

# Review of “Accurate and fast prediction of radioactive pollution by Kriging coupled with Auto-Associative Models” (egusphere-2024-3838)

In this manuscript, the authors propose an approach to predict the spatial distribution of radioactive pollution using a novel emulation methodology applies to numerical model outputs. The emulation methodology involves constructing a reduced-dimension representation of the high dimensional model outputs using a method called auto-associative models (AAMs). The mapping between the numerical model parameters and the reduced-dimension representation is constructed using a kriging approach. The authors compare their method to existing approaches for predicting nucleotide exposure in a French context and find it to be both accurate (in terms of false-negative and false-positive rates) and fast to run.

The significance of the work is well justified, and the emulation approach is well principled. I also find the application to be principled and, on the whole, well executed. However, I have major comments regarding the clarity and detail of the exposition, given below. I also think the authors need to do more to justify the use of AAM in place of the more traditional approach of using principal component analysis (PCA). Finally, I have some minor typographical comments.

My major comments are as follows:

## 1. Regarding the use of AAM:

- (a) The authors provide almost no technical detail on AAM at all. I think it is impossible to understand the results without at least some technical detail.
- (b) The authors claim that AAM is better able to “capture nonlinear structures” than PCA. What does this mean? Non-linear in what? PCA involves a linear combination of basis vectors, but each basis vector can contain non-linear structures in the original parameter space.
- (c) The authors ought to provide some evidence that AAM is better than PCA for their specific problem. A very simple way would be to repeat the validation analysis in Section 4.1.1 using PCA and compare the metrics. I think that would suffice, avoiding the authors the need to reconstruct the entire emulator using PCA.

## 2. Regarding the construction of the emulator:

- (a) Can the authors expand on how the dimension of the AAM was chosen? For example, can the metrics in Section 4.1.1 be given for different dimensions? Such a discussion would be valuable for someone wanting to use the method for a different problem.
- (b) Are the emulators fit independently to each AAM parameter? This can be justified for PCA through the orthogonality of the principal components, is there a similar justification for AAM?

## 3. Regarding the validation metrics:

- (a) I think that in Figure 7, the histogram, this is the FMS across the training samples, is that right? It would be good to clarify this in the text.
- (b) I find the FMS metric in Section 4.1.1 to be hard to interpret. I much prefer the separate treatments of false positives and false negatives that eventually occurs for the emulator in Section 4.2. Can the authors just use this here?

I think this is important because it speaks to how conservative the method is in different ways. Indeed, I think the whole application could be better structured by discussing how to manage the trade-off between false positives and false negatives (where I note that in the end the author’s method was best for both!)

- (c) In Section 4.1.2, the SMSE appears to equal to the conventional  $1 - R^2$  from linear regression. Is this correct? If so, why is the SMSE for Score 9 so bad, when the predictions look okay in Figure 5?
- (d) In Section 4.2, I don’t understand the x-axis for Figure 9 and its relationship to Table 3. Can the authors explain the metrics in more detail?

My minor comments are as follows:

1. The abstract states “The main limitation of emulation methods is that they can only predict scalar quantities.” This may be true for existing methods for radioactive pollution, but it is not true in general: many moderate- and high-dimensional emulators have been constructed for vector-valued outputs. The authors even cite some papers in atmospheric science in their introduction to this extent.  
A similar statement occurs around line 53, when in the very following paragraph the authors give some examples of vector-valued outputs.
2. The authors may wish to consider whether to cite the paper by Cartwright et al. (2023) which uses a related approach to emulating vector-valued outputs through neural networks.
3. It may be worth citing a standard text of kriging in Section 3.2, e.g., Cressie (1993), for some of the mathematical details.
4. In Figure 6, the legend is extremely small.

Some typographical comments:

1. When giving multiple parenthetic citations, please format these as (Name et al., 2024; Name et al., 2025), rather than (Name et al., 2024), (Name et al., 2025).
2. Line 35: there is a stray ( ) here.
3. Line 62: “sets of map” should be “sets of maps”?
4. Table 1: the formatting of the units is inconsistent.

## References

- Cartwright, L., Zammit-Mangion, A., and Deutscher, N. M. (2023). Emulation of greenhouse-gas sensitivities using variational autoencoders. *Environmetrics*, 34(2):e2754.
- Cressie, N. (1993). *Statistics for Spatial Data*. John Wiley & Sons.