Review of the article "Spatial pattern regression for meteorological fields interpolation"

In this manuscript, the authors introduce a spatial interpolation framework termed *Spatial Pattern Regression* (SPR), applied over North America. The method consists of extracting spatial patterns from Regional Climate Model (RCM) simulations using Principal Component Analysis (PCA), and then using these patterns within a spatial regression framework to derive gridded meteorological fields from station observations.

The manuscript addresses an important topic for the hydrological community. The increasing availability of RCM simulations indeed provides promising opportunities to improve the spatial interpolation of meteorological observations, especially in data-sparse regions. Overall, the manuscript is clearly written and scientifically relevant. However, several methodological clarifications and additional analyses are required before publication can be considered.

Major comments

1. **Fair comparison between SPR and benchmark interpolation methods**

   The tested approaches are not evaluated under equivalent settings. Specifically, IDW, OK, and KED are directly applied to station observations Z_d, whereas SPR is applied to anomalies relative to the RCM background field :$Z'_d = Z_d - Z_d^{grid}$. This makes the comparison difficult to interpret. It is possible that IDW, OK, or KED applied to the same anomaly fields could perform similarly or even outperform SPR. At present, the conclusions regarding the superiority of SPR remain insufficiently supported. I therefore strongly recommend evaluating all interpolation methods within the same anomaly-based framework.

   Morover, the authors should investigate the sensitivity of SPR to the definition of anomalies :
   — additive anomalies :$Z'_d = Z_d - Z_d^{grid}$
   — multiplicative anomalies : $Z'_d = \frac{Z_d}{Z_d^{grid}}$

   The additive formulation is generally more appropriate for temperature, while multiplicative or relative anomalies are often preferable for precipitation due heteroscedasticity.

2. **Robustness to station sampling and validation strategy**

   For both the synthetic and real-data experiments, the results may be highly sensitive to the specific sampling of training stations, particularly under low station-density scenarios.

   I recommend using a K-fold cross-validation framework (or repeated random subsampling) in which several independent training/validation splits are generated. Performance metrics (M) should then be averaged across folds K :

   $$\overline{M} = \frac{1}{K}\sum_{k=1}^{K} M_k$$

   This would provide more robust and statistically reliable conclusions.

3. **Ground truth used for SSIM and spatial field evaluation**

   The manuscript should clarify what is used as the "ground truth" for the SSIM calculations and spatial field comparisons. If the reference field is the RCM itself, this may introduce an important methodological bias. It is well known that RCMs tend to smooth spatial variability, particularly for precipitation extremes. Consequently, methods reproducing smoother spatial fields (such as SPR) may be artificially favored over approaches preserving higher local variability (e.g., KED). The discussion section should explicitly acknowledge that conventional RCMs at approximately 11 km resolution strongly smooth the spatial variability of meteorological fields, especially precipitation, and that the use of convection-permitting regional climate models (CP-RCMs), typically at 1-4 km resolution, represents a promising approach for improving the realism of spatial structures used within SPR.

Minor comments

5. **Lines 16–17**

   The manuscript separates "spatial heterogeneity" and "extremes", although these concepts are closely related. In this context, "variability" appears more appropriate than "heterogeneity". I suggest replacing : "spatial heterogeneity and extremes at fine spatial and temporal resolution" with "the fine spatio-temporal variability of meteorological fields, especially during extreme events".
6. **Lines 22–24**

   Meteorological radar products provide gridded precipitation estimates but do not fully belong to the three categories listed by the authors. Radar datasets can be used directly, without relying on station observations or reanalysis frameworks. This category should therefore be acknowledged separately.
7. **Lines 23–24**

   Several widely used gridded meteorological products and should be cited when discussing interpolation, reanalysis, and climate-model-based datasets.

   Examples include :

   — Cornes, R. C., Van Der Schrier, G., Van Den Besselaar, E. J., and Jones, P. D. (2018). An ensemble version of the E-OBS temperature and precipitation data sets. Journal of Geophysical Research : Atmospheres, 123(17), 9391-9409.

   — Munoz-Sabater, J., Dutra, E., Agustí-Panareda, A., Albergel, C., Arduini, G., Balsamo, G., ... and Thépaut, J. N. (2021). ERA5-Land : A state-of-the-art global reanalysis dataset for land applications. Earth system science data, 13(9), 4349-4383.

   — Caillaud, C., Somot, S., Alias, A., Bernard-Bouissières, I., Fumière, Q., Laurantin, O., ... and Ducrocq, V. (2021). Modelling Mediterranean heavy precipitation events at climate scale : an object-oriented evaluation of the CNRM-AROME convection-permitting regional climate model. Climate Dynamics, 56(5), 1717-1752.
8. **Lines 36–37**

   Climatological fields are also frequently derived directly from station observations. The article should state cite datasets/methods :

   — Daly, C., Taylor, G. H., and Gibson, W. P. (1997, October). The PRISM approach to mapping precipitation and temperature. In Proc., 10th AMS conf. on applied climatology (Vol. 675).

   Relevant reference :
9. **Lines 38–39**

   If I understand correctly, the spatial structures extracted from the RCM are climatological patterns rather than daily evolving fields. This point should be clarified explicitly. Regarding Equation (1), does $Z_{n,p}^{grid}$ represent all daily RCM fields ? If so, the indexing notation should probably be revised (e.g., $1 : n$) to better reflect the temporal dimension.

10. **Lines 40–41**

    SPR can only be classified as a hybrid between spatial interpolation and reanalysis if the RCM predictors vary dynamically over time (e.g., daily or sub-daily evolving structures). If SPR only relies on climatological information extracted from the RCM, then the method is conceptually closer to a spatial interpolation framework constrained by climatological covariates. Please clarify this distinction.

11. **Figure 1**

    Please add the station locations to Figure 1(b). This would greatly the interpretation of the geographical context.

12. **Lines 74–75**

    The statement that the method "does not require overlap" is true for precipitation but more questionable for temperature because of long-term warming trends. For temperature, inconsistencies between climatological periods may introduce systematic biases. This issue should be discussed, together with potential solutions such as detrending :

13. **Lines 105–110**

    The manuscript states that SPR exploits the covariance structure. However, the method actually exploits much richer information : spatial patterns extracted from the RCM.

    Using covariance structure alone would correspond to statements such as :

    $$\mathrm{Corr}(Z(x_i), Z(x_j)) \to 0 \quad \text{when} \quad ||x_i - x_j|| \to \infty$$

    SPR instead leverages spatial patterns derived from the RCM. This is potentially more informative, but also riskier because any regional structural bias in the RCM may directly influence the interpolation. This remark should be explicitly discussed. Some authors use RCM, CP-RCM simulations, NWP in another way, it should be mentionned in the discussion :

    — Dura, V., Evin, G., Favre, A. C., and Penot, D. (2025). Improving Precipitation Interpolation Using Anisotropic Variograms Derived from Convection-Permitting Regional Climate Model Simulations. EGUsphere, 2025, 1-25.

    — Khedhaouiria, D., Gasset, N., Fortin, V., Dimitrijevic, M., Bulat, M., and Wang, X. (2026). The Canadian Surface Reanalysis (CaSR) v3. 2 precipitation dataset : A 45-year high-resolution analysis for North America (1980–2024). EGUsphere, 2026, 1-40.

    — Vernay, M., Lafaysse, M., and Augros, C. (2025). Radar-based high-resolution ensemble precipitation analyses over the French Alps. Atmospheric Measurement Techniques, 18(8), 1731-1755.

14. **Lines 122–123**

    The manuscript states that SPR does not make distributional assumptions. This is not entirely correct. The regression residuals implicitly assume :$\varepsilon \sim \mathcal{N}(0, \sigma^2)$, with residuals being independent and identically distributed (IID). Therefore, SPR still relies on classical regression assumptions.

15. **Line 209**

    The sensitivity of the transformation step should be evaluated. In precipitation interpolation, square-root transformations are frequently used at the daily timescale to stabilize variance and reduce skewness.

    — Erdin, R., Frei, C., and Künsch, H. R. (2012). Data transformation and uncertainty in geostatistical combination of radar and rain gauges. Journal of Hydrometeorology, 13(4), 1332-1346.

16. **Line 237**

I believe the Kling–Gupta Efficiency (KGE) would be more informative than RMSE alone.

KGE explicitly evaluates :

— correlation,
— bias,
— variability ratio,

through :

$$\text{KGE} = 1 - \sqrt{(r-1)^2 + (\beta-1)^2 + (\gamma-1)^2}$$

where :

— r is the correlation,
— β the mean bias ratio,
— γ the variability ratio.

In the present context, the variability component is particularly relevant because it directly evaluates biases in spatial variability.

17. **Table 3**

I recommend replacing Table 3 with boxplots (or violin plots). This would make the distribution of RMSE values much easier to interpret visually and would better highlight :

— dispersion,
— outliers,
— robustness across experiments.