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Convection-permitting scales break climate invariance in machine-learned precipitation downscaling

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Abstract

Machine-learning precipitation downscaling trains a coarse-to-fine mapping operator applicable to future climate projections, avoiding the cost of km-scale numerical simulations. This implicitly assumes the climate-change signal is contained in the coarse input and the learned operator remains nearly invariant. Testing this assumption over Puerto Rico with current (2001-2021) and near-future (2041-2061) extreme-rainfall resimulations, we find current- and future-climate operators nearly indistinguishable at 48-25 and 25-12 km but diverge at 12-3 km, where the current-climate operator underestimates future fine-scale variance. Kinetic and available potential energy budgets of idealized MPAS squall-line simulations explain this scale dependence: diabatic heating and buoyancy conversion increase disproportionately below 25 km and reorganize shell-to-shell kinetic-energy transfers toward finer scales. Climate non-stationarity is strongest at scales coarse climate models do not explicitly resolve. Km-scale downscaling must therefore account for climate-dependent convection-permitting dynamics rather than rely on bias-correcting current-climate operators, with direct implications for flood-risk assessment and climate-resilience planning.

34 1 Introduction

35 Local meteorological data, such as precipitation, surface winds, and 2-meter temper-
 36 ature, are important for assessing climate risks under projected changes in extreme
 37 events [1]. However, climate models typically run at approximately 100 km spatial res-
 38 olution [2], with highest-resolution ensemble members reaching 25 km grids [3, 4]. On
 39 the other hand, convection-permitting models provide accurate details of precipita-
 40 tion but remain too expensive to integrate over climate timescales and large domains
 41 [5–8]. For the Caribbean, km-scale models indicate substantial mid-century changes
 42 in extreme rainfall over Puerto Rico that climate models cannot capture [9]. Other
 43 research shows that future rainfall increases more in km-scale than coarser resolution
 44 data [6, 10]. Hence, downscaling from climate model resolution to km-scale remains a
 45 crucial gap for accurate climate extreme projections.

46 Downscaling divides into dynamical, statistical, and machine-learning (ML)
 47 approaches [11–14]. Dynamical downscaling runs higher-resolution models, such as
 48 the Model for Prediction Across Scales (MPAS) [15] or the Weather Research and
 49 Forecasting (WRF) model [16]. Statistical downscaling includes methods like quan-
 50 tile mapping, regression, and Gaussian random fields. ML methods learn mappings
 51 between coarse- and fine-resolution fields generated by dynamical simulations or
 52 observations. Once ML downscaling functions are trained, the computational cost of
 53 inference is substantially lower than that of running dynamical downscaling models.

54 ML downscaling methods have progressed rapidly. Misra et al. [17] introduced
 55 precipitation downscaling using long short-term memory recurrent neural networks.
 56 Generative models like generative adversarial nets (GAN) [18, 19], U-Net-based dif-
 57 fusion models [20, 21], and Swin-Transformer models [22] have been applied to ML
 58 downscaling as well. Lupin-Jimenez et al. [23] also extended diffusion-based down-
 59 scaling to the ocean. ML downscaling models share the same challenges as ML-based
 60 weather forecast models: overly smooth and under-dispersive outputs [19, 24].

61 To address dynamics preservation in ML downscaling, physics-ML hybrid mod-
 62 els have been developed. Saha and Ravela [25] introduced the Dn-SPAL framework,
 63 whose GAN network takes an additional channel of orography-induced rainfall estima-
 64 tion alongside a statistical input channel from an ensemble-approximated conditional
 65 Gaussian process [26] to generate realistic rainfall fields.

66 A more fundamental challenge is whether the physical relationship between coarse-
 67 and fine-scale precipitation itself remains stationary as climate changes. Statistical
 68 methods already showed that downscaling functions trained in the historical climate
 69 degrade when applied to a warmer condition [27–29], and the same non-stationarity
 70 has been demonstrated for GAN-based downscaling [30]. However, degradation alone
 71 does not establish why the mapping fails. Extreme precipitation intensifies with warm-
 72 ing [31], and for downscaling, the critical question is whether this climate response is

73 already encoded in the coarse precipitation field, or needs to be represented in struc-
74 tural changes of downscaling operators, mapping energy and variance differently at
75 scales absent from the coarse input.

76 This potential distinction is particularly important for the convection-permitting
77 resolution, because the fine-scale convective processes are those that conventional cli-
78 mate models cannot explicitly resolve. Climate invariance is therefore a property not
79 only of the learning architecture [32], but also of the physical scale transition that the
80 operator represents.

81 We address this question using MPAS resimulations of extreme-precipitation events
82 over Puerto Rico in current and near-future climates. Events are simulated at 48, 25, 12
83 and 3 km resolution, allowing separate downscaling operators to be trained and cross-
84 tested at each scale transition. The coarser scales retain parameterized convection,
85 whereas the 3-km simulations explicitly resolve deep convection. We then combine
86 cross-climate operator diagnostics with a spectral energy budget [33] of idealized squall
87 lines subjected to controlled surface warming. This framework not only allows us
88 to locate where climate invariance breaks in the precipitation mapping, but also to
89 determine whether the same scale transition exhibits a climate-dependent change in
90 the underlying energetics.

91 In idealized squall-line experiments, the warming response at 3 km diverges system-
92 atically from its 25-km counterpart. The idealized energy budget provides a physical
93 explanation: warming increases diabatic heating and buoyancy conversion dispro-
94 portionately at fine scales, increases the kinetic-energy, and enhances transfers into
95 wavelengths below 25 km. The 3 km climate signal therefore enters the precipitation
96 field that the 25 km input cannot represent. Climate invariance is consequently not a
97 property of the network alone, but of the physical scale transition that breaks precisely
98 where convection changes from parameterized to explicitly resolved.

99 2 Results

100 Cross-climate comparisons of the trained operators

101 We follow the Dn-SPAL framework developed by Saha and Ravela [25] to train
102 two downscaling operators: a weakly nonlinear local model called the ensemble-
103 approximated conditional Gaussian process (EnsCGP) [26], and a deep learning
104 counterpart by GAN, with frequency-separated losses [34, 35]. While the EnsCGP is
105 fast in training and retains reasonable skills in 48-25 km scale mapping, the GAN
106 better captures fine-scale structure and variance. We perform cross-climate examina-
107 tion to see if ML downscaling operators trained in different climates generate different
108 fields upon given the same coarse future input.

109 Figure 1 shows an example of such cross-climate test: the 3 km target in panel
110 (d) represents convective cells that have no correspondence in the panel (a) coarse
111 12 km input, showing the convection-permitting model’s ability to capture fine scale
112 variability of mesoscale and isolated convection. Super-resolutions generated by the
113 two GAN operators trained in different climates but fed with the same input show
114 skills in replicating smaller scale details in panel (c) and (d).

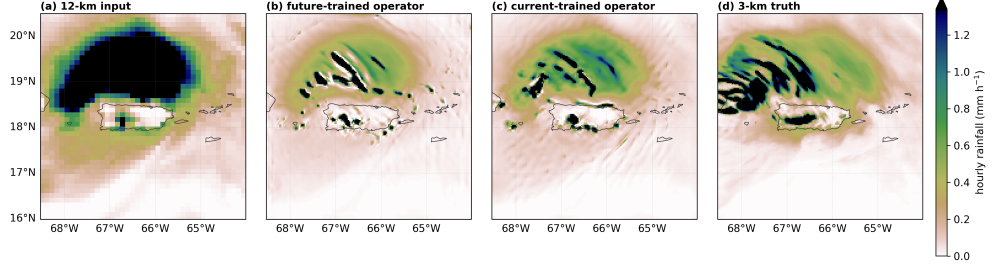


Fig. 1 One future testing case through the 12-3 km operators. (a) The coarse 12 km input of hourly precipitation. (b) The future-climate trained operator’s 3 km output generated from panel (a) input. (c) The current-climate trained operator’s 3 km output on the same input. (d) The 3 km MPAS run truth.

We use eigenspectral analysis to quantify how the variance of downscaled fields compares with the target across scales. The 48-12 km mapping is performed sequentially, using the generated 25-km field as input to the 25-12 km operator. The 48-25 and 25-12 operators are indistinguishable across climate and downscale well as shown in Figure 2 panel (a). But for the 12-3 km panel (b), where the downscaling operator is trained to learn the parameterization to explicit convection mapping, ML operators not only lose skill but also produce systematically different eigenspectra despite receiving identical inputs. This could be explained by panel (c), where the future 3-km targets exhibit significantly greater variance across all wavelength bands, while the two operators produce systematically different fine-scale spectra from the same 12-km precipitation input. This establishes a scale-selective climate dependence of the learned precipitation mapping: the coarse mappings remain nearly invariant, whereas the mapping into convection-permitting scales does not. The operator comparison alone does not identify the physical origin of this change, which we then analyze the underlying dynamics of energy transfers by wavelengths.

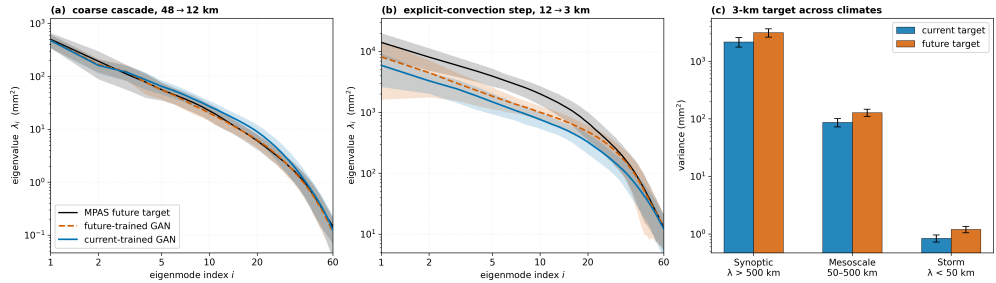


Fig. 2 (a) Eigenspectra of the MPAS future target in solid black curve, and of the downscaled fields from the current (future) climate trained operators in solid blue (dashed orange) curve for a two-step 48-25-12 km mapping. (b) Same as (a) but for 12-3 km mapping. (c) Variance separated by wavelengths in 3 km targets from the current (future) climate in blue (orange) with 90% bootstrapping confidence intervals.

Wavelength-dependent spectral response of the operators

Figure 2 panel (b) suggests that the climate signals structurally change the downscaling operators at km-scale mappings, since we control the input to be the same. We therefore probe the 12-3 km operator of each climate with a single-mode response diagnostic: prescribing a single-wavenumber rainfall input and recording how the power injected at each input wavelength emerges across output wavelengths using radially averaged power spectral density [36]. The result is an input-output spectral response matrix, normalized by the diagonal self-response, shown in Figure 3 panels (a)-(b). This diagnostic characterizes how each trained network redistributes and generates output power in response to input power at each wavelength.

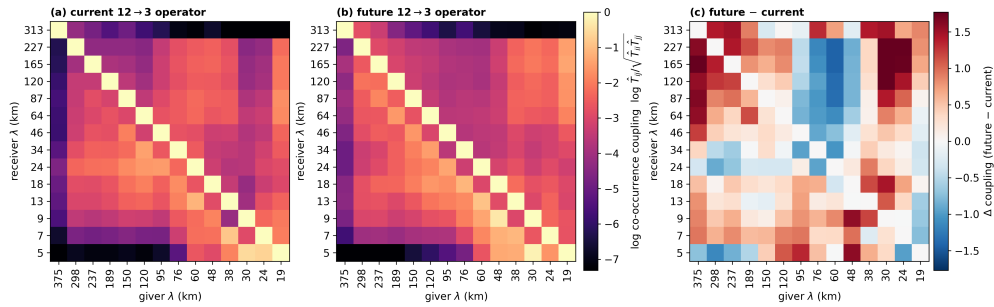


Fig. 3 Precipitation power-spectral response matrix of the GAN 12-3 km downscaling operator for each climate. (a) Current- and (b) future-climate trained operator, and (c) their difference.

Both operators redistribute spectral power broadly across output wavelengths rather than producing only a diagonal response. Their nonuniform differences, as shown in Figure 3 panel (c), indicate that warming changes this learned redistribution in a scale-dependent sense. For example, 7-18 km wavelength bands receive greater spectral power from a broad giver band (48-300 km), and the 24-48 km giver shell contributes more power across a range of receiving scales with warming. The 12-3 km operator therefore changes with climate not merely in amplitude, but in its scale-dependent redistribution of variance. The above finding is also consistent with previous works on rainfall intensification at scales the convection-resolving grid carries, increasing variances toward mesoscale wavelengths [37, 38].

Idealized squall line experiments for energy transfer

Diagnosing whether and why such wavelength dependent changes in Figure 3 panel (c) are true warming signals for convection-permitting scale downscaling requires a budget analysis. We choose to apply the three-dimensional energy transfer framework to idealized squall line simulations [39] at the same 3 km spacing (and a coarse 25 km counterpart) in doubly periodic MPAS domains. This provides a controlled dynamical analog of the scale transition that the ML operators are trained to emulate, serving

157 as a testbed for representing Puerto Rican extreme rainfall while maintaining feasible
 158 computational costs to simulate over a range of surface warming scenarios.

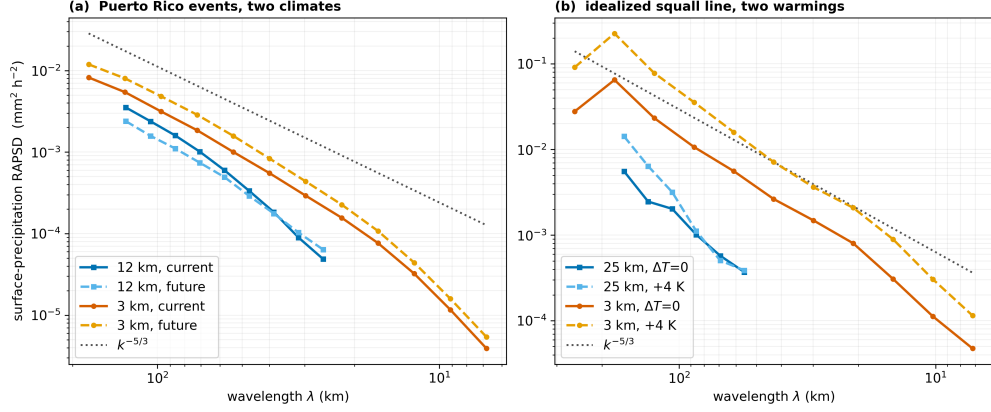


Fig. 4 (a) Radially averaged power spectral density (RAPSD) of Puerto Rican extreme precipitation events in current and future climates, at 12 and 3 km resolution. (b) RAPSD of idealized squall line simulations with $\Delta T = 0$ and $+4$ K at 25 and 3 km. The $k^{-5/3}$ reference slope is shown in both plots.

159 As shown in Fig. 4, both Puerto Rican simulations and the idealized squall line
 160 exhibit similar spectral structure with varying resolution and warming, close to a
 161 $k^{-5/3}$ reference slope at sub-synoptic scales [40]. This correspondence motivates the
 162 use of the idealized system as an analog to examine energy transfer sensitivity in a
 163 scale-dependent sense.

164 We diagnose the convective energetics using the spectral formulation of Augier and
 165 Lindborg [33]. At each horizontal wavelength, available potential energy E_A receives
 166 input from the condensational heating source G , is converted into kinetic energy
 167 E_K through buoyancy conversion C , and is redistributed across scales by horizontal
 168 spectral transfers T_K . Vertical energy fluxes $F_{K\uparrow}$ provide an additional pathway for
 169 redistributing the response in the vertical. All energy budget terms are mass-weighted
 170 over the lower troposphere (surface to 412 hPa) defined in Augier and Lindborg [33].

171 Figure 5 shows the energy budget in Equation (5)-(6) in the current-climate, the
 172 diabatic source is concentrated at storm event wavelengths and buoyancy conversion
 173 transfers this energy into the kinetic-energy at comparable scales, while horizontal
 174 kinetic-energy transfers redistribute energy towards finer scales, consistent with previ-
 175 ous literature [41, 42]. This provides an energy budget framework for identifying how
 176 warming modifies the scale transition.

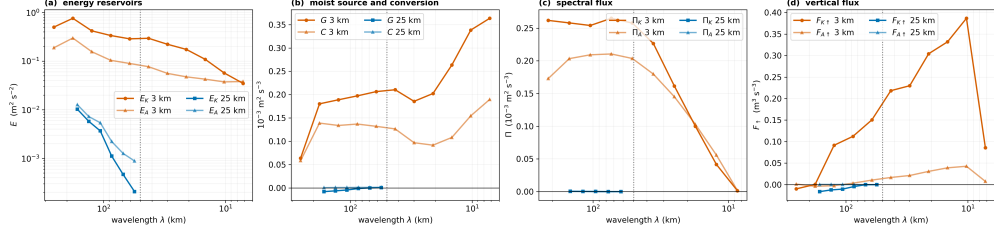


Fig. 5 The convective energy budget in the current climate. Idealized squall line at $\Delta T = 0$, 3 km convection-resolving (orange) versus 25 km parameterized (blue), mass-weighted over the lower troposphere, as a function of wavelength. (a) Kinetic energy E_K and available potential energy E_A , (b) the moist source G and the conversion C , (c) the kinetic and potential spectral fluxes Π_K and Π_A (positive means downscale), and (d) the vertical fluxes $F_{K\uparrow}$ and $F_{A\uparrow}$.

177 Warming does not alter the energy budgets at different wavelengths uniformly,
 178 as shown by the $\Delta T = +4$ and 0 K differences in Figure 6. Panel (b) shows that
 179 the diabatic source and the buoyancy conversion increase more at finer scales under
 180 warming. The vertical fluxes in panel (d) strengthen at fine scales in response to the
 181 extra buoyancy conversion, consistent with the sub-25 km peak of the kinetic-energy
 182 increase in panel (a).

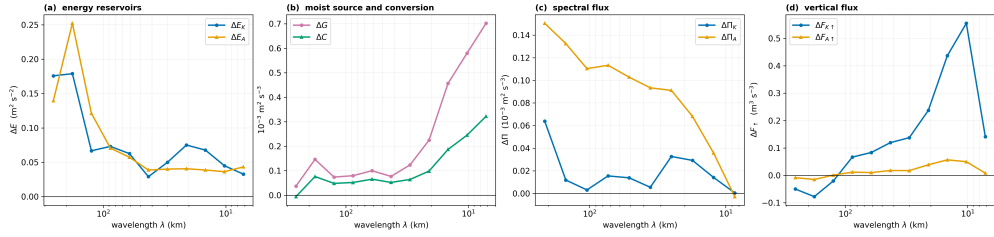


Fig. 6 Difference between $\Delta T = +4$ K and $\Delta T = 0$ K for the 3 km idealized squall line runs in lower troposphere. Panel (a) to (d) show the same terms as in Figure 5.

183 The additional kinetic energy at fine scales under warming is supplied by more dia-
 184 batic heating rather than by a more efficient conversion of heating into motion. In lower
 185 troposphere, the ratio of diabatic heating conversion from condensation G to buoy-
 186 ancy C remains broadly similar across wavelengths and changes little with warming.
 187 By contrast, the absolute increase in the diabatic source is strongly scale dependent:
 188 the warming sensitivity of both the source and the resulting kinetic-energy is substan-
 189 tially larger below 25 km. The enhanced source therefore supplies additional buoyancy
 190 conversion and kinetic energy at fine scales without requiring a corresponding increase
 191 in conversion efficiency. In this sense, warming does not make the convective heat
 192 engine more efficient. Rather, it supplies more fuel to it, with that additional fuel
 193 preferentially entering the fine-scale part of the spectrum.

194 The important feature of this response is not that convective energetics intensify
 195 with warming, but that their sensitivity to warming is strongly scale dependent. This
 196 scale dependence provides a plausible mechanism for what the current-climate ML
 197 operator fails to capture: the largest different response occurs below approximately 25
 198 km, the smallest wavelength that a 12-km precipitation input can represent, and within
 199 the range that becomes available only as the model approaches convection-permitting
 200 resolution. The climate signal therefore enters the downscaling problem through scales
 201 absent from the climate-model resolution input, and a wavelength-blind correction
 202 cannot recover the missing response. This scale selectivity is robust across the choices
 203 of atmospheric column height and to the choices of convection scheme, indicating
 204 that it is not tied to a particular vertical domain or parameterization (Figure 7 and
 205 Supplementary Figures S3 and S4). It is also the scale transition at which the current-
 206 and future-climate precipitation operators cease to be invariant: the statistical and
 207 dynamical analyses identify the same part of the spectrum having the strongest climate
 208 non-stationarity. The distinction between the two climate-trained operators is thus
 209 consistent with a climate dependence of the fine-scale dynamics, rather than being
 210 attributable solely to the ML architecture or the amount of training data from a single
 211 climate.

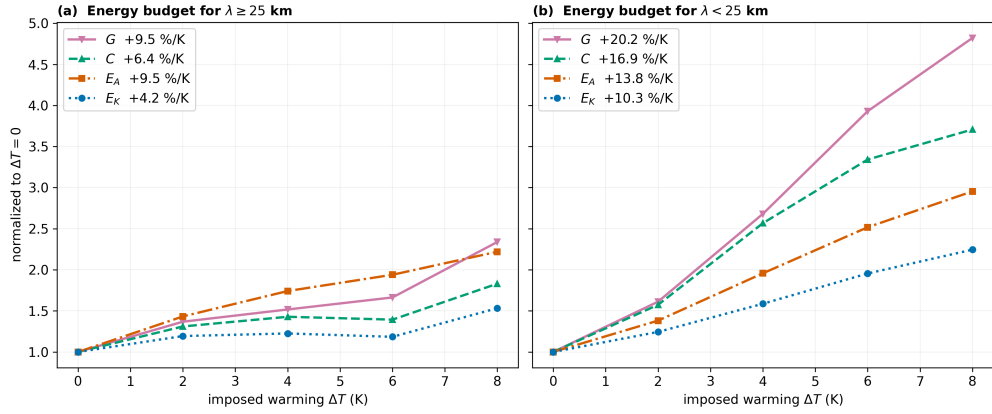


Fig. 7 The warming sensitivity of energy budget terms diabatic heating source G , buoyancy conversion C , available potential energy E_A , and kinetic energy E_K . Five experiments of $\Delta T = 0, +2, \dots, +8K$ are repeated for the 3 km squall line runs, and cut off at 25 km wavelength to regress for linear sensitivities for coarse and fine scales, respectively in panel (a) and (b). Each series normalized to its $\Delta T = 0$ value.

212 Complementing the network response matrices of Figure 3, we now construct the
 213 physical kinetic-energy transfer matrix that downscaling operators must implicitly rep-
 214 resent in Figure 8. Wavelength modes are binned into shells to quantify which bands
 215 become more active givers or receivers of kinetic energy with warming. The matri-
 216 ces in panels (a) and (b) satisfy $T_K[Q, P] = -T_K[P, Q]$: the energy transfer matrix is
 217 antisymmetric by construction [43]. Qualitatively prominent differences across warm-
 218 ing emerge in two clusters: larger scales transfer more kinetic energy to sub-25 km

219 scales, and the transfer from wavelengths below 36 km into wavelengths below 25 km
 220 increases further.

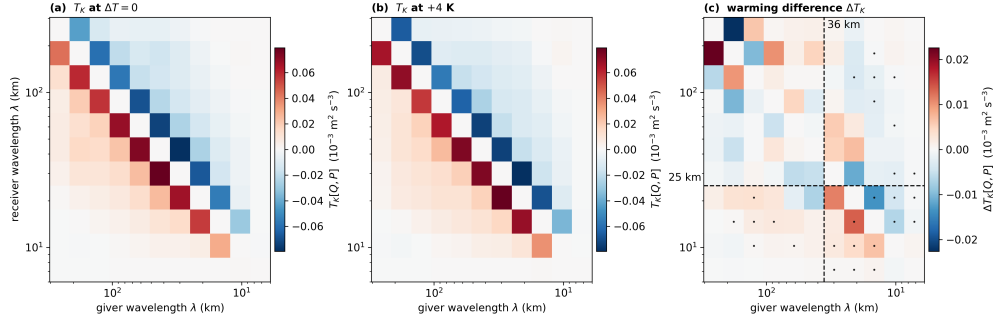


Fig. 8 Shell-to-shell KE transfer T_K (giver wavelength by receiver wavelength, lower troposphere) at $\Delta T = 0$ (panel a), $+4$ K (panel b), and taking the difference (panel c). Dashed lines sit on the shell edges separating 36 km (giver) and 25 km (receiver). Stippling marks cells whose transfer changes with a single sign at every increment of the $\Delta T = 0$ to $+8$ K sweep.

221 Taken together, the precipitation and energy-transfer analyses provide comple-
 222 mentary diagnostics of the same scale-selective non-stationarity. Figure 2 and 3 show
 223 that the learned coarse-to-fine precipitation transformation remains nearly invariant
 224 at coarser resolutions but changes at the 12-3 km mapping. Figures 6 to 8 show that
 225 warming changes the source, conversion, and transfer of atmospheric energy dispropor-
 226 tionately at wavelengths below the coarse-input resolution. The fine-scale precipitation
 227 response is therefore not being governed by a climate-invariant physical process. A
 228 current-climate downscaling operator can reproduce the future response only if the
 229 climate-induced change in the unresolved fine-scale dynamics is encoded within its
 230 training data, or through certain physical constraints.

231 3 Methods

232 3.1 Extreme-event selection and MPAS resimulations

233 Following Dougherty et al. [9], extreme-precipitation days over the Puerto Rico
 234 region (68.53° - 64° W, 15.97° - 20.5° N) are identified in a 10-member ensemble of high-
 235 resolution Community Earth System Model (CESM) simulations MESACLIP [3, 4],
 236 excluding the first member. Using the spatial average of daily accumulated rainfall, we
 237 select 78 extreme days from 2001-2021 current and 77 days from 2041-2061 near future
 238 under RCP8.5 scenario, approximately the 99th percentile of days in each period.
 239 Each event is resimulated with MPAS [15] at four resolutions: a global quasi-uniform
 240 48-km mesh and variable-resolution 92-25 km, 46-12 km and 60-3 km circular meshes
 241 whose refined interiors cover the study region. Each simulation is run 36 hours with
 242 scale-aware Grell-Freitas scheme [44] and comprises 12 hours of spin-up, with hourly
 243 precipitation extracted on regular grids of 48, 25, 12, and 3 km. Data are split 70/15/15
 244 into training, validation and test sets per climate.

245 3.2 Weakly nonlinear baseline: EnsCGP

246 The ensemble-approximated conditional Gaussian process (EnsCGP) [25, 26, 35]
 247 treats coarse and fine fields ($\mathbf{x}, \mathbf{y}$) as jointly Gaussian. With demeaned anomalies, the
 248 posterior mean is given by:

$$\hat{\mathbf{y}} = \bar{\mathbf{y}} + \mathcal{M}(\mathbf{x} - \bar{\mathbf{x}}), \quad \mathcal{M} = \mathcal{K}_{YX}(\mathcal{K}_{XX} + \sigma_{\text{obs}}^2 \mathcal{I})^{-1} \quad (1)$$

249 where $\mathcal{K}_{XX}$ is the covariance of the coarse anomalies, $\mathcal{K}_{YX}$ is the cross-covariance
 250 between fine and coarse anomalies, and σ_{obs}^2 is a regularization term selected via gen-
 251 eralized cross-validation [45]. We employ ensemble-based reduced-rank square-root
 252 methods [46, 47] to efficiently compute large matrix inversions and covariance matrices.
 253 The EnsCGP-GAN comparison at the two coarse transitions is shown in Supplemen-
 254 tary Figure S1. These comparisons locate a practical linear-adequacy boundary near
 255 25→12 km. The paper’s major conclusions do not depend on specific ML structure.

256 3.3 Deep-learning model: frequency-separated ESRGAN

257 The deep learning model is an enhanced super-resolution GAN (ESRGAN) [48, 49]
 258 with frequency-separated losses [34, 35]. Coarse precipitation is bicubically interpo-
 259 lated to the target grid and normalized before training. The generator is a deterministic
 260 residual-in-residual dense-block network [50]. The discriminator is a VGG-style deep
 261 convolutional classifier [51]. Target and generated fields are decomposed by Gaussian
 262 blur into low- and high-frequency components. The generator minimizes

$$\mathcal{L}_G = 1.0 \|\hat{y}_{\text{LF}} - y_{\text{LF}}\|_{L1} + 0.1 \mathcal{L}_{\text{spec}}(\hat{y}, y) + 0.03 \mathcal{L}_{\text{RaGAN}}^{(G)}(y_{\text{HF}}, \hat{y}_{\text{HF}}), \quad (2)$$

263 where the spectral term $\mathcal{L}_{\text{spec}}$ penalizes the mean-squared difference of log radially-
 264 averaged power spectra of generated and target precipitation. The adversarial term is
 265 implemented with binary cross-entropy-with-logits loss in relativistic-average form,

$$\mathcal{L}_{\text{RaGAN}}^{(G)} = \mathbb{E}_{y, \hat{y}} [\text{BCE}(\mathcal{D}_\phi(\hat{y}_{\text{HF}}) - \mathbb{E}_y[\mathcal{D}_\phi(y_{\text{HF}})], 1)], \quad (3)$$

266 and the discriminator loss function is given in the same form as [35]:

$$\mathcal{L}_D = \frac{1}{2} \mathbb{E}_{y, \hat{y}} [\text{BCE}(\mathcal{D}_\phi(y_{\text{HF}}) - \mathbb{E}_{\hat{y}}[\mathcal{D}_\phi(\hat{y}_{\text{HF}})], 1) + \text{BCE}(\mathcal{D}_\phi(\hat{y}_{\text{HF}}) - \mathbb{E}_y[\mathcal{D}_\phi(y_{\text{HF}})], 0)]. \quad (4)$$

267 3.4 Idealized squall-line and energy budget

268 The mechanism experiments use idealized squall lines [39] in doubly periodic MPAS
 269 domains at 3-km and 25-km spacing with Thompson microphysics [52] and the Grell-
 270 Freitas scheme [44] on or off. Surface warming adds uniform $\Delta T \in \{0, +2, +4, +6, +8\}$
 271 K at fixed relative humidity under Clausius-Clapeyron rate of 7.0 % K⁻¹. The setups
 272 are shown in Supplementary Figure S2. Spin-up time is 4 hours with total 12 hours

per simulation. We cast the budget in the formulation of Augier and Lindborg [33].
For horizontal-wavenumber shell k at model level z ,

$$\partial_t E_K(k, z) = T_K(k, z) + C(k, z) - \partial_z F_{K\uparrow}(k, z) - D_K(k, z), \quad (5)$$

$$\partial_t E_A(k, z) = T_A(k, z) + G(k, z) - C(k, z) - \partial_z F_{A\uparrow}(k, z) + J(k, z) - D_A(k, z), \quad (6)$$

Hats denote horizontal Fourier transforms on the doubly periodic domain, $\langle \cdot \rangle_k$ the corresponding co-spectral density at shell k , and primes denote anomalies about the reference state, defined as the horizontal-and-time mean over the analysis window. The thermodynamic variable is the density potential temperature [53], with reference profile $\theta_\rho(z)$, static stability N^2 and APE weight $\gamma(z) = g^2/(\bar{\theta}_\rho^2 N^2)$. The budget carries the kinetic energy $E_K = \frac{1}{2}|\hat{\mathbf{u}}'|^2$ of the velocity anomaly $\mathbf{u}' = (u', v', w')$, such that the APE density, the conversion by buoyancy, and the diabatic source are:

$$E_A = \frac{\gamma}{2}|\hat{\theta}'_\rho|^2, \quad C = (g/\bar{\theta}_\rho) \text{Re}[\hat{\theta}'_\rho \hat{w}'^*], \quad G = \gamma \text{Re}[\hat{\theta}'_\rho \hat{\theta}'_{\text{cond}}^*], \quad (7)$$

where $\hat{\theta}'_{\text{cond}}$ is the anomalous condensational heating rate estimated from the resolved moisture budget. The vertical fluxes and the adiabatic term for vertical motions are

$$F_{K\uparrow} = \langle w' \varphi' \rangle_k + \frac{1}{2} \langle w' |\mathbf{u}'|^2 \rangle_k, \quad F_{A\uparrow} = \frac{\gamma}{2} \langle w' \theta'^2_\rho \rangle_k, \quad J = \frac{1}{2} \langle \partial_z \gamma \rangle \langle w' \theta'^2_\rho \rangle_k, \quad (8)$$

where φ' is the pressure perturbation. D_K, D_A are defined as budget residuals by dissipation. The spectral flux is the cumulative transfer $\Pi_X(k) = \sum_{Q \geq k} \sum_{P < k} T_X[Q, P]$. Layer budgets are then vertically integrated with a mass weighting $\bar{\rho} dz$. See detailed derivations in Supplementary Text.

4 Discussion

This study identifies a scale-selective breakdown of climate invariance in machine-learning downscaling for extreme rainfall events. Across the Puerto Rico experiments, the two coarser mappings remain invariant across climate, whereas the 12-3 km, convection-resolving transition does not. The non-stationarity therefore does not appear uniformly across the downscaling hierarchy. Rather, it becomes strongest at the fine scales that conventional climate models do not explicitly resolve. This creates a fundamental difficulty for km-scale downscaling, because the climate dependence that matters most emerges where the coarse driving model contains the least direct information, concentrated at the transition from parameterization to explicitly resolved deep convections.

The coupled energy budget provides a mechanistic explanation. Condensational heating supplies available potential energy, which is converted into kinetic energy through buoyancy and redistributed across wavelengths by nonlinear transfers. This atmospheric heat engine is not equally sensitive across scales: under warming, the condensational source and associated buoyancy conversion increase disproportionately at fine wavelengths, strengthening the kinetic-energy and the transfer of energy toward scales below 25 km in wavelength. The resulting deficit in the ML downscaling operator

is therefore not a peculiarity of a particular network, but the energetic signature of a climate-dependent scale transition.

This finding reframes the question of climate invariance [32] in downscaling. Invariance is not necessarily a property of the neural network itself, but of the physical mapping between scales that the network represents. The critical failure occurs exactly at the scales for which kilometer-scale products are most valuable. Emulation-plus-downscaling systems trained on single-climate storm-resolving archives [20, 21] face the same constraint: their finest-scale mapping can become climate dependent even when their coarser mappings remain robust. The practical implication is therefore targeted rather than wholesale: retraining, fine-tuning or explicit climate conditioning should focus on the convection-resolving transition, while the coarser mappings may be retained.

Nor can a wavelength-blind correction recover this response. The energetics imply that any such correction must be scale dependent: under warming, the moist source intensifies on sub-25 km scales at twice the rate of the scales resolved by the input, while its spectral peak shifts towards finer wavelengths. Meanwhile, changes in rainfall organization can increase absolute fine-scale power even as its fractional spectral contribution declines. Calibrating an operator trained in a single climate against a future mean, an extreme quantile or a Clausius-Clapeyron factor would therefore adjust a single scalar to compensate for a spectrally varying bias that is largest below the smallest wavelength represented by the coarse input, where the input provides no constraint. Single statistics would not reveal this failure: integrated across wavelengths, the source remains consistent with its thermodynamic baseline. The concern is not the thermodynamic amplification reported for extreme precipitation [54], but a scale redistribution that diagnostics cannot detect.

Our results further suggest that downscaling operators should be audited not only by predictive skill, but by the physical consistency of the scale transitions they represent under climate perturbation. A simple, repeatable idealized experiment, here a surface warming sweep of a squall line, can isolate the scales at which resolved dynamics respond to climate change, and therefore identify where an operator’s assumed invariance breaks down. Such tests provide a computationally inexpensive complement to the convection-permitting projections that the operator is designed to emulate. More generally, scale-aware physical auditing could provide a practical route for identifying where climate invariance fails before the failure is propagated through a multiscale downscaling system.

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Data availability

The MESACLIP ensemble is publicly available from the NSF NCAR Climate Data Gateway (historical: doi:10.5065/7N1X-K278; RCP8.5: doi:10.5065/PNCR-5S34) [3, 4]. The processed MPAS event fields at 48/25/12/3 km, the idealized squall-line simulations, and the data for each figure are deposited on Zenodo (10.5281/zenodo.22086480) and are available to editors and reviewers during peer review. They will be made publicly available upon acceptance.

Code availability

MPAS is open source at <https://github.com/MPAS-Dev/MPAS-Model>. Trained weights, diagnostics, and energy-budget code will be archived on Zenodo with a DOI at acceptance. The codes for downscaling models and for the spectral energy-budget diagnostics, together with trained model weights, are deposited on Zenodo (10.5281/zenodo.22086480) and are available to editors and reviewers during peer review. They will be made publicly available upon acceptance.

Author information

Contributions

X.Y. designed the study, machine-learning experiments, spectral energy-budget analyzes and verification, and wrote the manuscript. A.S. developed the EnsCGP and frequency-separated GAN methodology. E.M.D. developed the extreme-event identification, performed the MPAS resimulations, and edited the manuscript. S.R. conceived the EnsCGP and GAN framework, supervised the research and edited the manuscript. All authors discussed the results and reviewed the manuscript.

Ethics declarations

The authors declare no competing interests.

Use of AI

Large language models (Anthropic Claude) assisted with analysis code and refining the language. AI use did not introduce new intellectual content, and the authors take full accountability for the analysis, figures, and text.

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