Responses to Reviewers' Comments

for

A Multivariate Analysis of Atmospheric Drivers for Western European Heatwaves

https://doi.org/10.5194/egusphere-2025-2460

Submitted to

Earth System Dynamics

by

Aytaç Paçal[1,2], Birgit Hassler[1], Katja Weigel[2,1], Miguel-Ángel Fernández-Torres[3], Gustau Camps-Valls[4], Veronika Eyring[1,2]

[1] Deutsches Zentrum für Luft- und Raumfahrt (DLR), Institut für Physik der Atmosphäre, Oberpfaffenhofen, Germany

[2] University of Bremen, Institute of Environmental Physics (IUP), Bremen, Germany

[3] Department of Signal Theory and Communications, Universidad Carlos III de Madrid (UC3M), Leganés, Madrid, Spain

[4] Image Processing Laboratory (IPL), Universitat de València (UV), Paterna, València, Spain

Authors’ Response to the Editor

Dear Dr. Kai Kornhuber,

We would like to thank you and the reviewers for the constructive and valuable feedback, which has notably improved the quality of our manuscript. In response to the reviewers’ comments, we have conducted additional statistical analyses to ensure the robustness of our findings.

The revised manuscript now includes a comprehensive temporal split analysis using detrended and non-detrended dataset to validate distributional shifts in the latent space. We have also refined our discussion to distinguish between thermodynamic and dynamical shifts and have carefully revised claims regarding the monitoring of climate change. All changes are highlighted in the annotated version of the manuscript.

We hope that these revisions address all remaining concerns, and we kindly ask you to consider the revised manuscript for publication in Earth System Dynamics.

Sincerely,

Aytaç Paçal, Birgit Hassler, Katja Weigel, Miguel-Ángel Fernández-Torres, Gustau Camps-Valls, Veronika Eyring

Response to Reviewer 1 Comments

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[4] Image Processing Laboratory (IPL), Universitat de València (UV), Paterna, València, Spain

Authors' Response to Reviewer 1

General Comments. Dear Authors,
thanks a lot for revising the manuscript. You have addressed most of my comments and the quality of the manuscript has improved notably.
However, one open point remains: I still believe the random split is the valid one. I agree that it confirms that the heatwaves somewhat cluster by seasonality in latent space. But to me it becomes clear that the mentioned shift in summer heat wave patterns is a mere artifact of the chosen temporal splitting. To convince me otherwise, you would have to prove this shift statistically. For example by showing that the mean embedding of summer time heatwaves in the random splitting setting changes between 1950-1990 and 2000-2020 in the test set. Otherwise, please revise the article in such way that the claim of a change in heatwave patterns is not mentioned (eg. Line 11f. in the abstract).
Thanks again and best wishes!

Response: Thank you for your positive feedback on our revisions and for highlighting the remaining open point regarding the data splitting strategy.

To address your concern, we conducted statistical validation of seasonal shifts in the latent space to compare the training (1941–1990) and test (2001–2022) periods. VAE captures variations across seasons even with the detrended dataset. To separate a warming effect from dynamical contributions to temporal shifts, we expanded our analysis to include both detrended and non-detrended data. In non-detrended data, summer (JJA) shows the largest latent space shift (Mahalanobis distance $D = 2.00$, $p < 0.001$), followed by autumn ($D = 1.23$), spring ($D = 0.89$), and winter (D=0.43). However, after detrending to remove a warming signal, this pattern reverses; winter shifts become strongest ($D = 1.40$), while summer shifts reduce dramatically ($D = 0.34$) as shown in Table 1 for non-detrended data, Table 2 for detrended data. This indicates that the evolution of summer heatwaves is dominated by thermodynamic intensification, whereas winter changes reflect dynamical reorganization of circulation patterns. We revised the text to better clarify these findings.

Abstract
$\cdots$ The VAE was trained on heatwave samples from 1941 to 1990 and evaluated using samples from 2001 to 2022, effectively clustering heatwave events by season

and identifying known dynamical regimes, such as summer blocking highs and winter omega blocks. The VAE model captures the interplay and temporal evolution between different atmospheric variables in their contributions to heatwaves over Western Europe.

Notably, the VAE identifies distinct atmospheric circulation patterns that align with seasonal dynamics even when applied to detrended and deseasonalized data. When analyzing non-detrended data, recent summer heatwaves occupy a distinct region in the latent space, reflecting the thermodynamic intensification of these events.

However, analyses on detrended data reveal that significant structural shifts in atmospheric configurations persist across all seasons, suggesting that the model captures genuine changes in multivariate dynamics beyond simple mean warming. Composite anomaly maps further show coherent pre-onset patterns across variables. These results demonstrate the utility of VAEs for extracting physically meaningful, multivariate representations of heatwave dynamics from reanalysis data, highlighting changes in their atmospheric drivers over recent decades.

...

New Paragraph after Line 251

To further validate that the observed latent space shifts are not merely artifacts of global warming trends or the data split, we performed a secondary analysis using detrended variables. We quantify distributional shifts using Mahalanobis distance (D), which measures how far the center of the test-period distribution has moved from the training-period distribution in units of standard deviations (De Maesschalck, Jouan-Rimbaud, and Massart 2000). While we focus on non-detrended data in this study to capture the full thermodynamic intensification of recent heatwaves, the detrended data analysis reveals that statistically significant shifts ($p < 0.001$) persist across all seasons between training (1941-1990) and test (2001-2022) periods (See Appendix Table A2 and Figure A8. This suggests that, beyond mean-temperature increases, the multivariate structure of atmospheric patterns associated with heatwaves is evolving. Interestingly, in the detrended dataset, summer (JJA) samples exhibits a smaller shift ($D = 0.34$), while winter (DJF) shows a much more robust dynamical evolution ($D = 1.40$). In the non-detrended dataset, summer samples show a higher shift, pointing to a thermodynamical warming (See Appendix Table A3 and Figure A9). This finding is consistent with recent projections that changes in internal variability and moisture limitations can enhance land-atmosphere feedbacks, particularly in central and northern Europe, thereby altering the nature of extreme events (Beobide-Arsuaga et al. 2025). By capturing these residual shifts in the detrended data, the VAE identifies distribution changes in high-dimensional atmospheric states that are not solely attributable to thermodynamic warming.

Line 452-469

Meanwhile, positive anomalies in total cloud cover (*tcc*) are observed before the onset of summer heatwaves in cluster *#2*. Still, they gradually transition into negative anomalies in total cloud cover (*tcc*) over Central Europe as the heatwave evolves. Despite the data being standardized, the VAE organizes heatwave samples into clusters that align with seasonal differences, suggesting that seasonal signals are embedded in the atmospheric patterns of the test period.

Our statistical validation confirms that these latent space shifts are not mere artifacts of the temporal split or thermodynamic trends. The Hotelling's T^2 tests reveal highly significant temporal shifts ($p < 0.001$) across all seasons in both detrended and non-detrended data. The contrasting seasonal responses to detrending suggest that different physical mechanisms drive changes in heatwave patterns across seasons. While the separation of recent summer heatwaves is strongly influenced by thermodynamic intensification, the robust shifts maintained in other seasons demonstrate that the VAE successfully captures genuine structural changes in atmospheric dynamics that were not present during the training period. This finding aligns with previous studies, which have shown that climate change impacts seasonal cycles (Wang et al. 2021; Paçal et al. 2023). Similarly, Beobide-Arsuaga et al. (2025) showed that forced changes in internal variability under global warming are projected to further intensify summer heatwaves in central and northern Europe, highlighting that frequent moisture limitations in these regions enhance land-atmosphere feedbacks, increasing both the intensity and variability of heatwaves. This study highlighted the potential of machine learning methods to improve our understanding of heatwaves. By using a VAE, we uncovered a data-driven classification of heatwave events that not only aligns with known atmospheric circulation regimes from previous studies but also reveals their seasonal and dynamical characteristics from several days before the onset of the heatwave until several days after. Our results showed that the VAE's latent space effectively captures key atmospheric patterns previously linked to extreme heat events, such as blocking highs, omega blocks, and persistent ridges, similar to those identified by Happé et al. (2024) and Rouges et al. (2023). The VAE's ability to identify these distributional changes in the latent space without supervision suggests that unsupervised learning techniques can be a valuable tool for identifying non-stationary shifts in high-dimensional atmospheric states (Behrens et al. 2022; Shamekh et al. 2023; Mooers et al. 2023; Camps-Valls et al. 2025).

Table 1: Temporal shift analysis of seasonal embeddings in detrended data (1941–1990 vs. 2001–2022). Samples are grouped by seasons based on their dates, not by GMM assignment. Different total sample counts compared to non-detrended data (Table 2) result from independent heatwave detection on detrended temperature fields.

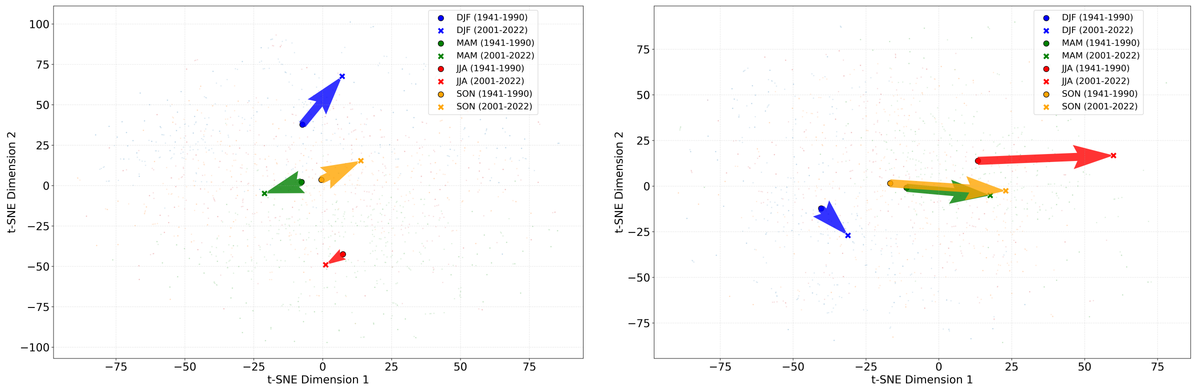
Season	n_{train}	n_{test}	p**-value**	**Mahalanobis** D	**Significance**
DJF (Winter)	395	172	1.11×10^{-16}	1.395	***
MAM (Spring)	398	233	3.23×10^{-6}	0.419	***
JJA (Summer)	441	212	3.38×10^{-4}	0.336	***
SON (Autumn)	398	183	1.94×10^{-7}	0.504	***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Temporal shift analysis of seasonal embeddings in non-detrended data (1941–1990 vs. 2001–2022). Samples are grouped by seasons based on their dates, not by GMM assignment.

Season	$n_{\mathbf{train}}$	$n_{\mathbf{test}}$	p**-value**	**Mahalanobis** D	**Significance**
DJF (Winter)	334	209	7.30×10^{-6}	0.434	***
MAM (Spring)	355	262	1.11×10^{-16}	0.894	***
JJA (Summer)	380	235	1.11×10^{-16}	2.002	***
SON (Autumn)	339	222	1.11×10^{-16}	1.231	***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$



(a) Detrended data

(b) Non-detrended data

Figure 1: Temporal evolution of seasonal atmospheric patterns in the VAE latent space, comparing detrended (a) versus non-detrended (b) datasets. Each panel displays the shift in mean latent embeddings for heatwave samples between train (1941–1990) and test period (2001–2022). Vectors (arrows) indicate the direction and magnitude of the distributional drift for each season: Winter (DJF, blue), Spring (MAM, green), Summer (JJA, red), and Autumn (SON, orange). All seasonal shifts are statistically significant ($p < 0.001$). In detrended data (a), winter patterns exhibit the most substantial displacement (Mahalanobis distance $D = 1.40$), indicating primarily dynamical changes. In non-detrended data (b), summer patterns show the largest shift ($D = 2.00$), dominated by thermodynamic warming (contributing 83% of the signal). This reversal demonstrates that summer heatwave evolution is primarily thermodynamic, while winter changes reflect genuine circulation regime reorganization.

Response to Reviewer 2 Comments

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[3] Department of Signal Theory and Communications, Universidad Carlos III de Madrid (UC3M), Leganés, Madrid, Spain

[4] Image Processing Laboratory (IPL), Universitat de València (UV), Paterna, València, Spain

Authors' Response to Reviewer 2

General Comments. I thank the authors for the thorough revisions; the manuscript has improved substantially. However, I still have reservations about the interpretability of the clusters, and have outlined my concerns in more detail below.

We thank the reviewer for their positive assessment of our revisions and for recognizing the improvements made to the manuscript. We have carefully considered the remaining concerns regarding cluster interpretability.

Major Comment 1

The authors state: "However, our goal is not to quantify frequency changes but to characterize the structural and dynamical patterns of heatwaves. The model focuses on circulation-related variability rather than long-term thermodynamic shifts." Because the heatwave threshold is based on 1940–1980, some events in the later period are likely still influenced by thermodynamic changes, i.e. events whose circulation patterns would not have produced a heatwave under 1950s baseline conditions. Combined with the absence of detrending in the input variables to the VAE, this raises concerns that the identified clusters could reflect climate-change-related thermodynamic shifts (e.g., Hadley cell expansion, enhanced land–atmosphere coupling) rather than distinct circulation regimes. This speculation is also consistent with the authors' own statement in the Discussion: "Our preliminary results did not show a clear predictive signal, suggesting that these large-scale configurations can occur without always leading to a heatwave." (L488) So indeed, one plausible explanation is that the model identifies circulation states that appear associated with heatwaves only because the underlying temperature field has been thermodynamically shifted upward. This issue seems particularly evident when comparing Figure 4 (manuscript) with Figure 1 (response letter), where the entire test set falls outside the range of Figure 4. Have the authors compared the statistical properties of the train/validation/test sets? Is there a detectable shift in these dynamical variables over time?

Response: We thank the reviewer for this insightful comment regarding the potential effects of thermodynamic shifts versus genuine dynamical circulation changes.

To address concerns that our results might reflect a global warming signal or insufficient detrending, we have conducted a comparative analysis using both non-detrended and detrended input variables for the VAE. As shown in Table 1 (non-detrended data), the latent space shift for summer (JJA) is indeed very high ($D = 2.002$), which likely reflects the strong thermodynamic signal the reviewer noted. However, when the linear trend is removed from the variables prior to VAE training (Table 2), we observe the following:

- Even after removing the linear trend, the shift between training (1941–1990) and test (2001–2022) periods remains statistically significant across all seasons ($p < 0.001$).
- Interestingly, in the detrended data, the largest shift occurs in winter (DJF, $D = 1.40$), while the summer shift is substantially reduced ($D = 0.34$). This suggests that while summer heatwaves are heavily influenced by thermodynamic warming, the underlying circulation patterns have also undergone a small but detectable change.
- The VAE continues to group samples by season in the detrended latent space, indicating that the model is capturing robust dynamical configurations rather than just mean temperature shifts.

We have revised the manuscript to acknowledge that thermodynamic trends contribute significantly to the separation in the latent space. We added the results of our temporal shift analysis comparing the detrended and non-detrended datasets to the manuscript. Since the mean seasonal embeddings show statistically significant shifts, we added a new paragraph to the results explaining these findings.

New Paragraph after Line 251

To further validate that the observed latent space shifts are not merely artifacts of global warming trends or the data split, we performed a secondary analysis using detrended variables. We quantify distributional shifts using Mahalanobis distance (D), which measures how far the center of the test-period distribution has moved from the training-period distribution in units of standard deviations (De Maesschalck, Jouan-Rimbaud, and Massart 2000). While we focus on non-detrended data in this study to capture the full thermodynamic intensification of recent heatwaves, the detrended data analysis reveals that statistically significant shifts ($p < 0.001$) persist across all seasons between training (1941-1990) and test (2001-2022) periods (See Appendix Table A2 and Figure A8. This suggests that, beyond mean-temperature increases, the multivariate structure of atmospheric patterns associated with heatwaves is evolving. Interestingly, in the detrended dataset, summer (JJA) samples exhibits a smaller shift ($D = 0.34$), while winter (DJF) shows a much more robust dynamical evolution ($D = 1.40$). In the non-detrended dataset, summer samples show a higher shift, pointing to a thermodynamical warming (See Appendix Table A3 and Figure A9). This finding is consistent with recent projections that changes in internal variability and moisture limitations can enhance land-atmosphere feedbacks, particularly in central and northern Europe, thereby altering the nature of extreme events (Beobide-Arsuaga et al. 2025). By capturing these residual shifts in the detrended data, the VAE identifies distribution changes in high-dimensional atmospheric states that are not solely attributable to thermodynamic warming.

Major Comment 2

The manuscript interprets the emergence of a distinct latent-space cluster with recent summer heatwaves as 1) that this indicates a shift in atmospheric dynamics consistent with climate change, 2) as a result of changes in seasonality, and 3) the potential of VAEs for climate-change monitoring:

1. "Notably, recent summer heatwaves form a distinct cluster within the latent space, pointing to a shift in atmospheric dynamics consistent with climate change." L10

2. "Heatwave samples corresponding to summer months are separated in the learned representation, reflecting distinct atmospheric conditions unprecedented in the training period. This suggests that parts of the changes in latent space are due to a changing seasonal cycle of atmospheric variables related to heatwaves." L455

3. "Furthermore, we observed that recent summer heatwaves form a distinct cluster separated from the historical distribution of events. This separation is consistent with the increasing intensity and changing nature of heatwaves under anthropogenic climate change (IPCC, 2021). The VAE's ability to detect these shifts in the latent space without supervision suggests that unsupervised learning techniques can be a powerful tool for monitoring climate change (Behrens et al., 2022; Shamekh et al., 2023; Mooers et al., 2023; Camps-Valls et al., 2025)." L464

However, these conclusion depends directly on the concerns raised above (in comment 1). The appearance of a separate cluster does not necessarily imply that the VAE can monitor climate change, particularly if the separation results from the train–test split or the lack of detrending rather than a genuine emergence of new circulation regimes. Both findings may be true, but at present the manuscript does not convincingly demonstrate a causal link between the latent-space shift and climate-change monitoring capability. Nor do I understand the conclusion that there is a shift in atmospheric dynamics consistent with climate change and a change in atmospheric dynamics of seasonality, because you find a separate cluster with recent summer heatwaves (again, the fact that you find these new heatwaves is also a direct result from the way you select the heatwaves). I would strongly suggest clarifying these points of discussion in your manuscript.

Response: We thank the reviewer regarding the interpretation of the VAE's "monitoring" capabilities.

We have clarified the manuscript to more clearly distinguish between shifts caused by the train-test split and genuine emerging dynamics. Our updated analysis demonstrates that:

1. The "distinct cluster" observed for recent summer heatwaves in the original manuscript was indeed amplified by thermodynamic trends. In the detrended analysis, this separation is less distinct but remains statistically significant (Table 2). This clarifies that the VAE is sensitive to changes in the multivariate relationship of the input variables.

2. We have tempered our conclusions on climate change monitoring. Rather than claiming the VAE "detects" climate change, we now describe it as a tool for identifying distribution shifts in high-dimensional atmospheric states. We acknowledge that the magnitude of this shift is seasonally dependent, with winter dynamics showing much stronger evidence of unprecedented configurations than summer.

3. We have clarified that the latent space shift reflects changes in the seasonal expression of heatwave-related variables. By analyzing the distance (D) across seasons, we show that the nature of these events changes disproportionately throughout the year.

We have revised the Abstract (L10) and Discussion (L455, L464) to reflect these nuanced findings, specifically emphasizing the role of winter dynamics and the reduction of the summer cluster separation upon detrending.

> **Abstract**
> $\cdots$ The VAE was trained on heatwave samples from 1941 to 1990 and evaluated using samples from 2001 to 2022, effectively clustering heatwave events by season and identifying known dynamical regimes, such as summer blocking highs and winter omega blocks. The VAE model captures the interplay and temporal evolution between different atmospheric variables in their contributions to heatwaves over Western Europe.
> Notably, the VAE identifies distinct atmospheric circulation patterns that align with seasonal dynamics even when applied to detrended and deseasonalized data.

When analyzing non-detrended data, recent summer heatwaves occupy a distinct region in the latent space, reflecting the thermodynamic intensification of these events.
However, analyses on detrended data reveal that significant structural shifts in atmospheric configurations persist across all seasons, suggesting that the model captures genuine changes in multivariate dynamics beyond simple mean warming. Composite anomaly maps further show coherent pre-onset patterns across variables. These results demonstrate the utility of VAEs for extracting physically meaningful, multivariate representations of heatwave dynamics from reanalysis data, highlighting changes in their atmospheric drivers over recent decades.
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Meanwhile, positive anomalies in total cloud cover (*tcc*) are observed before the onset of summer heatwaves in cluster *#2*. Still, they gradually transition into negative anomalies in total cloud cover (*tcc*) over Central Europe as the heatwave evolves. Despite the data being standardized, the VAE organizes heatwave samples into clusters that align with seasonal differences, suggesting that seasonal signals are embedded in the atmospheric patterns of the test period.
Our statistical validation confirms that these latent space shifts are not mere artifacts of the temporal split or thermodynamic trends. The Hotelling's T^2 tests reveal highly significant temporal shifts ($p < 0.001$) across all seasons in both detrended and non-detrended data. The contrasting seasonal responses to detrending suggest that different physical mechanisms drive changes in heatwave patterns across seasons. While the separation of recent summer heatwaves is strongly influenced by thermodynamic intensification, the robust shifts maintained in other seasons demonstrate that the VAE successfully captures genuine structural changes in atmospheric dynamics that were not present during the training period. This finding aligns with previous studies, which have shown that climate change impacts seasonal cycles (Wang et al. 2021; Paçal et al. 2023). Similarly, Beobide-Arsuaga et al. (2025) showed that forced changes in internal variability under global warming are projected to further intensify summer heatwaves in central and northern Europe, highlighting that frequent moisture limitations in these regions enhance land-atmosphere feedbacks, increasing both the intensity and variability

of heatwaves. This study highlighted the potential of machine learning methods to improve our understanding of heatwaves. By using a VAE, we uncovered a data-driven classification of heatwave events that not only aligns with known atmospheric circulation regimes from previous studies but also reveals their seasonal and dynamical characteristics from several days before the onset of the heatwave until several days after. Our results showed that the VAE's latent space effectively captures key atmospheric patterns previously linked to extreme heat events, such as blocking highs, omega blocks, and persistent ridges, similar to those identified by Happé et al. (2024) and Rouges et al. (2023). The VAE's ability to identify these distributional changes in the latent space without supervision suggests that unsupervised learning techniques can be a valuable tool for identifying non-stationary shifts in high-dimensional atmospheric states (Behrens et al. 2022; Shamekh et al. 2023; Mooers et al. 2023; Camps-Valls et al. 2025).

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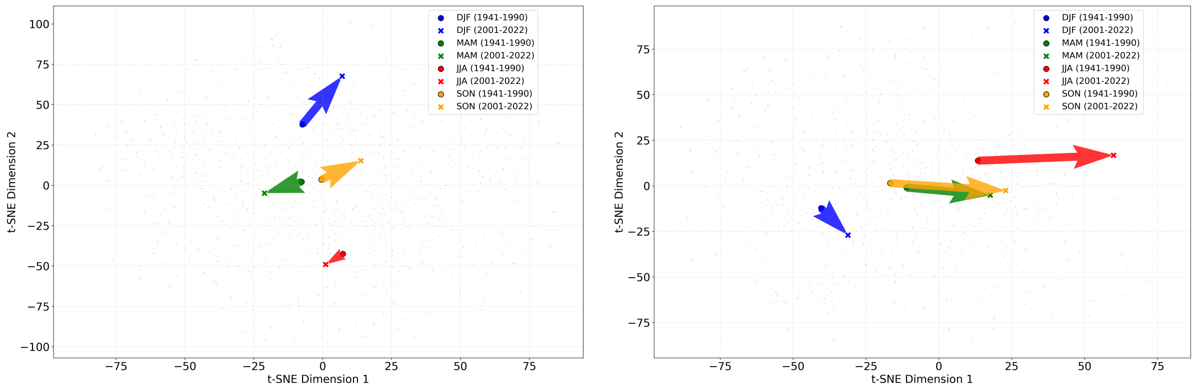

(a) Detrended data

(b) Non-detrended data

Figure 1: Temporal evolution of seasonal atmospheric patterns in the VAE latent space, comparing detrended (a) versus non-detrended (b) datasets. Each panel displays the shift in mean latent embeddings for heatwave samples between train (1941–1990) and test period (2001–2022). Vectors (arrows) indicate the direction and magnitude of the distributional drift for each season: Winter (DJF, blue), Spring (MAM, green), Summer (JJA, red), and Autumn (SON, orange). All seasonal shifts are statistically significant ($p < 0.001$). In detrended data (a), winter patterns exhibit the most substantial displacement (Mahalanobis distance $D = 1.40$), indicating primarily dynamical changes. In non-detrended data (b), summer patterns show the largest shift ($D = 2.00$), dominated by thermodynamic warming (contributing 83% of the signal). This reversal demonstrates that summer heatwave evolution is primarily thermodynamic, while winter changes reflect genuine circulation regime reorganization.

Table 2: Temporal shift analysis of seasonal embeddings in non-detrended data (1941–1990 vs. 2001–2022). Samples are grouped by seasons based on their dates, not by GMM assignment.

Season	$n_{\textbf{train}}$	$n_{\textbf{test}}$	p**-value**	**Mahalanobis** D	**Significance**
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References

Behrens, Gunnar et al. (2022). "Non-Linear Dimensionality Reduction With a Variational Encoder Decoder to Understand Convective Processes in Climate Models". In: *Journal of Advances in Modeling Earth Systems* 14.8, e2022MS003130. DOI: https://doi.org/10.1029/2022MS003130. eprint: https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2022MS003130.

Beobide-Arsuaga, Goratz et al. (Oct. 2025). "Increasing central and northern European summer heatwave intensity due to forced changes in internal variability". en. In: *Nature Communications* 16.1, p. 9485. DOI: 10.1038/s41467-025-65392-w.

Camps-Valls, Gustau et al. (2025). "Artificial intelligence for modeling and understanding extreme weather and climate events". en. In: *Nature Communications* 16.1, p. 1919. DOI: 10.1038/s41467-025-56573-8.

De Maesschalck, R., D. Jouan-Rimbaud, and D. L. Massart (Jan. 2000). "The Mahalanobis distance". In: *Chemometrics and Intelligent Laboratory Systems* 50.1, pp. 1–18. DOI: 10.1016/S0169-7439(99)00047-7.

Happé, T. et al. (2024). "Detecting Spatiotemporal Dynamics of Western European Heatwaves Using Deep Learning". In: *Artificial Intelligence for the Earth Systems* 3.4, e230107. DOI: 10.1175/AIES-D-23-0107.1.

Mooers, Griffin et al. (2023). "Comparing storm resolving models and climates via unsupervised machine learning". In: *Scientific Reports* 13.1, p. 22365. DOI: 10.1038/s41598-023-49455-w.

Paçal, Aytaç et al. (2023). "Detecting Extreme Temperature Events Using Gaussian Mixture Models". In: *Journal of Geophysical Research: Atmospheres* 128.18, e2023JD038906. DOI: https://doi.org/10.1029/2023JD038906. eprint: https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2023JD038906.

Rouges, Emmanuel et al. (2023). "European heatwaves: Link to large-scale circulation patterns and intraseasonal drivers". In: *International Journal of Climatology* 43.7, pp. 3189–3209. DOI: https://doi.org/10.1002/joc.8024. eprint: https://rmets.onlinelibrary.wiley.com/doi/pdf/10.1002/joc.8024.

Shamekh, Sara et al. (2023). "Implicit learning of convective organization explains precipitation stochasticity". In: *Proceedings of the National Academy of Sciences* 120.20, e2216158120. DOI: 10.1073/pnas.2216158120. eprint: https://www.pnas.org/doi/pdf/10.1073/pnas.2216158120.

Wang, Jiamin et al. (2021). “Changing Lengths of the Four Seasons by Global Warming”. In: *Geophysical Research Letters* 48.6, e2020GL091753. DOI: https://doi.org/10.1029/2020GL091753. eprint: https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2020GL091753.