

Introduction

The consequences of global warming are not homogeneous. The observed warming in the Western Mediterranean (WMed) region during the last decades is expected to continue and grow larger than the global mean, which is why it has been pointed out as a climate change hotspot [1]. But even within a relatively small region such as the WMed, spatial and temporal climate variability can lead to a variety of extreme weather and climate events that may exacerbate the vulnerabilities of the countries.

This study focuses on the detection and attribution of long-term trends of temperature and precipitation in the WMed region, using a climate regionalization that considers the region's climatic heterogeneity.

Methodology

A regionalization process was made using monthly temperature and precipitation data from ERA5 during 1950-2020. A pre-filtering procedure was performed employing Empirical Orthogonal Functions, retaining 90% of the variance. After this, a non-hierarchical K-Means clustering was performed.

A timescale decomposition was used to extract trend-like changes with the global warming signal [2]. The trend component (as a regression with global mean surface temperature from GISTEMPv49), decadal component (via 10-yr low-pass filtering of the trend residuals), and interannual variability (residuals of trends and decadal) were obtained.

Data from 11 CMIP6 models (see Fig. 2) were used for preliminary attribution. Time of emergence (TOE) [3] was obtained using the pre-industrial runs. The probability ratio (PR) of exceeding observed trends was obtained using Historical and Natural-only runs (from DAMIP experiments [4]). Trends by external factor were obtained using GHG-only and Aerosols-only [5].

Results

Observed Regional Long-term Trends:

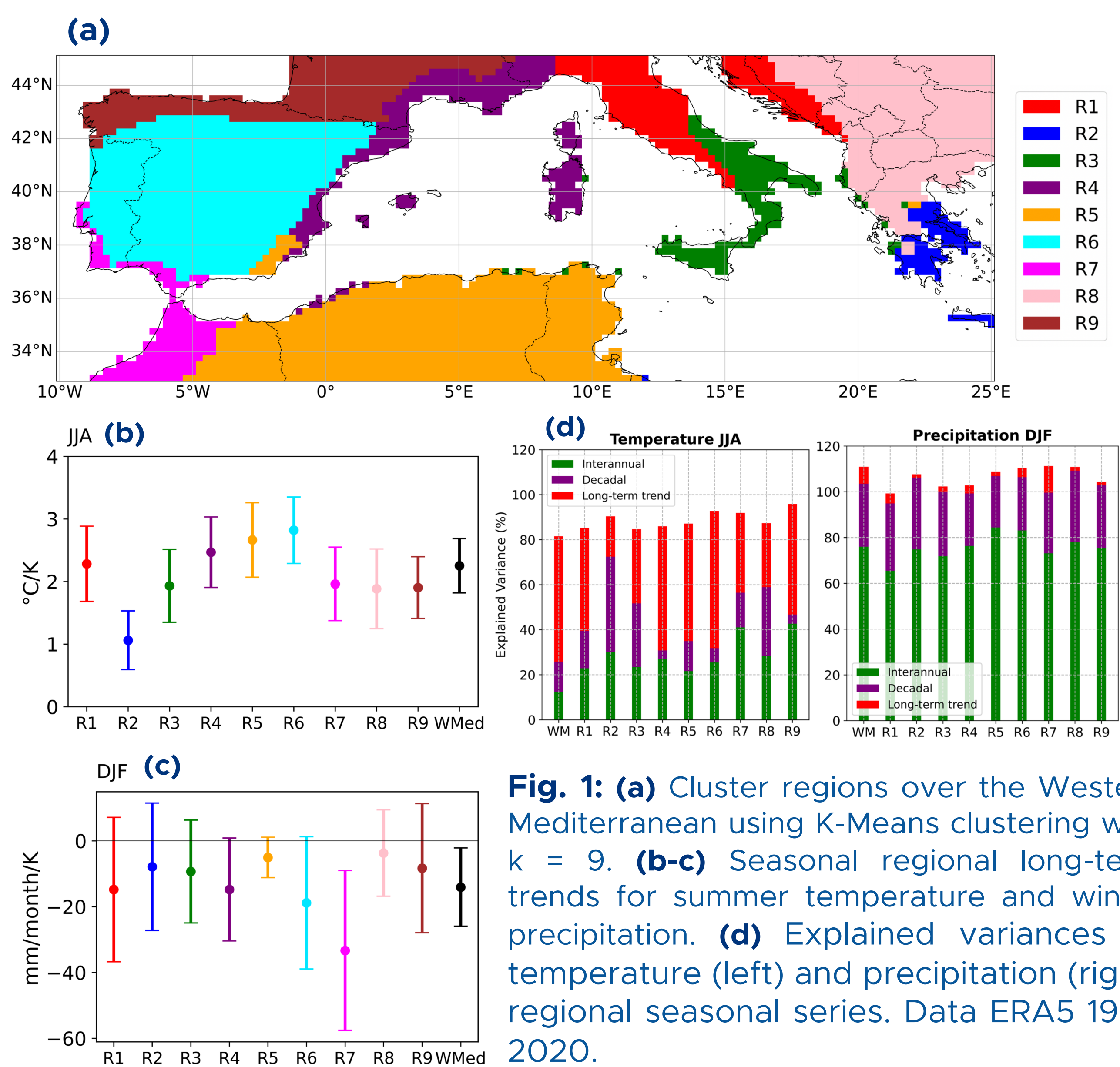


Fig. 1: (a) Cluster regions over the Western Mediterranean using K-Means clustering with $k = 9$. (b-c) Seasonal regional long-term trends for summer temperature and winter precipitation. (d) Explained variances of temperature (left) and precipitation (right) regional seasonal series. Data ERA5 1951-2020.

Time of Emergence of Trends:

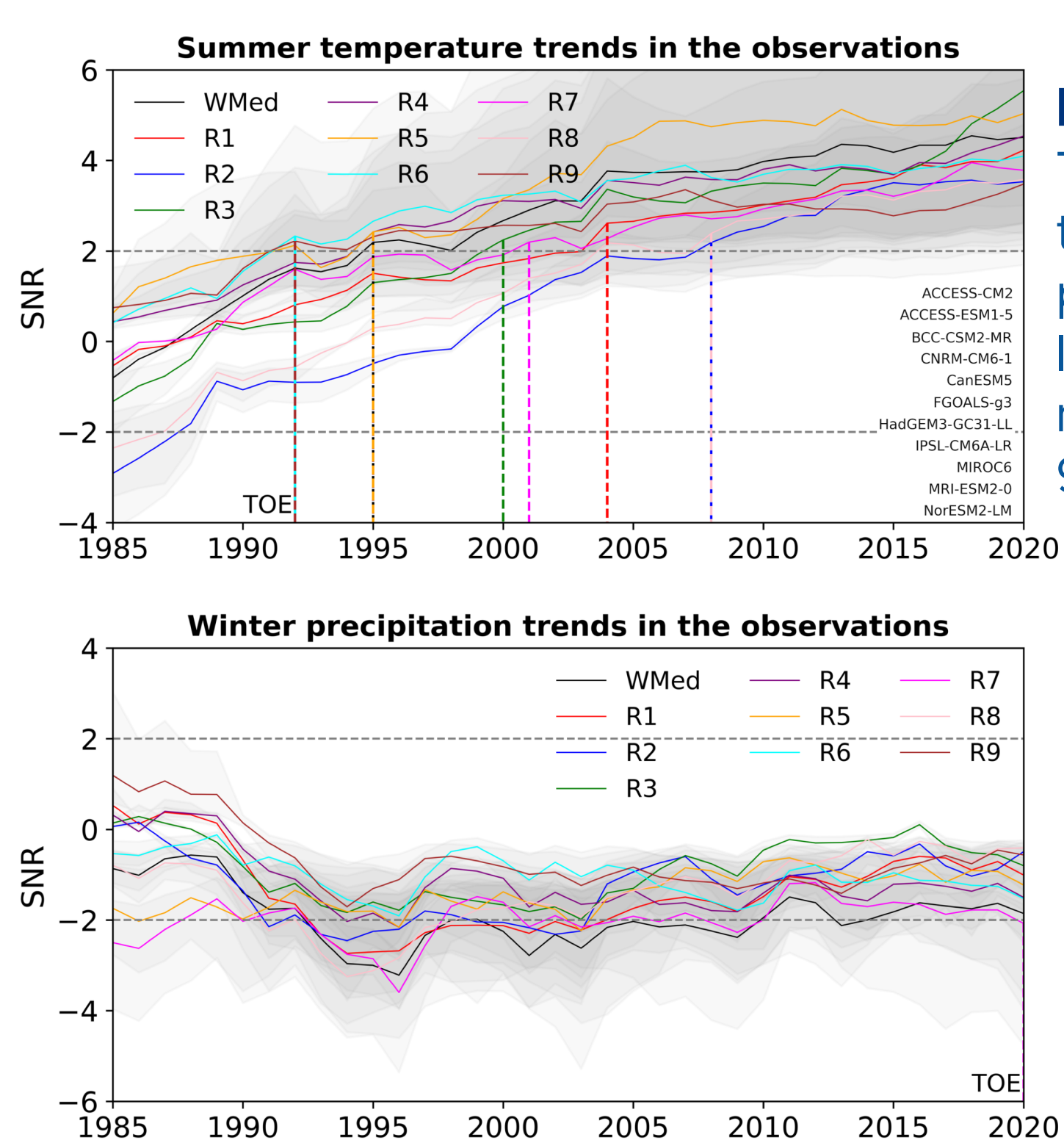


Fig. 2: Signal to Noise Ratio (SNR) and Time of Emergence (TOE) for summer temperature trends (above) and winter precipitation trends (below). Vertical lines show the TOE year based on the mean SNR. Grey shaded shows the 95% confidence interval.

Signal is defined as the mean regional seasonal trend from ERA5, CRU, Berkeley Earth (for temperature), and GPCC (for precipitation) starting at 1951. Noise is defined as the standard deviation of all possible trends in the pre-industrial period (120 years of piControl runs) using 11 CMIP6 models. After Chemke & Coumou, 2024.

Concluding remarks

- A long-term warming signal was detected in all regional series, with slight differences. These trends contribute more to the overall variance of the series in summer, especially in regions on the west side of the Western Mediterranean.
- Long-term drying was detected in all regional series in winter. Nevertheless, natural variability explains significantly more variance than the long-term trends associated with global warming and trends do not emerge from natural variability.
- Models capture the summer warming in the WMed region; nevertheless, the differences among regions are not complete. R2 is the region in which the trend emerges first in the models (not shown), opposite from the observations.
- Since the natural variability exceeds the signal of climate change (long-term trend) in precipitation series, obtaining high signal-to-noise ratios from global models in the region is challenging in detecting and attributing long-term trends.

Regional Long-term Trends in the Models:

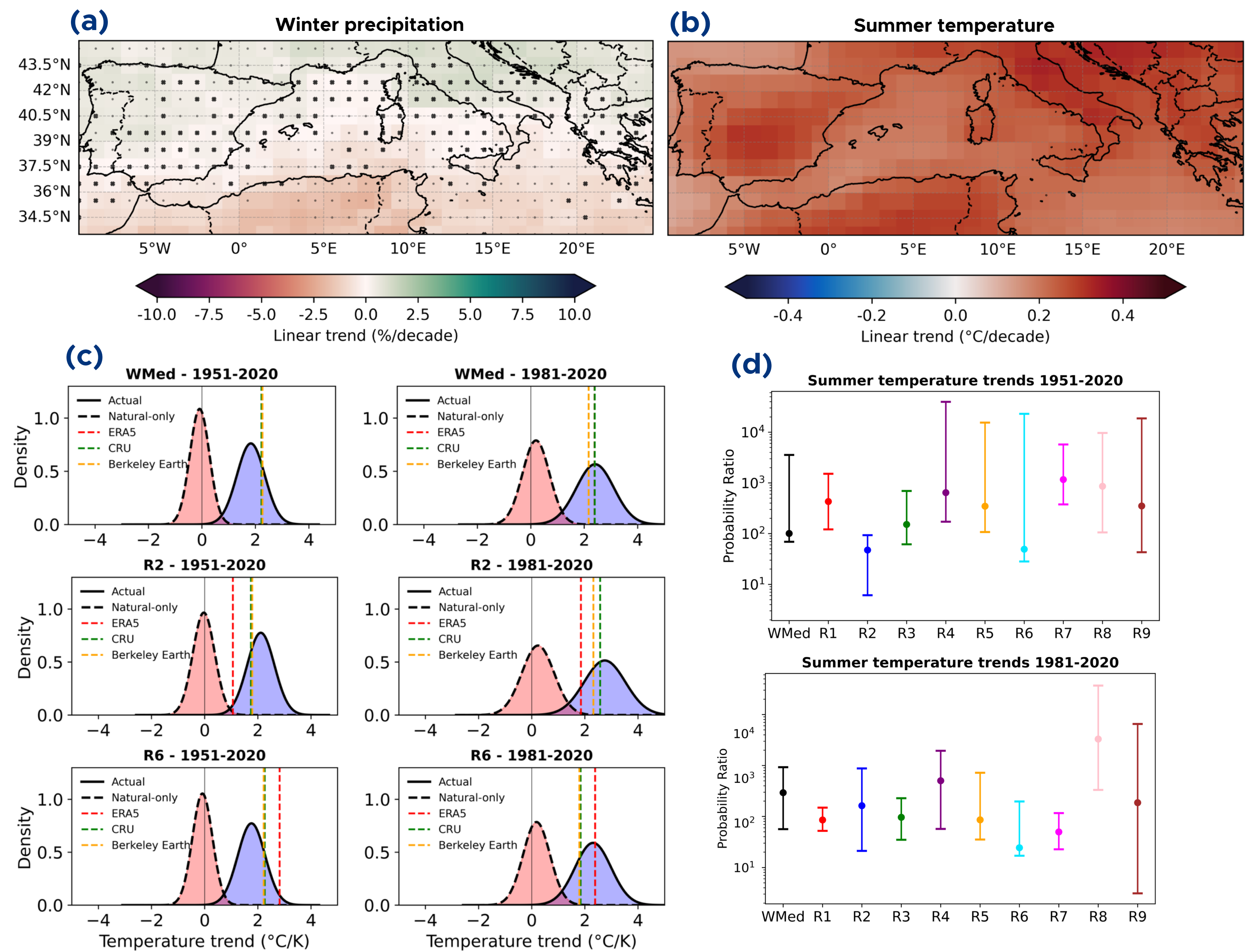


Fig. 3: (a-b) Trend agreement (on sign of the trend) among models. Based on mean linear trend in each grid box: Big dots <70% of agreement, small dots 70-90% of agreement, no dot >90% of agreement. (c) PDFs (Gaussian) of temperature trends in Natural-only runs and Historical runs (Actual). Vertical lines are observed trends. (d) Probability ratio of exceeding observed trends obtained from Natural-only and Actual PDFs.

Regional Long-term Trends by External Factor:

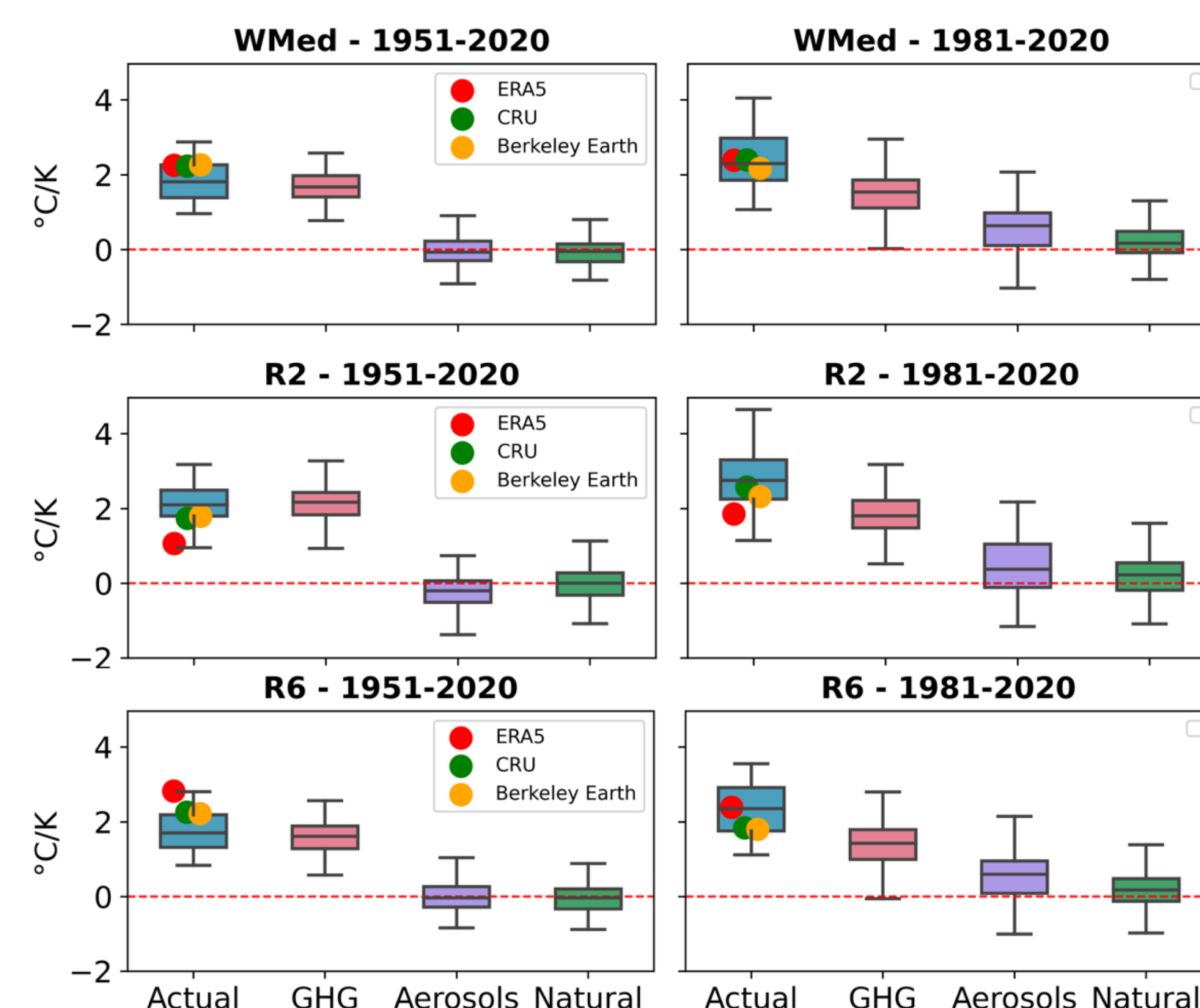


Fig. 4: Trends by external factor using the DAMIP experiment runs. For Actual climate, Historical (1951-2014) + SSP245 Scenario (2015-2020) were used. For greenhouse gases-only (GHG), anthropogenic aerosols-only (Aerosols) and Natural-only, runs from the DAMIP experiments were used. Dots show the observed regional trends. Two periods were used, 1951-2020 and 1981-2020 (also for Fig. 3).

References

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Acknowledgments

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