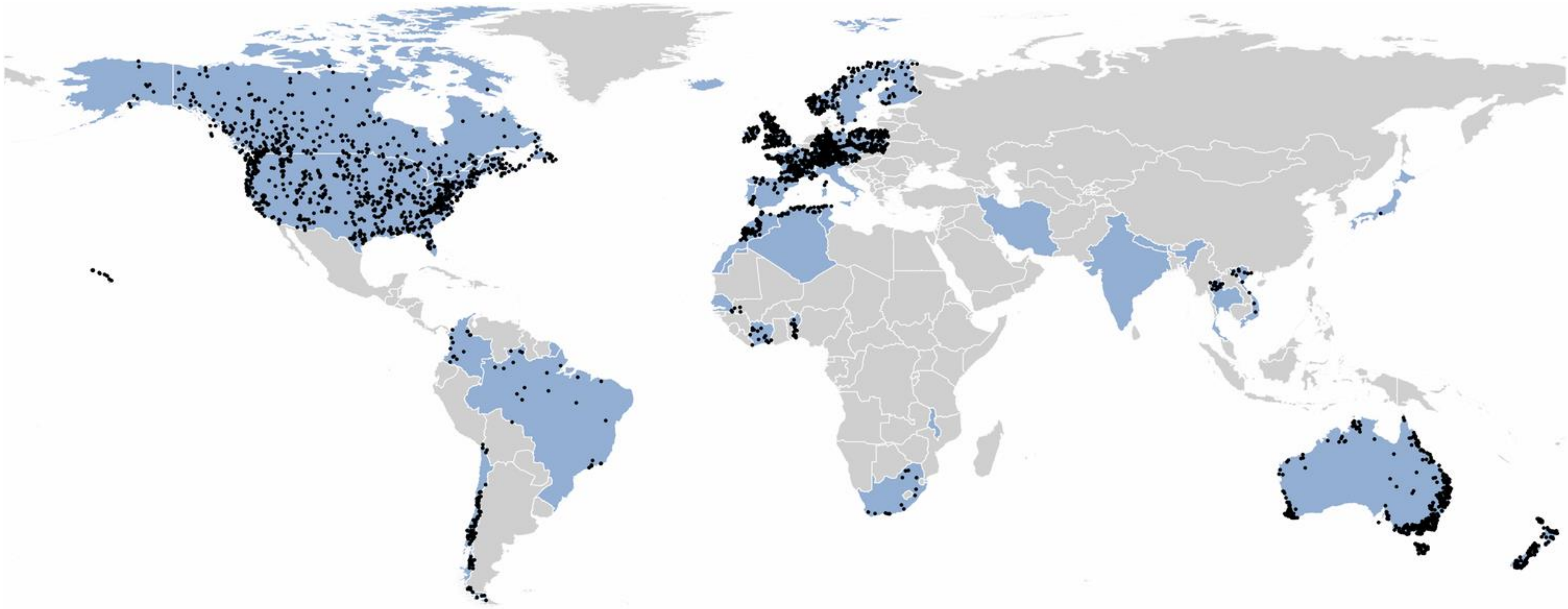
Understanding the impacts of Climate Variability on Global Near-Natural River Flows



Emma Ford PhD ML & Hydrology @ Uni of Oxford

Supervised by Wilson Chan (UKCEH), Amulya Chevuturi (UKCEH), Eugene Magee (UKCEH), Rachael Armitage (UKCEH) and Bastien Dieppois (Coventry University)

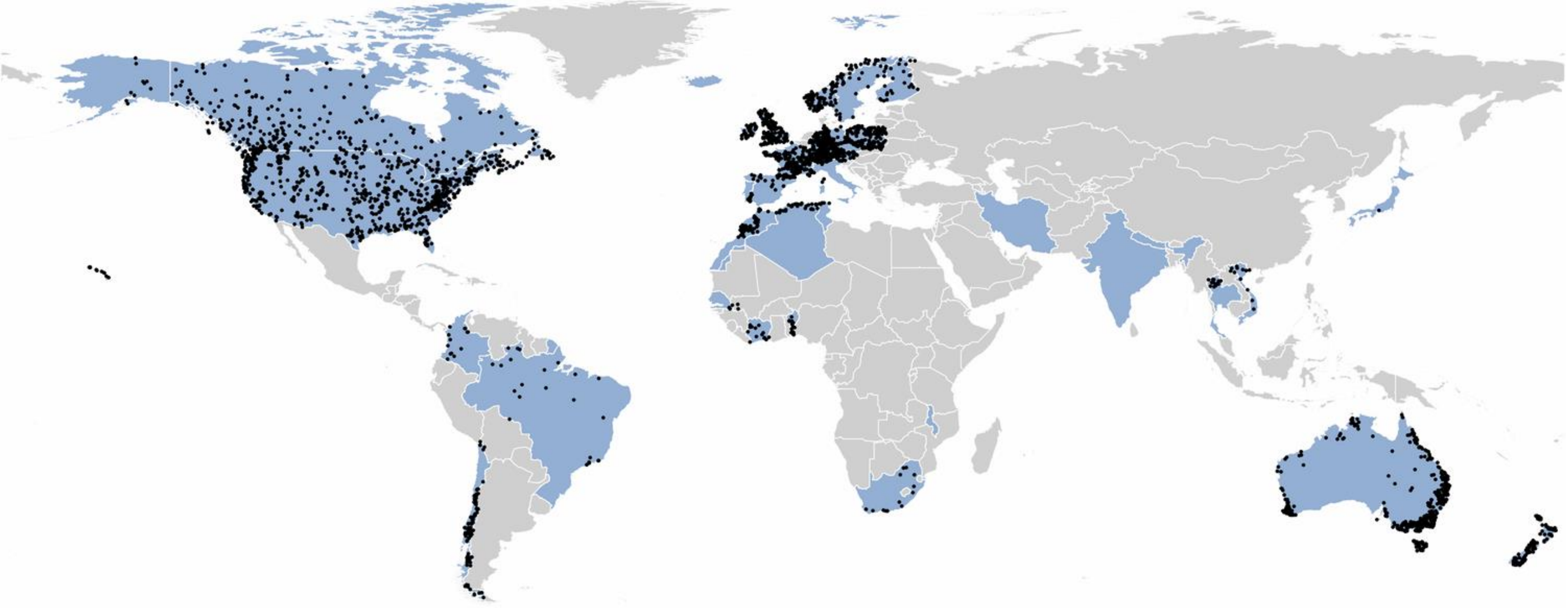


Fig 1 – the distribution of the countries involved in the ROBIN Network (blue) and the black dots indicate stations included in the first phase of the dataset. Taken from Turner et al. (2025).

- Near Natural Catchments
- River Flow Records
- Focus is on High Flows and Extremes
- Understanding the driving large-scale climate influences without anthropogenic signals (e.g., dams and reservoirs).

Building a Robust Methods Workflow and Code Library

Phase	Target	Analysis	Statistics
1.0 Trend Analysis (High Flows)	POT, AMAX, Q5, Q10	Set Trends (1981-2010) and Multi-Temporal Trends	Mann-Kendall Theil-Sen Slope P-Values
2.0 Transition Analysis (Extremes)	Intensity, Duration, Frequency (Wet and Dry Extremes)	Accumulation Periods SSI 1 – 24 Thresholds Moderate, Severe, Extreme	*(as above)*
3.0 Climate Variability	Climate Indices (e.g., ENSO, NAO, AMO)	Concurrent and Lagged (3-9 month) associations with High Flow and Transition Metrics	Pearsons Correlations
4.0 Comparison with Diverse Catchments	GSIM Global Dataset	*Repeat all work above*	*Repeat all work above*
5.0 Machine Learning Model Framework	*POT frequency and magnitude*	*Process attribution through feature importance*	*SHAP, PDPs, ALE, LIME*

1.0 Trend Analysis

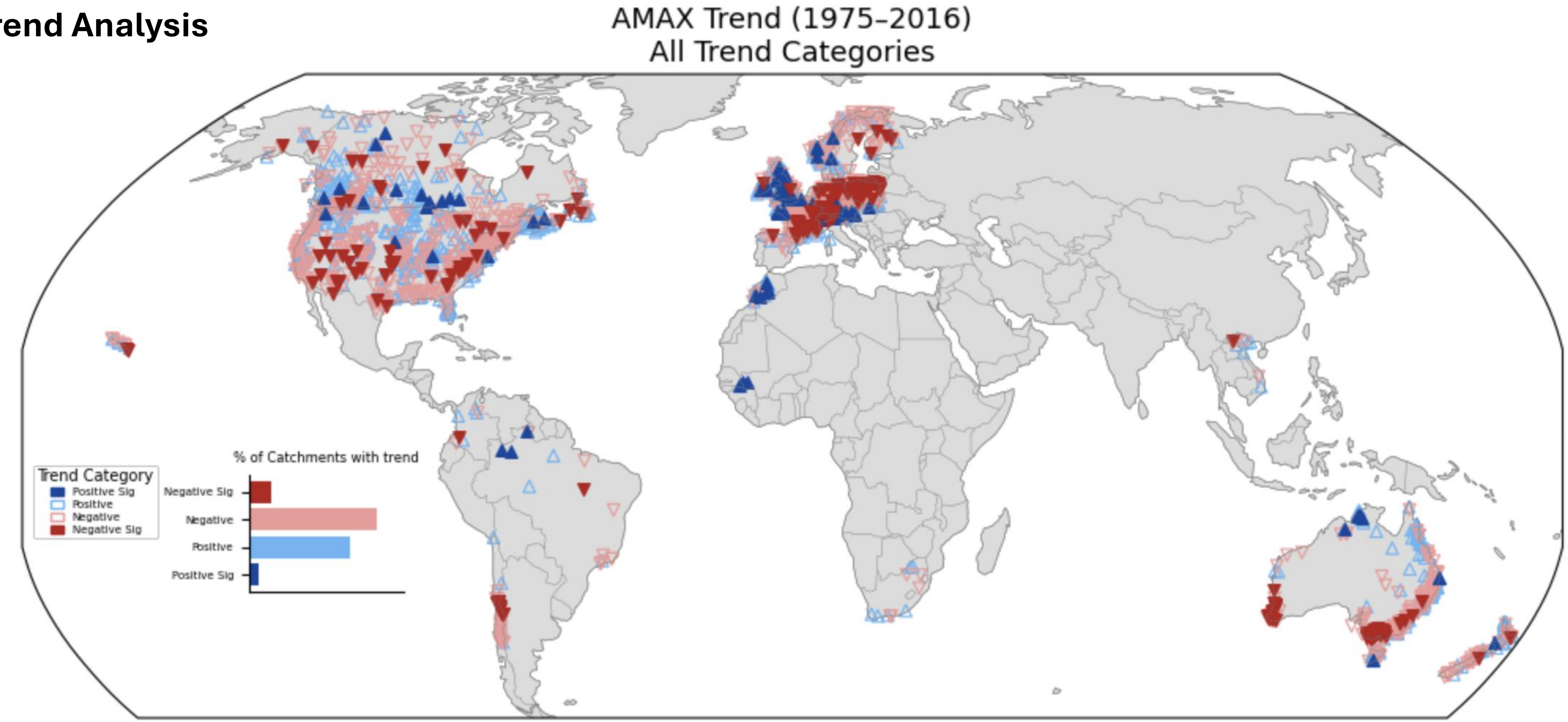


Fig 2 - global distribution of AMAX trends for 1975–2016, derived using the Mann–Kendall Z statistic. Upward triangles indicate increasing peak flows, downward triangles indicate decreasing flows; filled symbols denote statistically significant trends (|Z| > 1.96), while open symbols are non-significant.

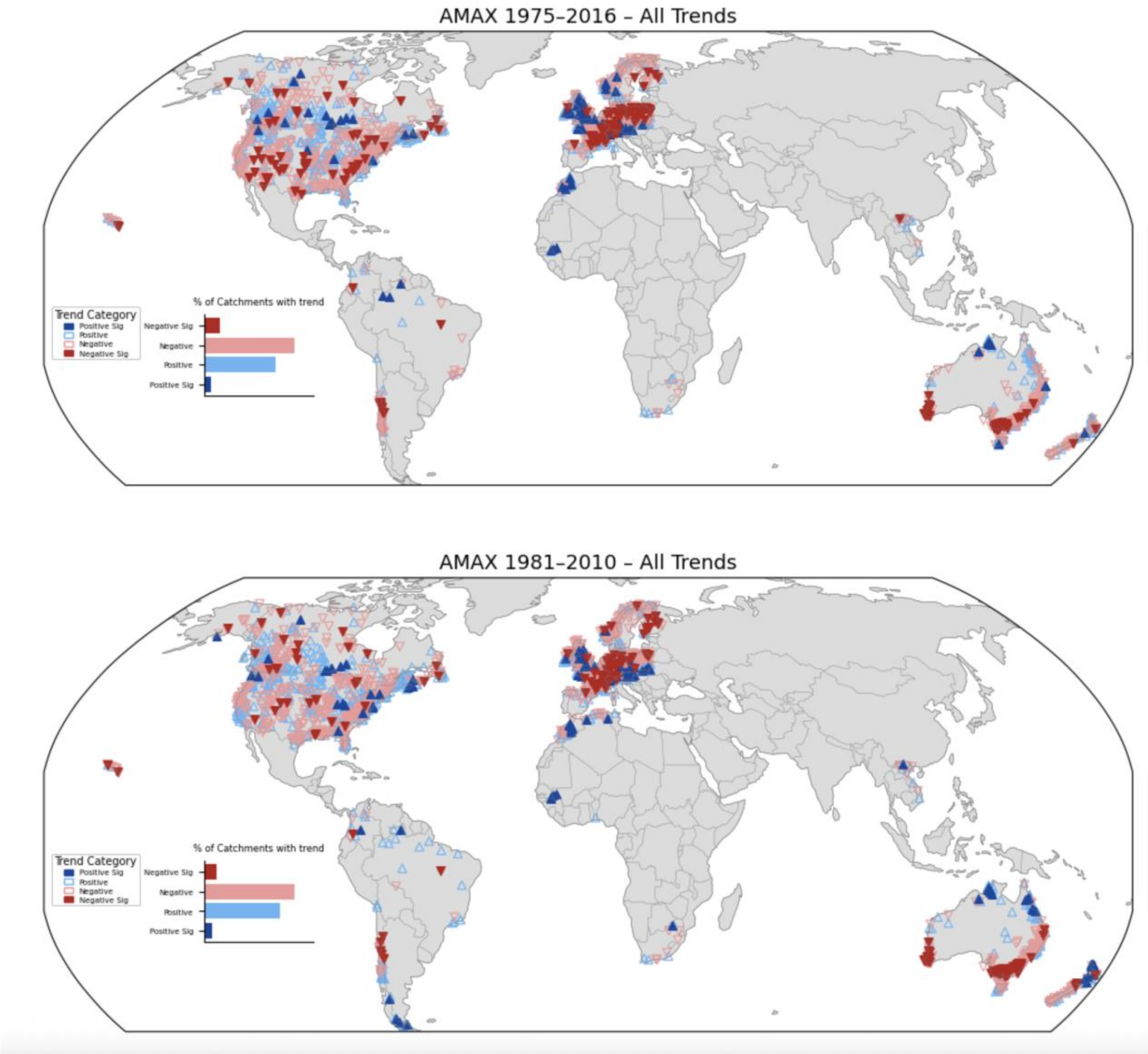


Fig 3 - global distribution of AMAX trends for 1975–2016, and 1981-2010 derived using the Mann–Kendall Z statistic. Upward triangles indicate increasing peak flows, downward triangles indicate decreasing flows; filled symbols denote statistically significant trends (|Z| > 1.96), while open symbols are non-significant.

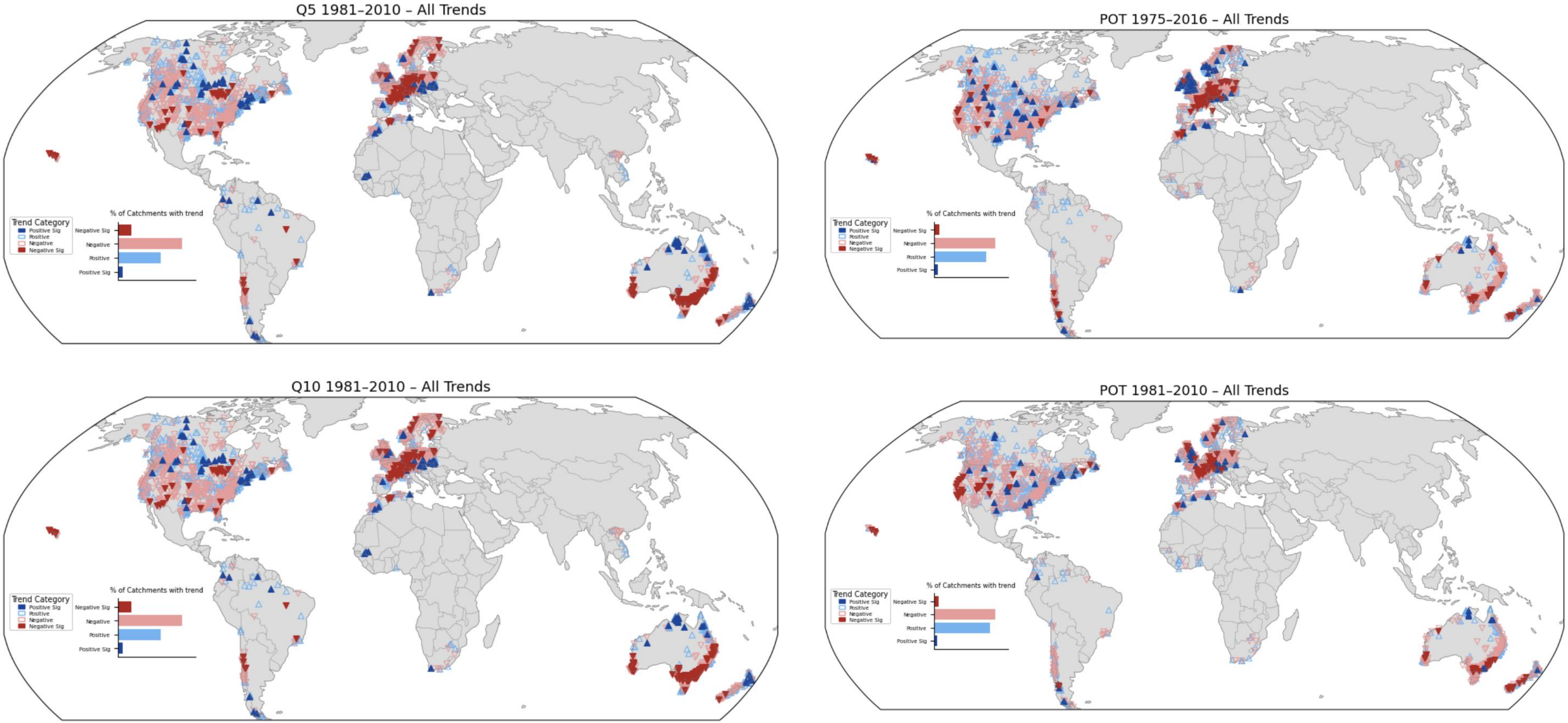


Fig 4 - global distribution of high flow (Q5 and Q10) trends for 1981-2010 (left), and POT 1981-2010 and 1976-2016 (right) derived using the Mann–Kendall Z statistic.

1.1 Multi-Temporal Trend Analysis (e.g., AMAX)

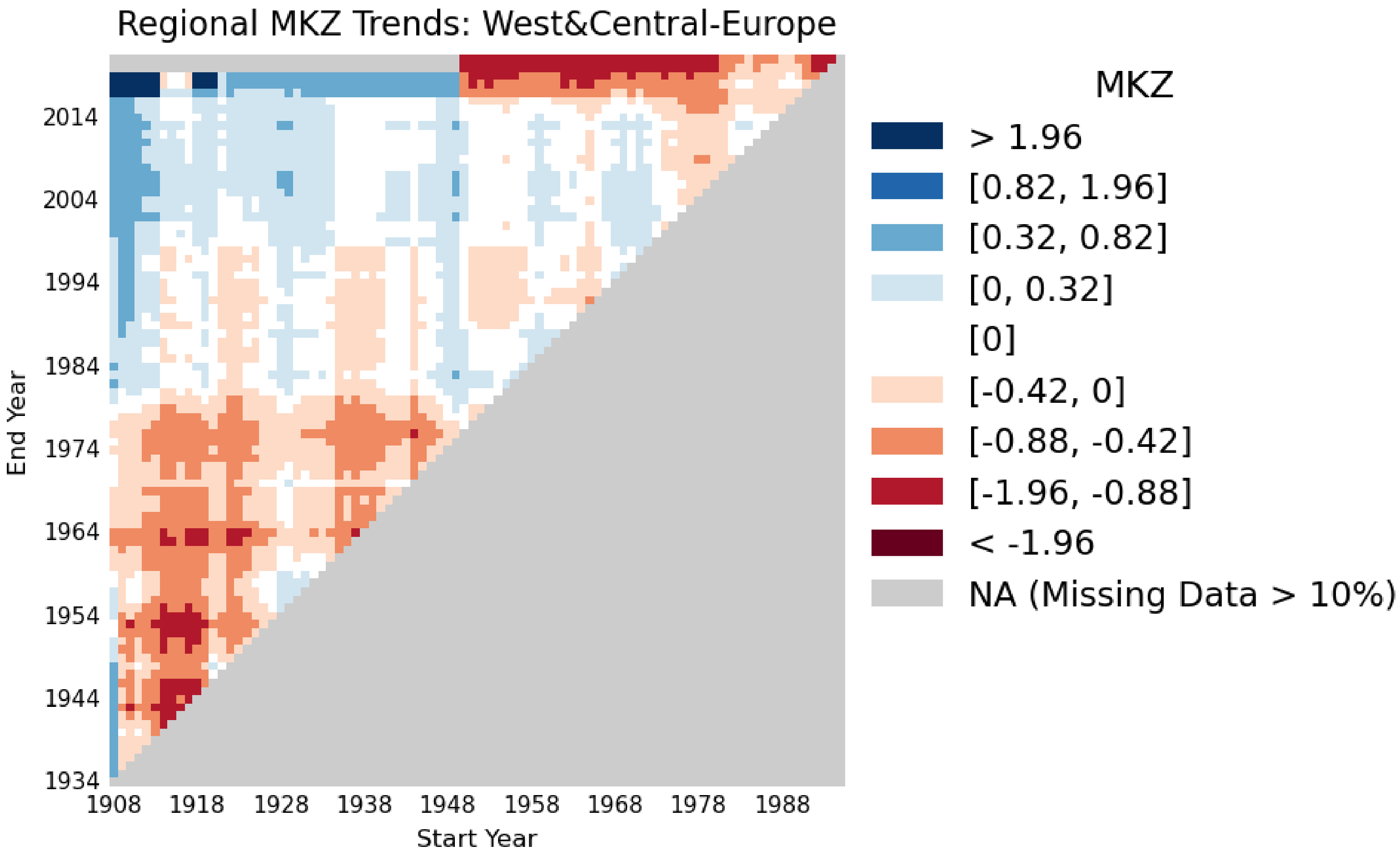


Fig 5 - Regional Mann–Kendall Z-scores for AMAX (annual maximum flow) in European catchments, calculated over varying combinations of start and end years. Colours indicate the magnitude and direction of monotonic trends, with warm tones representing increasing trends and cool tones representing decreasing trends. The multi-temporal approach allows assessment of how detected trends vary with the chosen period, providing insights into temporal stability and sensitivity to period selection.

2.0 Transition Analysis (Catchment Mean)

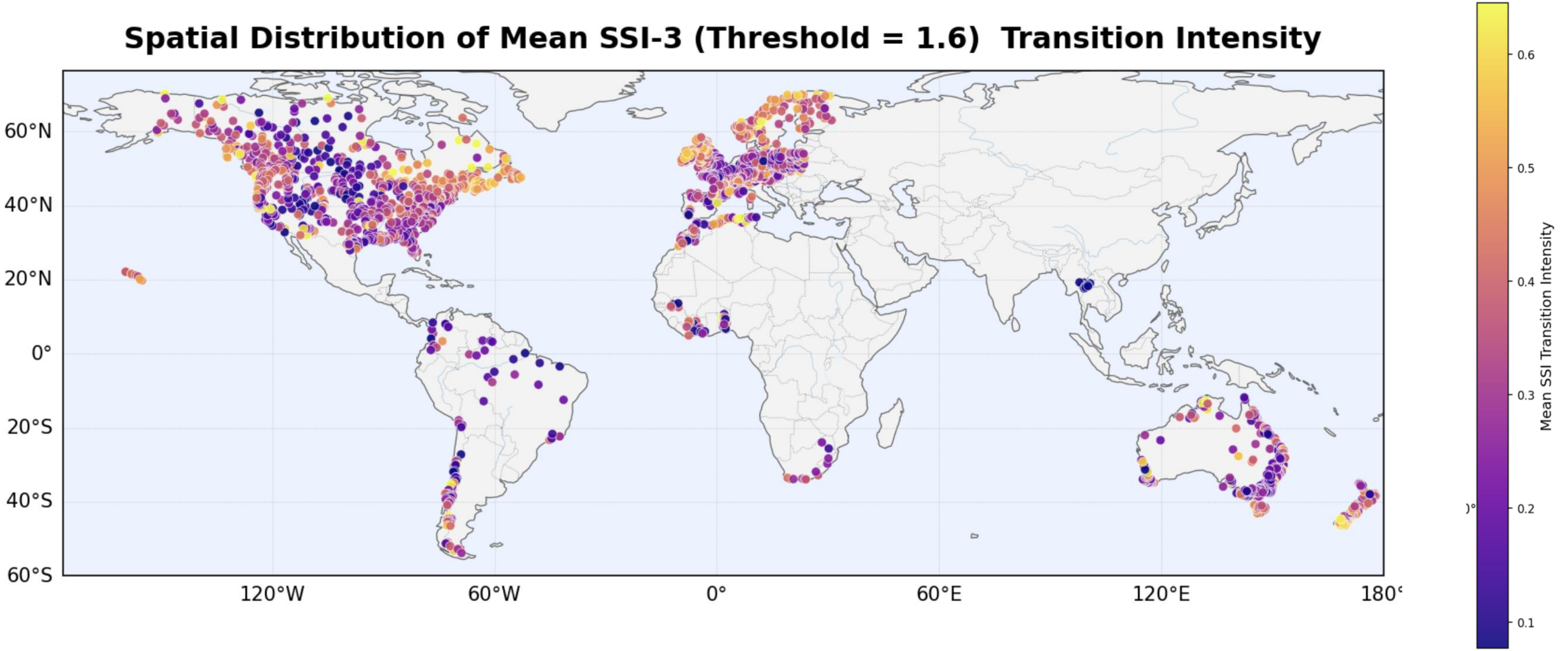


Fig 6 - Spatial distribution of mean SSI-3 (Standardised Streamflow Index, 3-month) transition intensity for all analysed catchments globally, using a transition threshold of 1.6. Colours represent the mean intensity of identified transitions between drought and wetness states over the study period, with warmer colours indicating stronger average transitions.

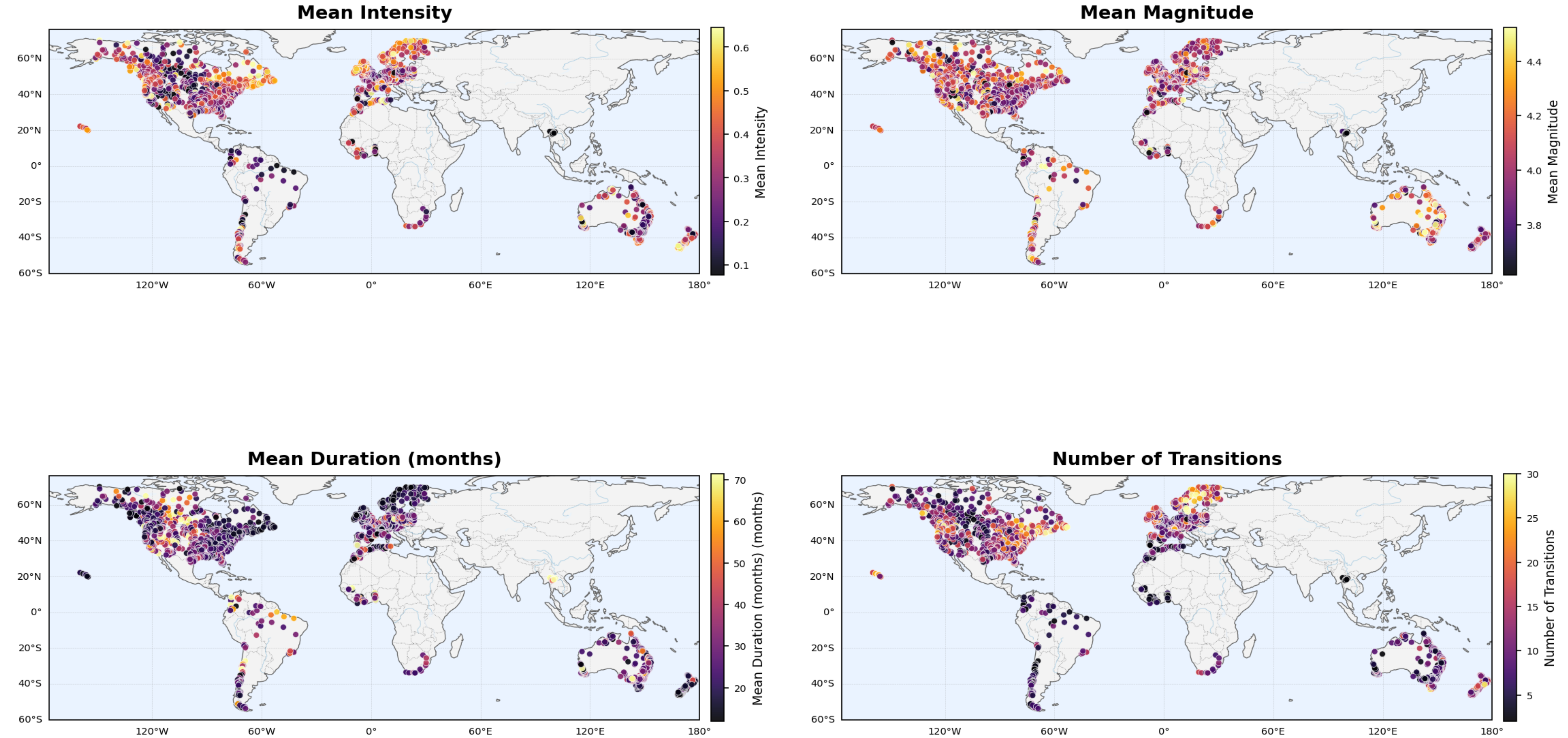


Fig 7 - Spatial patterns of SSI-3 (threshold = 1.6) transition metrics across European catchments. (a) Mean intensity of transitions, (b) mean magnitude, (c) mean duration in months, and (d) number of transitions. Metrics are computed per catchment over the full analysis period, with colors indicating relative magnitude and dots representing station locations.

3.0 Climate Index Seasonal Mean Concurrent and Lagged Correlation with POT Seasonal Frequencies

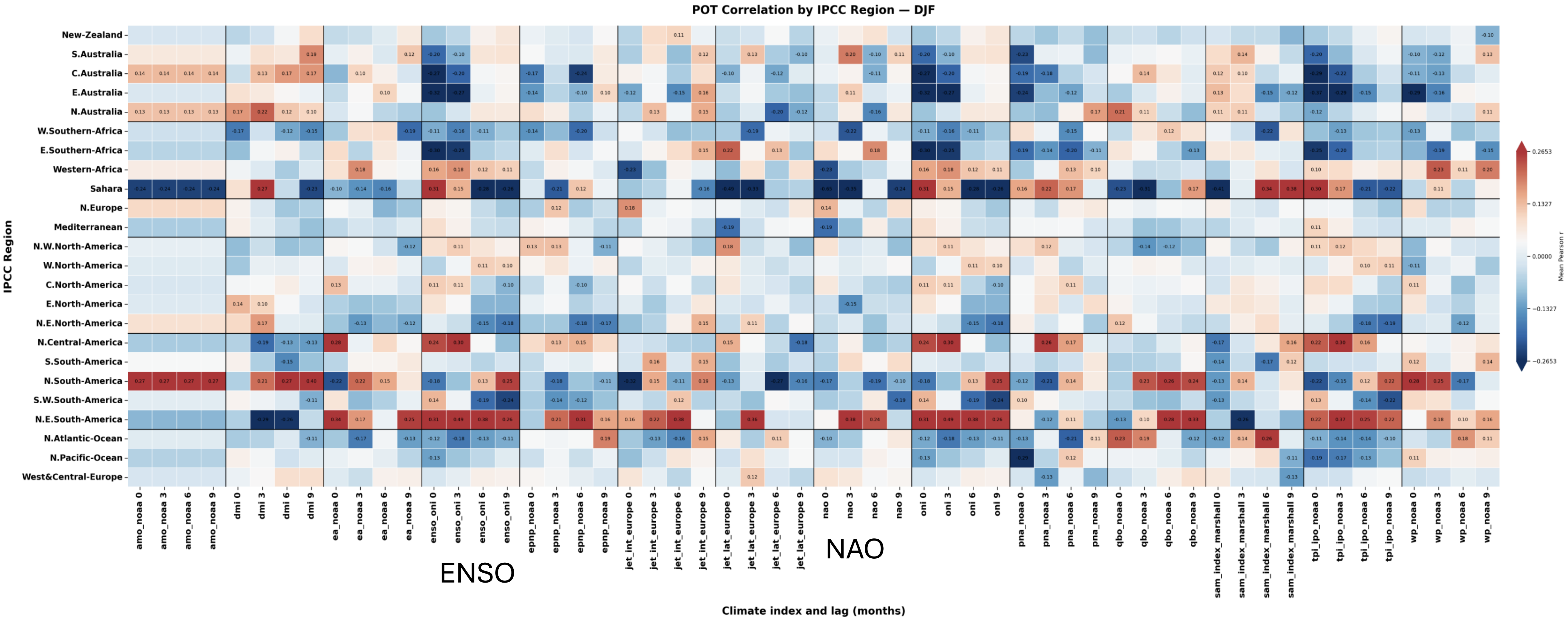


Fig 8 - Heatmap of mean Pearson correlation coefficients between seasonal climate indices and Peak-Over-Threshold (POT) extreme flow metrics for the DJF (December–February) season, aggregated by IPCC reference region. Rows correspond to regions, while columns represent combinations of climate indices and time lags (in months) relative to the extreme flow events. Red shading indicates positive correlations (higher index values associated with higher extreme flows), and blue shading indicates negative correlations (higher index values associated with lower extreme flows), with colour intensity proportional to correlation strength.

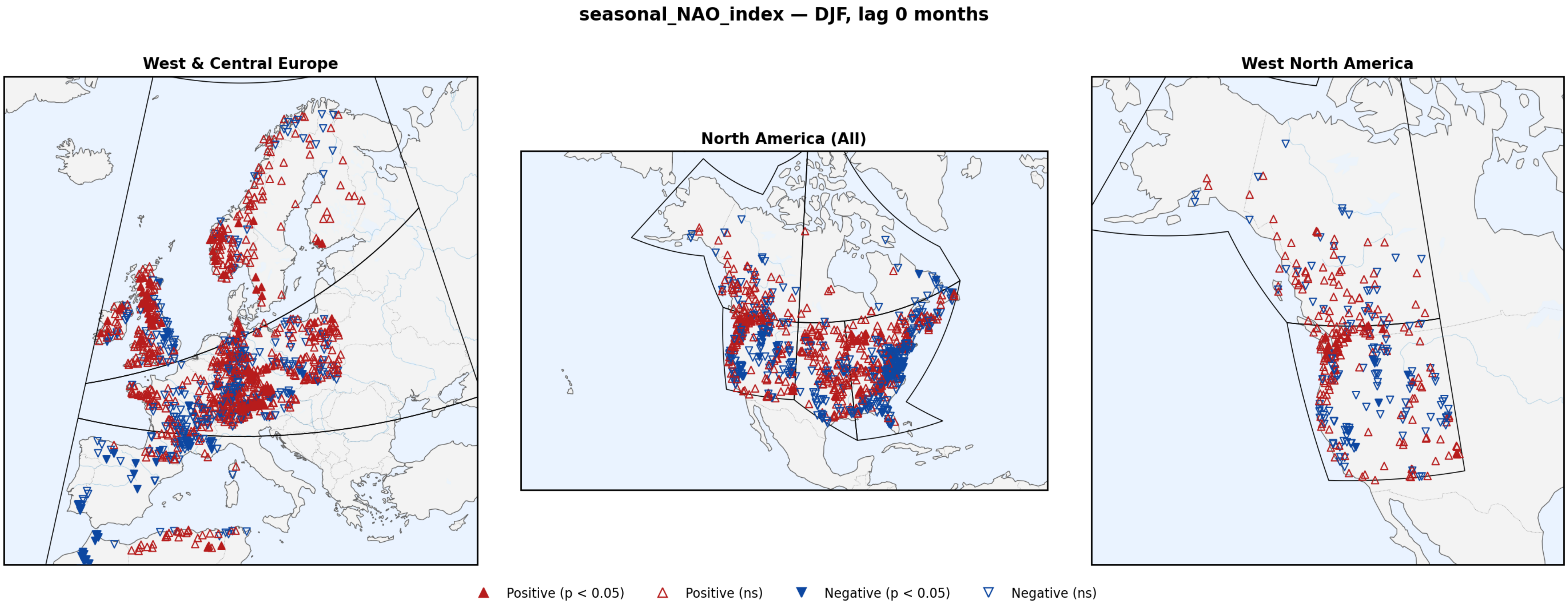


Fig 9 - Regional correlation maps showing the relationship between the NAO (DJF, lag 0 months) and Peak-Over-Threshold extreme flows. Marker orientation indicates correlation sign (▲ positive, ▼ negative), and fill indicates statistical significance ($p < 0.05$). Panels show West & Central Europe, North America, and western North America, highlighting spatial variations in the NAO's influence on winter flood extremes.

Europe: POT correlations • DJF, lag 0 months

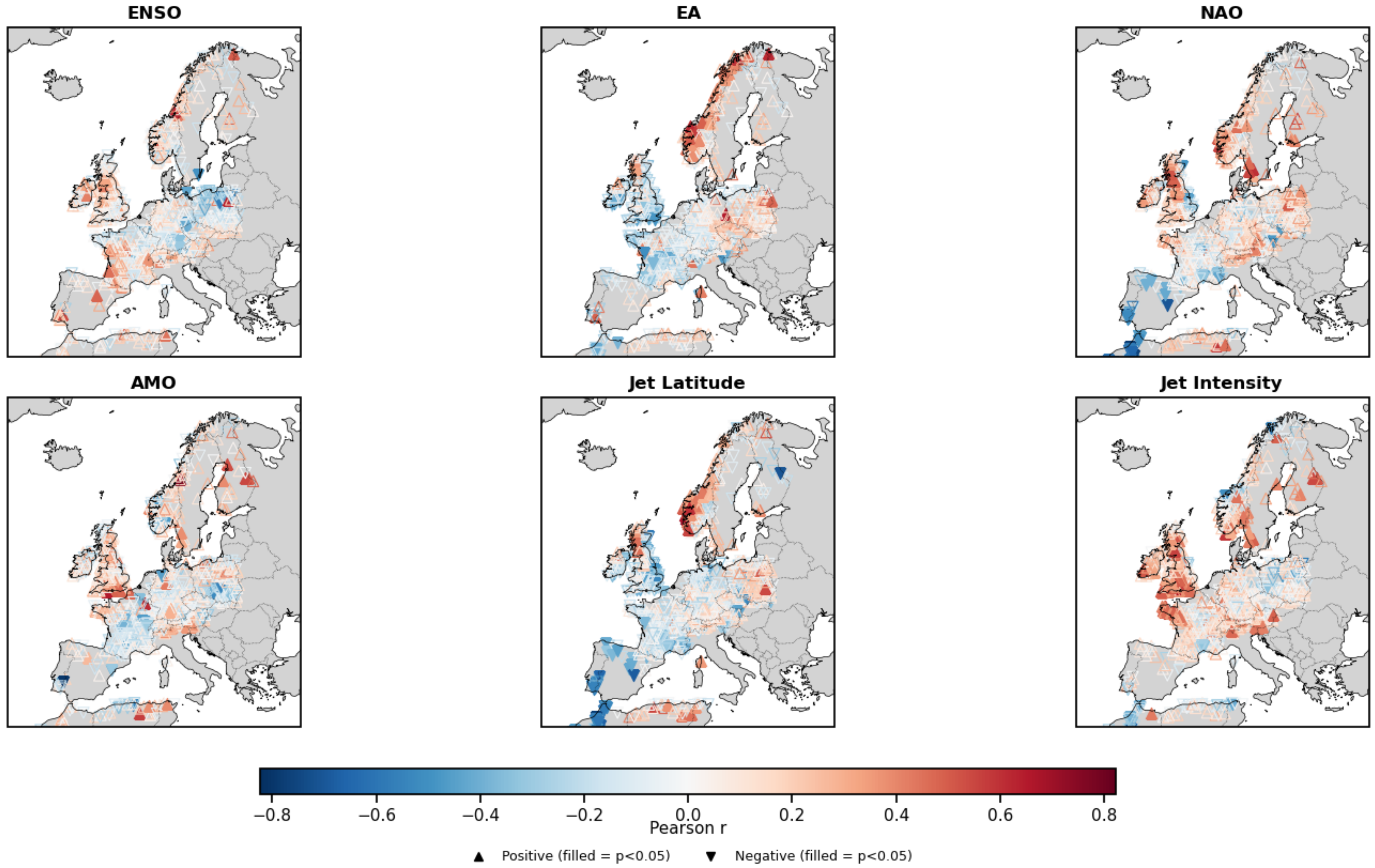


Fig 10 -Spatial correlations between seasonal high-flow magnitudes and selected climate drivers (ENSO, EA, NAO, AMO, Jet Latitude, Jet Intensity) for Europe in DJF at lag 0 months. Upward triangles = positive correlations; downward triangles = negative correlations; filled markers = statistically significant ($p < 0.05$). Colours indicate Pearson r values.

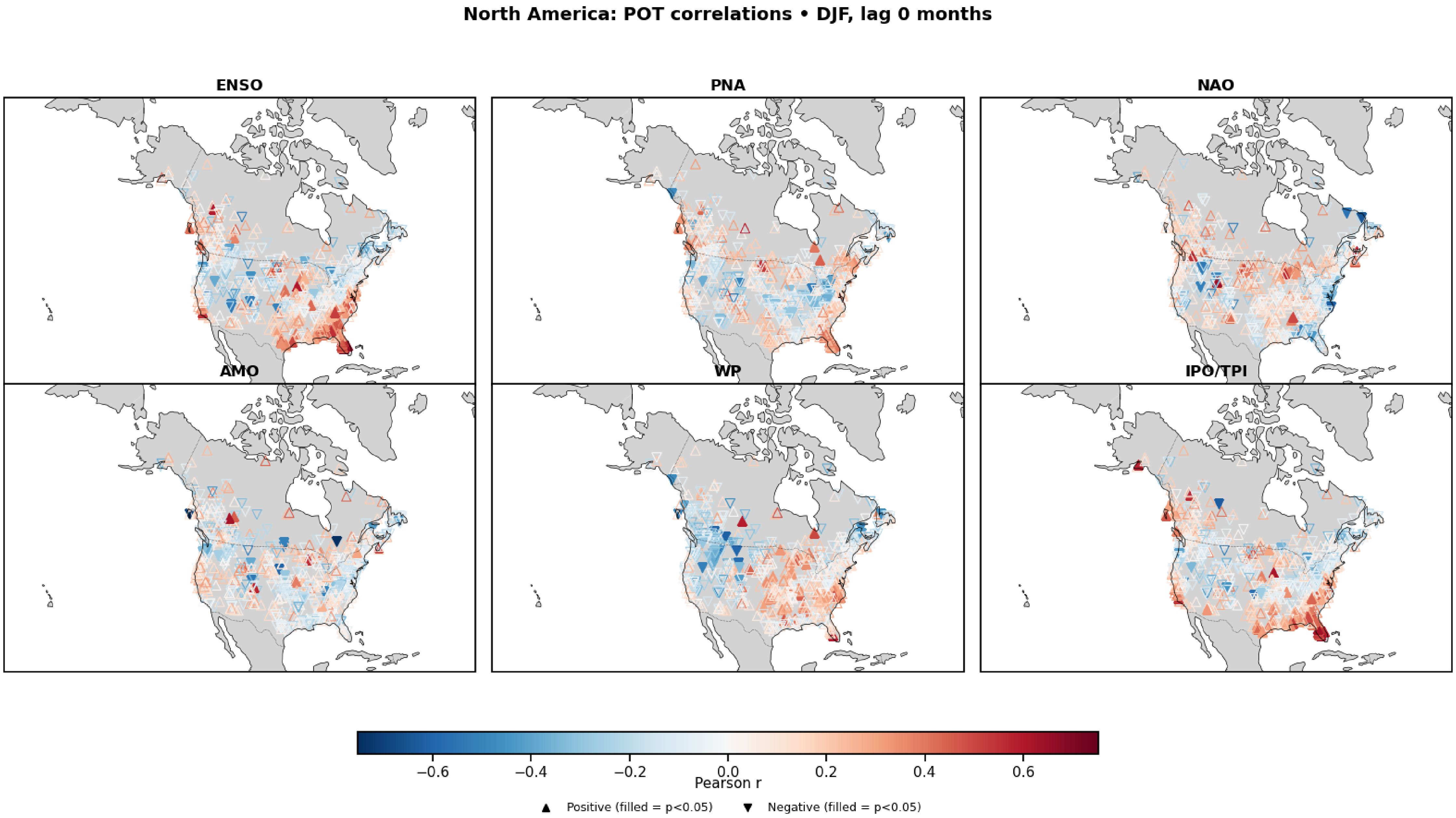


Fig 11 -Spatial correlations between seasonal peak-over-threshold (POT) high-flow anomalies and six key climate drivers for North America (DJF, lag = 0 months). Triangles indicate positive correlations, and inverted triangles indicate negative correlations; filled symbols denote statistically significant relationships ($p < 0.05$). Colours represent Pearson correlation coefficients, highlighting regional variations in hydroclimatic sensitivity to each driver.

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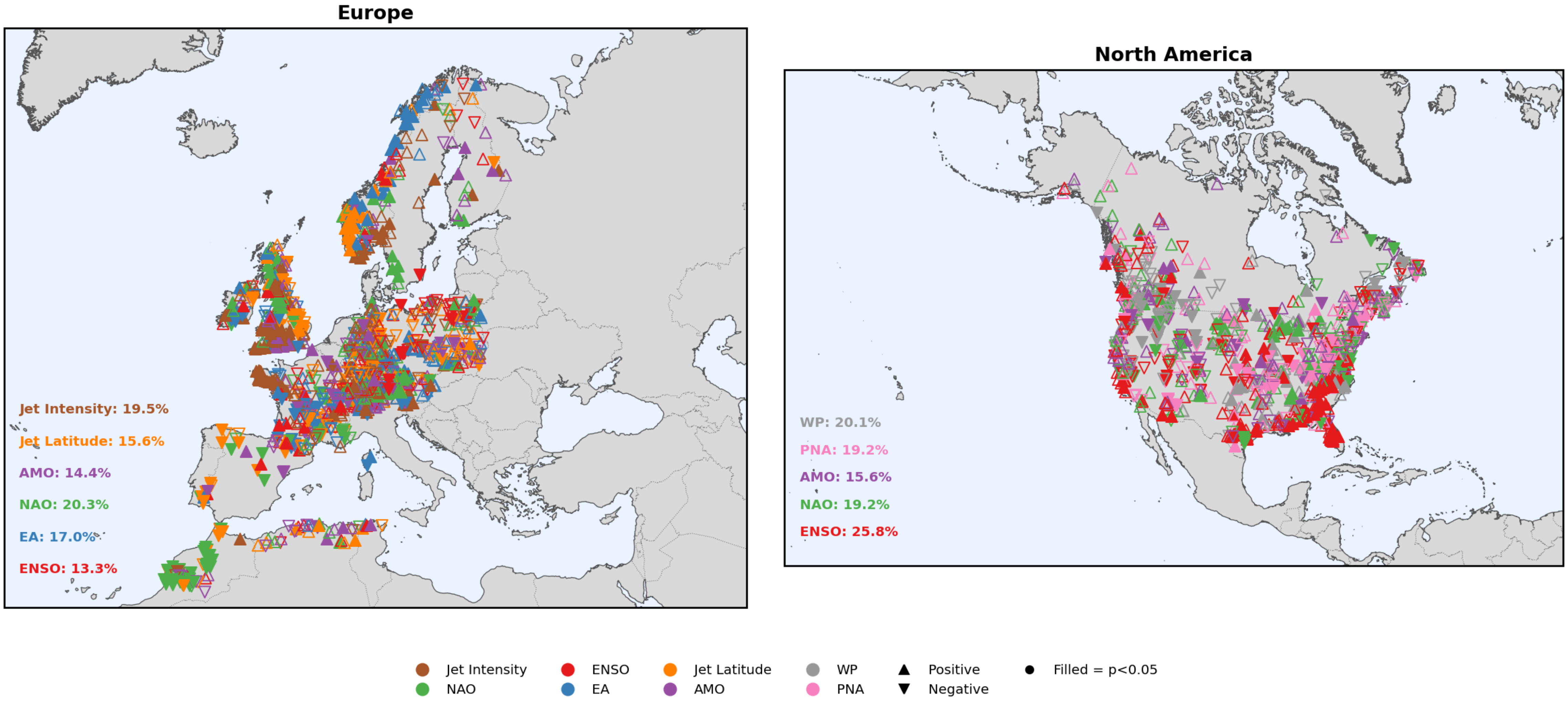

Fig 12 -Dominant climate driver for POT during DJF at lag 0months. For each catchment, the climate driver with the largest absolute Pearson correlation was selected with marker shape indicating the correlation sign (▲ positive, ▼negative) and filled markers denoting statistical significance at $p < 0.05$. Colors correspond to different climate drivers.

Next Steps?

1. Complete analysis on “Understanding the impacts of climate variability on global near-natural river flows”

    1.1 Transition Trend Analysis

    1.2 GSIM Diverse Catchment Comparison

    1.3 Digging in to explaining the relationship between climate drivers and floods/flood trends

2. Phase II of the Project leveraging Machine Learning Models

5.0 Machine Learning Models for ROBIN Catchments – University of Oxford Project for 2026

Professor Louise Slater, Professor Hannah Christensen, and Professor Manuela Brunner *(ML & Hydrology Supervision Team)* + *UKCEH ROBIN Supervisors*

- ROBIN catchment dataset provides global coverage with rich hydro-climatic timeseries, look at climate driver importance
- ML accounts for nonlinear relationships, and quantifies driver importance over space and time
- Attribute seasonal differences in hydrological response to multiple climate drivers and catchment processes
- Random Forests, XGBoost, SHAP

Identify climate process attributions, what drivers dominate, when and where, for extreme flood events?

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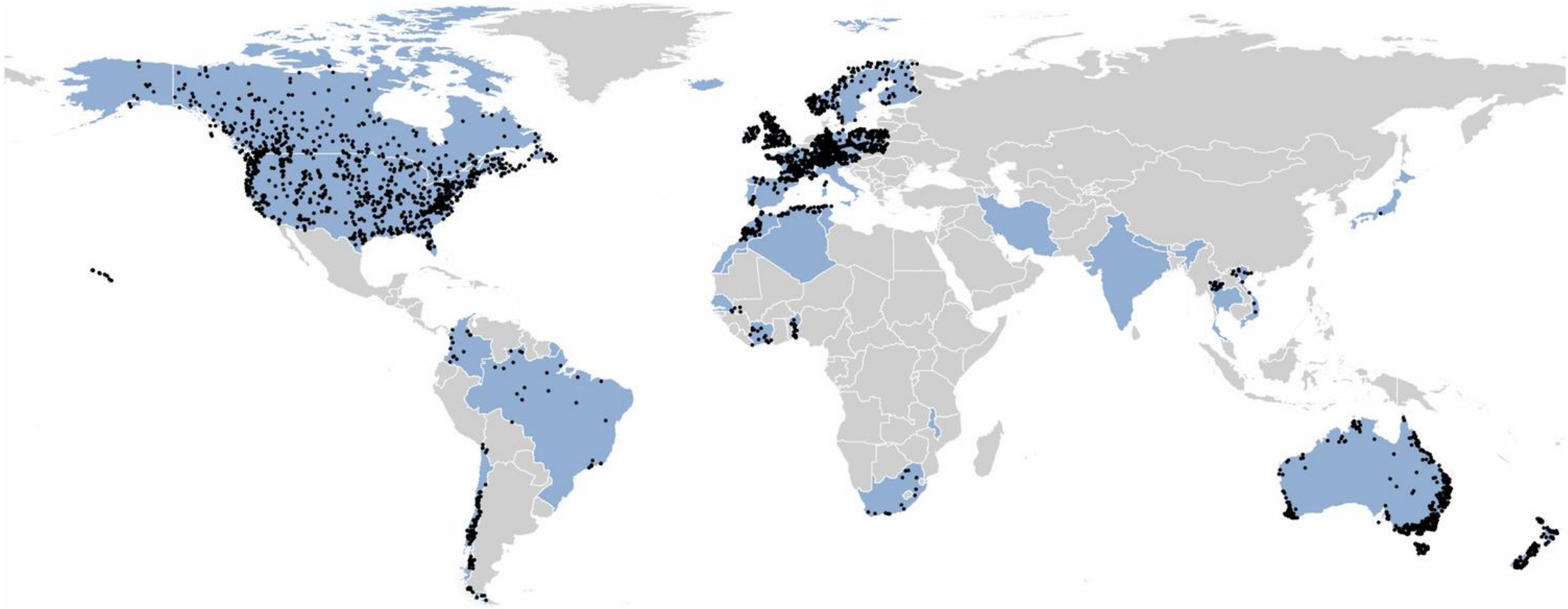
THANK YOU !



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