ± 2.0	6.6 ± 2.0



RSDS	OP (%)		NRMSE (%)	
	Reinitialized	Continuous	Reinitialized	Continuous
Ocean	82.4 ± 4.0	85.3 ± 3.9	9.3 ± 1.4	7.8 ± 1.2
Coast	83.0 ± 5.6	85.8 ± 3.9	9.6 ± 2.0	8.8 ± 2.0
Land	80.3 ± 6.5	83.3 ± 4.5	9.3 ± 2.7	9.0 ± 2.7
Mountain	81.2 ± 5.7	83.4 ± 3.6	7.8 ± 1.8	7.5 ± 1.9



PSFC	OP (%)		NRMSE (%)	
	Reinitialized	Continuous	Reinitialized	Continuous
Ocean	89.2 ± 3.7	89.1 ± 3.7	2.2 ± 1.7	2.3 ± 1.8
Coast	80.3 ± 15.0	80.2 ± 15.2	5.9 ± 9.3	5.9 ± 9.3
Land	83.0 ± 12.8	82.9 ± 12.9	5.4 ± 7.0	5.2 ± 7.0
Mountain	60.1 ± 27.3	60.0 ± 27.4	19.2 ± 20.7	19.0 ± 20.8



Tables. OP and NRMSE between WRF and ERA5 for the continuous and reinitialized simulations, spatially averaged according to the soil type, and standard deviation.
Figures (a). Difference in OP between the reinitialized and continuous simulations.
Figures (b). Difference in NRMSE between the continuous and reinitialized simulations.

Conclusion

The reinitialized method, offering approximately 30 times lower computational cost, is the preferred choice when its results match or surpass those of continuous downscaling. It enables efficient high-resolution climate modeling without sacrificing accuracy in most cases.

W10: Both methods excel in marine regions but are less reliable in mountainous areas. They correlate well climatically with reference data in coastal and land areas, though instantaneous correlation is moderate.

T2 and DPT2: Both yield excellent overall results, except in coastal regions, where the continuous method shows moderate performance.

RAIN: Climatological performance is excellent, but instantaneous results are moderate.

PSFC: Both methods perform well, particularly over oceans, but are unreliable in mountainous areas.

RSDS: Good results overall, with the continuous simulation slightly ahead.

IVT: Both methods achieve excellent and comparable results in all scenarios.

$$\mathrm{OP}(\%) = 100 * \sum_{i=1}^{n} \mathrm{minimum}\left(Z_i^{WRF}, Z_i^{ERA5}\right) \quad (1)$$

$$\mathrm{NRMSE}(\%) = \sqrt{\frac{\sum_{t=1}^{T}\left(x_t^{WRF} - x_t^{ERA}\right)^2}{T}} \Big/ \left(x_{max}^{ERA} - x_{min}^{ERA}\right) \quad (2)$$

$$\Delta\mathrm{OP}(\%) = \mathrm{OP}^{Reinitialized} - \mathrm{OP}^{Continuous} \quad (3)$$

$$\Delta\mathrm{NRMSE}(\%) = \mathrm{NRMSE}^{Continuous} - \mathrm{NRMSE}^{Reinitialized} \quad (4)$$