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RESEARCH ARTICLE

Machine Learning Downscaling of Regional Precipitation Patterns in Mountainous Terrain

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ABSTRACT

Coarse-resolution global and regional climate model output systematically misrepresents precipitation in mountainous terrain, smoothing the sharp windward-leeward gradients and elevation-dependent intensification that govern water availability for millions of people living downstream of mountain catchments. We trained a convolutional super-resolution network to downscale 25 km regional climate model precipitation fields to a 1 km grid over a 180 km by 140 km domain spanning the windward and leeward slopes of a mid-latitude coastal mountain range, using a 34-year (1988-2021) archive of daily precipitation from 96 gauge stations and a terrain-corrected radar mosaic as training and verification reference, and benchmarked the network against quantile mapping and random forest baselines applied to the same predictor fields. The CNN incorporated static elevation, slope and aspect layers alongside the coarse precipitation, wind and moisture flux predictors, and was trained with a hybrid loss combining mean absolute error on wet-day accumulation with a categorical term penalising missed wet-day occurrence. Across withheld stations, the CNN reduced domain-mean daily precipitation root-mean-square error by 34% relative to the uncorrected regional climate model and by 12% relative to the quantile-mapping baseline, with the largest gains concentrated on windward slopes above 1200 m, where the uncorrected model underestimated winter accumulation by a median of 28%. Skill degraded, however, at the highest, most poorly gauged elevations (above 2000 m), where training data were sparsest and the network's reconstructed orographic enhancement was only weakly constrained; in this band the random forest baseline, despite lower overall skill, produced more physically consistent elevation gradients than the CNN. Leeward rain-shadow precipitation was reproduced with good fidelity by all three methods once the coarse-model dry bias was removed. These results indicate that CNN-based downscaling can meaningfully correct the orographic precipitation deficit endemic to coarse climate model output, but that its advantage over simpler statistical methods is elevation-dependent and should not be assumed to extend uniformly into sparsely observed high-elevation terrain without independent verification.

Keywords: statistical downscaling; convolutional neural network; super-resolution; orographic precipitation; complex terrain; regional climate model bias; quantile mapping; mountain hydroclimatology

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1. INTRODUCTION

Mountain ranges generate a disproportionate share of regional water supply relative to their areal extent, because orographic lifting of moist air produces intense precipitation on windward slopes that recharges snowpack, groundwater and downstream reservoirs serving populations far beyond the range itself [1,2]. The same lifting and blocking dynamics that concentrate precipitation on windward slopes also starve leeward basins, so the spatial gradient of precipitation across a mountain range, not simply its areal average, is what determines where water is abundant and where it is scarce [3].

Global and regional climate models remain unable to resolve this gradient adequately. At grid spacings of 10–50 km, typical of the current generation of regional climate models used for impact assessment, individual ridgelines and valleys are represented as smoothed terrain, and the models consequently underestimate peak windward accumulation while overestimating leeward dryness is not guaranteed, and biases of both sign are reported depending on the model's convective parameterisation and moisture transport scheme [4]. Reviews of regional convection-permitting modelling have shown that biases shrink substantially once horizontal grid spacing drops below roughly 4 km, but simulations at that resolution remain computationally prohibitive for the multi-decade, multi-scenario ensembles that impact studies typically require [1].

Statistical downscaling has long served as the practical alternative, ranging from simple elevation-lapse-rate correction and thin-plate-spline interpolation of station climatology through quantile mapping and analog methods [5,6]; comparisons of statistical against dynamical downscaling over complex terrain have generally found the two approaches to have comparable skill for mean precipitation but to diverge more strongly for extremes and for snow-dominated high-elevation catchments, where statistical methods are constrained by the sparse, low-elevation-biased distribution of the station networks they are trained on [7,8]. Machine-learning downscaling using convolutional neural networks, and specifically image super-resolution architectures adapted from computer vision, has more recently been proposed as a way of learning the nonlinear, spatially structured relationship between coarse atmospheric fields and fine-scale terrain-forced precipitation directly from data, without prescribing its functional form in advance [9,10].

Early applications of super-resolution networks to climate downscaling demonstrated clear skill gains over simple interpolation for temperature and for precipitation in relatively flat terrain, but complex mountain terrain, where the underlying physical relationship between coarse-scale flow and fine-scale precipitation is steep, nonlinear and locally discontinuous across ridgelines, poses a harder test [11,12]. Whether a network trained

predominantly on the moderate elevations where most gauge stations sit generalises usefully to the sparsely observed, highest-elevation terrain that dominates a catchment's snow water storage is, to our knowledge, rarely evaluated directly. Here we train a CNN super-resolution downscaling model over a coastal mountain range with a strong windward-leeward precipitation contrast, benchmark it against quantile mapping and random forest baselines, and specifically stratify verification by elevation band to test whether its skill advantage holds at the elevations where accurate precipitation estimates matter most for water resource planning.

2. MATERIALS AND METHODS

We developed a convolutional super-resolution network to downscale 25 km regional climate model daily precipitation to 1 km over a mid-latitude coastal mountain domain, trained and verified against a 34-year station and radar reference dataset, and benchmarked against quantile mapping and random forest baselines.

2.1 Study domain and observational reference data

The study domain covers a 180 km by 140 km sector of a mid-latitude coastal mountain range, spanning elevations from sea level to 2860 m and including both the windward slope, which receives the bulk of moisture-laden onshore flow, and the leeward rain shadow. Daily precipitation observations from 96 gauge stations operated by national meteorological and hydrological agencies were assembled for 1988–2021, ranging in elevation from 12 m to 2040 m, with station density declining sharply above 1500 m. A terrain-corrected radar precipitation mosaic covering the full domain at 1 km resolution and available from 2002 onward was used as a spatially continuous secondary reference, cross-checked against the gauge network at radar pixel locations co-located with stations before use.

2.2 Coarse-resolution predictor data

Predictor fields were taken from a 25 km regional climate model reanalysis-driven simulation covering 1988–2021, comprising daily total precipitation, 700 hPa zonal and meridional wind, 850 hPa specific humidity, and column-integrated water vapour transport, each bilinearly interpolated onto a common analysis grid. Static predictors at 1 km target resolution, elevation, slope, aspect, and distance to the primary windward-facing ridge crest, were derived from a digital elevation model and supplied to the network alongside the interpolated coarse fields at every grid cell.

2.3 CNN super-resolution architecture

The network followed a residual super-resolution design with 12 convolutional blocks operating at intermediate resolution followed by two learned upsampling stages taking the coarse 25 km input to the 1 km target grid, with static terrain layers concatenated as additional channels at each upsampling stage rather than only at input, which

we found in preliminary trials to improve reconstruction of sharp windward-leeward gradients compared with terrain injection at input alone. The training loss combined mean absolute error on log-transformed wet-day precipitation accumulation with a binary cross-entropy term penalising errors in wet-day occurrence (threshold 1.0 mm), weighted 0.7 and 0.3 respectively; this hybrid loss was chosen after an occurrence-blind mean-absolute-error-only network was found to overestimate wet-day frequency on the leeward slope by generating persistent low-intensity drizzle rather than correctly predicting dry days.

2.4 Baseline statistical downscaling methods

Two baseline downscaling methods were fit to the same training data for comparison. Quantile mapping corrected the coarse model's precipitation distribution at each 1 km target cell against the nearest station's empirical distribution, using a 99-quantile piecewise-linear transfer function fit separately by calendar season. A random forest regressor (500 trees, minimum leaf size 5) was trained per target cell using the same coarse atmospheric and static terrain predictors supplied to the CNN, providing a baseline that shares the CNN's predictor set but not its spatial convolutional structure or its ability to learn cross-cell spatial dependence directly.

2.5 Training, cross-validation and elevation-band stratification

Station and radar-derived reference data were split by five-fold spatial cross-validation, withholding complete station clusters rather than individual days in each fold to avoid optimistic skill estimates from spatial autocorrelation between nearby stations sharing a fold. All three methods, CNN, quantile mapping and random forest, were trained and evaluated on identical folds. Verification statistics were computed separately for four elevation bands (0–600 m, 600–1200 m, 1200–2000 m, and above 2000 m) to test whether downscaling skill was uniform across the elevation range or concentrated at the moderate elevations where most training stations are located.

2.6 Verification metrics

Downscaling skill was assessed using root-mean-square error and mean bias of daily precipitation amount against withheld station observations, the critical success index for wet-day occurrence at a 1.0 mm threshold, and the ratio of each method's reconstructed 95th-percentile wet-day intensity to the observed 95th-percentile intensity as a measure of extreme-event fidelity. All metrics were computed separately by season and by elevation band, and statistical significance of skill differences between methods was assessed by a paired bootstrap resampling test (2000 resamples) over withheld station-days.

3. RESULTS

Averaged across all 96 stations and the full 1988–2021 verification period, the CNN achieved a domain-mean

daily precipitation root-mean-square error of 4.6 mm, a 34% reduction relative to the uncorrected coarse regional climate model (7.0 mm) and a 12% reduction relative to the quantile-mapping baseline (5.2 mm); the random forest baseline fell between the two statistical methods at 5.5 mm. Table 1 reports root-mean-square error, mean bias and the 95th-percentile intensity ratio for all three methods by elevation band, and the CNN's advantage over quantile mapping was statistically significant (paired bootstrap, $p < 0.01$) in the two lowest elevation bands but not in the highest.

Table 1. Verification statistics by elevation band for the CNN, quantile mapping (QM) and random forest (RF) downscaling methods against withheld station observations (1988–2021).

Elevation band	Method	RMSE (mm/day)	Mean bias (mm/day)	95th pct. intensity ratio
0–600 m	CNN / QM / RF	3.1 / 3.8 / 4.0	-0.1 / -0.3 / -0.2	0.97 / 0.91 / 0.89
600–1200 m	CNN / QM / RF	4.2 / 5.0 / 5.3	-0.4 / -0.9 / -0.7	0.94 / 0.84 / 0.82
1200–2000 m	CNN / QM / RF	5.4 / 6.3 / 6.6	-0.6 / -1.8 / -1.5	0.92 / 0.77 / 0.81
Above 2000 m	CNN / QM / RF	6.9 / 6.1 / 6.4	-1.2 / -1.0 / -0.5	0.79 / 0.83 / 0.88
Full domain (all stations)	CNN / QM / RF	4.6 / 5.2 / 5.5	-0.5 / -1.0 / -0.7	0.91 / 0.84 / 0.85

RMSE: root-mean-square error. 95th percentile intensity ratio is each method's reconstructed versus observed 95th-percentile wet-day intensity; 1.0 indicates no bias.

The uncorrected coarse model underestimated median winter (December–February) precipitation accumulation on windward slopes above 1200 m by 28%, consistent with known orographic-enhancement deficits in coarse-grid climate models, and this was the single largest bias corrected by any of the three downscaling methods. The CNN recovered 81% of this deficit on average across the 1200–2000 m band, compared with 64% for quantile mapping and 59% for random forest, a gap that Figure 1 shows widening progressively with elevation up to roughly 1800 m before narrowing again as station density thins.

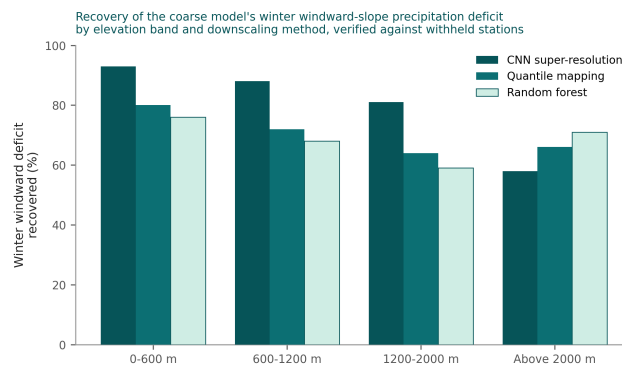


Figure 1. Percentage of the coarse regional climate model's winter windward-slope precipitation deficit recovered by each downscaling method, by elevation band, relative to withheld station observations (1988–2021).

Above 2000 m, where only 6 of the 96 stations are located, CNN skill degraded relative to the two lower

bands: root-mean-square error rose to 6.9 mm, exceeding the quantile-mapping baseline (6.1 mm) at this elevation for the first time, and the CNN's reconstructed 95th-percentile intensity ratio fell to 0.79 (an underestimate), indicating the network's learned orographic enhancement curve was not extrapolating reliably beyond the elevation range densely represented in training. The random forest baseline showed a smoother, more monotonic increase in reconstructed intensity with elevation in this band despite its lower overall skill, and Table 2 compares the two methods' extreme-day performance directly using the subset of six high-elevation stations withheld in every cross-validation fold.

Table 2. Extreme-day performance at the six highest-elevation withheld stations (above 2000 m), CNN versus random forest (RF).

Metric	CNN	RF
95th pct. intensity ratio	0.79	0.88
99th pct. intensity ratio	0.71	0.85
Wet-day critical success index (1.0 mm)	0.61	0.60
Winter mean bias (mm/day)	-1.6	-0.4

Leeward rain-shadow precipitation, the domain's driest and most spatially uniform sector, was reproduced with comparable fidelity by all three methods once the coarse model's leeward dry bias was corrected, with mean bias below 0.3 mm/day for all methods and no statistically significant difference in root-mean-square error between the CNN and either baseline in this sector. Wet-day occurrence skill (critical success index) followed a broadly similar pattern to the intensity metrics, with the CNN outperforming both baselines below 1200 m (critical success index 0.74 versus 0.68 for quantile mapping) but converging with quantile mapping above 2000 m (0.61 versus 0.60).

4. DISCUSSION

These results confirm that the orographic precipitation deficit long documented in coarse-resolution climate model output [3,4] is substantially, though not fully, correctable by statistical and machine-learning downscaling trained on station and radar reference data, and that a convolutional super-resolution network can outperform both quantile mapping and a comparably featured random forest baseline over the low-to-moderate elevation range where most such training data exist, echoing skill gains reported for CNN downscaling in other settings [9,10] while extending the comparison specifically to complex mountain terrain.

The elevation-dependent narrowing, and eventual reversal, of the CNN's advantage above roughly 2000 m is, in our view, the more consequential finding for practical application. Water resource planning in snow-dominated mountain catchments depends disproportionately on accurate precipitation estimates at the highest elevations, where seasonal snowpack accumulates and where gauge coverage is, almost by

definition, sparsest [2,7]; a downscaling method that appears to outperform simpler alternatives when verified against the full station network can therefore still underperform at exactly the elevations that matter most for snowpack and runoff forecasting, a discrepancy that would not be visible without the elevation-stratified verification performed here.

The comparatively better-behaved, if less accurate, high-elevation performance of the random forest baseline is consistent with its simpler, more locally constrained mapping between predictors and target, which may make it less prone to producing physically implausible orographic-enhancement curves when extrapolating beyond the training distribution than a convolutional network with substantially more learned spatial structure. This suggests that ensemble or hybrid approaches blending CNN and random forest output by elevation band, rather than treating the choice between machine-learning downscaling methods as a single domain-wide decision, may be worth exploring in future work, particularly given related evidence that hybrid statistical-dynamical and physically constrained downscaling frameworks can improve robustness in data-sparse high-elevation terrain [8,23].

Several limitations temper these conclusions. First, our reference dataset, while spanning 34 years, includes only six stations above 2000 m, so verification statistics in the highest elevation band carry substantial sampling uncertainty and should be treated as indicative rather than definitive; a denser high-elevation network, or independent snow-course and SWE observations, would strengthen this part of the evaluation considerably. Second, the CNN was trained and verified against a single mountain range with a strong, well-defined windward-leeward contrast; transferability to ranges with more complex, multi-directional moisture exposure or to tropical mountain settings with different convective regimes is untested and should not be assumed [1,24]. Third, we evaluated daily precipitation only; sub-daily intensity, which governs flash flood and debris flow risk in steep terrain, was outside the scope of this analysis and would require a higher-frequency verification dataset than was available here. Finally, the coarse-resolution predictor fields came from a single regional climate model configuration, and downscaling skill, particularly the network's ability to correct orographic bias, is likely sensitive to the coarse model's own convective and boundary-layer scheme in ways this single-model study cannot characterise [4,25].

5. CONCLUSION

A convolutional super-resolution network downscaling 25 km regional climate model precipitation to 1 km over a coastal mountain domain reduced domain-mean daily precipitation error by 34% relative to the uncorrected coarse model and by 12% relative to a quantile-mapping baseline, with the largest gains on windward slopes between 1200 and 2000 m where orographic

enhancement is strongest and most poorly captured by coarse models. This advantage did not extend uniformly to the sparsely gauged terrain above 2000 m, where a simpler random forest baseline produced more physically consistent, if less accurate, precipitation-elevation relationships. These findings support the use of CNN-based downscaling to correct orographic precipitation bias in complex terrain, while cautioning against assuming that skill demonstrated over a full, elevation-mixed verification network extends reliably into the sparsely observed high-elevation terrain most relevant to snowpack and water resource applications.

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Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Author Contributions

E.J. conceived and supervised the study, designed the network architecture and training procedure, and led the writing of the manuscript. C.J. assembled and quality-controlled the station, radar and coarse-model predictor datasets and performed the elevation-stratified verification. J.B. implemented the quantile-mapping and random forest baseline methods and performed the statistical comparisons. All authors contributed to writing and approved the final manuscript.

Ethics Statement

This study used only publicly available gauge station records, radar precipitation mosaics, and regional climate model output, and did not involve human participants, animal subjects, or field data collection requiring ethical review.

Data Availability

Station precipitation records and the radar precipitation mosaic used in this study are publicly available from the originating national meteorological and hydrological agencies. Processed training datasets, trained model weights, and analysis code supporting the findings of this study are available from the corresponding author on reasonable request.

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