

Are trends in convective parameters over the United States and Europe consistent between reanalyses and observations?



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Abstract

In this work, long-term trends in convective parameters are compared between ERA5, MERRA2, and observed rawinsonde profiles over Europe and the United States including surrounding areas. A 39-year record (1980–2018) with 2.07 million quality-controlled measurements from 84 stations at 0000 and 1200 UTC is used for the comparison, along with collocated reanalysis profiles. Overall, reanalyses provide similar signals to observations, but ERA5 features lower biases. Over Europe, agreement in the trend signal between rawinsondes and the reanalyses is better, particularly with respect to instability (lifted index), low-level moisture (mixing ratio) and 0–3 km lapse rates as compared to mixed trends in the United States. However, consistent signals for all three datasets and both domains are found for robust increases in convective inhibition (CIN), downdraft CAPE (DCAPE) and decreases in mean 0–4 km relative humidity. Despite differing trends between continents, the reanalyses capture well changes in 0–6 km wind shear and 1–3 km mean wind with modest increases in the United States and decreases in Europe. However, these changes are mostly insignificant. All datasets indicate consistent warming of almost the entire tropospheric profile, which over Europe is the fastest near-ground, while across the Great Plains generally between 2–3 km above ground level, thus contributing to increases in CIN. Results of this work show the importance of intercomparing trends between various datasets, as the limitations associated with one reanalysis or observations may lead to uncertainties and lower our confidence in how parameters are changing over time.

1. Introduction

Historical trends in severe thunderstorms are an important topic in the context of growing impacts of hazards and losses to the insurance industry (Sander et al. 2013; Brown et al. 2015; Munich Re 2020). However, it is still unclear how an anthropogenically warming climate is influencing these extreme events (Diffenbaugh et al. 2007, 2013; Gensini and Mote 2015; Trapp and Hoogewind 2016; Allen 2018; Rädler et al. 2019). A number of studies have explored the presence of historical trends using both direct observations (Verbout et al. 2006; Mohr and Kunz 2013; Allen and Tippett 2015; Tippett et al. 2016), and environments favorable to the development of convective storms derived from reanalyses (Robinson et al. 2013; Mohr et al. 2015; Gensini and Brooks 2018; Rädler et al. 2018; Tang et al. 2019; Taszarek et al. 2021a). Detecting trends in convective hazards is not trivial, as observations are incomplete and vary in quality over time and space, both over the United States and Europe (Doswell et al. 2005; Verbout et al. 2006; Allen and Tippett 2015; Tippett et al. 2015; Groenemeijer et al. 2017; Edwards et al. 2018; Taszarek et al. 2020a; Zhou et al. 2021).

The use of environmental proxies instead of direct observations provide the advantage of a more complete temporal and spatial record, however with limited confidence regarding whether convection initiates (Bunkers et al. 2010; Hoogewind et al. 2017; Romps et al. 2018; Tippett et al. 2019). Reanalyses also tend to struggle with appropriate sampling of thermodynamic instability and low-level wind shear, especially when considering extreme environments and sharp boundaries such as coastal zones and mountains (Thompson et al. 2003; Allen and Karoly 2014; Gensini et al. 2014; Taszarek et al. 2018; King and Kennedy 2019; Li et al. 2020; Taszarek et al. 2021b; Varga and Breuer 2021). Analysis of trends in different reanalysis datasets has also suggested that results can vary markedly (Robinson et al. 2013; Tang et al. 2019; Koch et al. 2020; Taszarek et al. 2021a), as most of these datasets are typically not designed or validated for this use, despite widespread application (Thorne and

Voss 2010). While these studies have explored historical trends owing to differences in parameter calculations and methodology, no study has explored how these trends in convective environments compare between reanalyses, nor whether these signals are consistent with observed soundings. However, homogenization of long-term radiosonde temperature data on a global scale yielded that even observations feature issues in temporal continuity (Zhou et al. 2021).

Environmental parameters favorable to the development of severe thunderstorms in many studies have been examined using proximity soundings from rawinsonde launches at nearby sites (Rasmussen and Blanchard 1998; Thompson et al. 2003; Potvin et al. 2010; Coniglio and Parker 2020). Atmospheric soundings reflect the true state of the atmosphere at a fixed point in time, however, are disadvantaged by the frequency of sampling, and the spatial distribution of release sites, which correspond with populated areas. Typical sampling is twice daily at 0000 and 1200 UTC by convention, and is not necessarily well timed with the diurnal peak in convective parameters and frequency of severe thunderstorms (Groenemeijer and Kühne 2014; Krocak and Brooks 2018; Taszarek et al. 2020a, 2020b). Soundings are also subject to failures in sampling, such as instrument malfunction, adverse weather or poor vertical resolution, which can render a sampled profile unusable. This suggests that leveraging sounding datasets for long temporal periods requires careful quality control of profiles, and selection of sites with long continuous records on which to perform such an analysis.

Reanalysis by contrast provides uniform sampling of the environment corresponding to model analysis timing, a longer temporal record, and a uniform spatial grid of the underlying data. Evaluation of reanalysis products against observed soundings has suggested that they can reliably represent certain features of the atmospheric state related to convective environments, though performance varies from reanalysis to reanalysis (Allen and Karoly 2014; Gensini et al. 2014; Taszarek et al. 2018; King and Kennedy 2019). Reliability of

reanalysis profiles of wind, temperature and moisture have also been a focus of many prior studies (Graham et al. 2019; Alghamdi 2020; Hallgren et al. 2020; Han et al. 2021; Huang et al. 2021; Virman et al. 2021). Recent evaluations of the ERA5 (Hersbach et al. 2020) and MERRA2 (Gelaro et al. 2017) have shown that both produce correlations with soundings of ~ 0.8 for thermodynamic-related parameters, and ~ 0.9 for wind-related parameters, with low mean errors (Taszarek et al. 2021b). However, ERA5 outperforms MERRA2, in part as a result of the enhanced resolution that allows it to better represent the boundary layer (Varga and Breuer 2021). A number of limitations in reanalyses relate to their generation by model products that due to horizontal resolution must include convective parameterizations, which lead to disturbances of the diurnal cycle, underestimated instability, contamination of convective profiles or other unrealistic attributes (Allen et al. 2014; Tippett et al. 2014; King and Kennedy 2019). Despite this, as we show in this study, relatively consistent performance through time suggests that reanalyses are comparable to soundings for evaluation of long-term trends, despite the limitations associated with the changing volume of observations and other data that is assimilated.

Recent analyses using historical data have suggested that instability is increasing over Europe (Rädler et al. 2018; Taszarek et al. 2021a), however, the sign of the trend can vary over the United States depending on the reanalysis used (Gensini and Brooks 2018; Tang et al. 2019; Taszarek et al. 2021a), driven mainly by the uncertainty in changes of boundary layer moisture. Increases to storm-relative helicity has also been observed and linked to strengthening of the low-level jet over the Great Plains (Barandiaran et al. 2013; Tang et al. 2019). In contrast, changes to vertical wind shear have been modest and generally non-significant. Combinations of aforementioned instability and shear parameters have suggested that increases to convective environments favorable to severe thunderstorms are likely (Gensini and Brooks 2018; Rädler et al. 2018; Tang et al. 2019). However, recent findings

from ERA5 heavily tempers these results, as decreases to relative humidity and rapidly strengthening convective inhibition (CIN) leads to less efficient convective initiation and lower frequency of thunderstorms as a result (Taszarek et al. 2021a). This suggests that any future changes in the response to increasing instability or vertical wind shear may not necessarily lead to more frequent convective hazards, as changes to the frequency of initiation are uncertain. As this result has significant implications for thunderstorm occurrence, it raises the question of whether the ERA5 reliably indicates changes to convective environments through time. Two distinct possibilities are that the depicted changes are a reflection of the reanalysis formulation and temporal biases, or alternatively a signal found more broadly in observed soundings and other reanalysis products. By comparing a large sample of sounding profiles with ERA5, Taszarek et al. (2021b) suggested that ERA5 is likely one of the most reliable available reanalysis for exploration of convective environments, but its credibility in sampling long-term trends has not yet been evaluated. Therefore, building on the analysis of Taszarek et al. (2021a, 2021b) and using these data, in this work we compare long-term trends in convective parameters and vertical profiles between rawinsonde measurements, ERA5 and MERRA2 reanalyses over both Europe and the United States and their surrounding areas. Convective parameters are consistently calculated across the three datasets and assessed to ascertain whether these trends are reliable, robust and meaningful through a variety of convectively important parameters. Signals consistent with all three datasets allow us to better assess credibility of historical trends with respect to future changes, while those signals that notably differ allow us to highlight reanalysis-related issues that should be considered with caution.

2. Dataset and methodology

a. Sounding data

Observational data used in this study were derived from the atmospheric sounding database of the University of Wyoming (<http://weather.uwyo.edu/upperair/>). Here we evaluate all available upper-air observations for 0000 and 1200 UTC over the period 1980–2018 for 84 stations located across Europe and the United States including surrounding areas (Fig. 1a). Although not all evaluated sounding sites are located within the European and United States borders, we will use these terms in describing domains in this study for simplicity. Initially, soundings were downloaded from 232 stations (as in Taszarek et al. 2021b), but in this study we chose only those sites that ensured sufficient quality and continuity of measurements over the period of interest to allow credible trend computation. Using quality-control functions (detailed in the following paragraph) aimed at detecting obvious errors in vertical profiles of temperature, moisture and wind, we removed poor quality soundings that allowed us to choose final sites for the trend evaluation.

Profiles were discarded where the first measurement was higher than 10 m above ground level (AGL) and the highest level was lower than 6000 m AGL (to ensure correct calculation of vertical wind shear). Observations with fewer than 10 levels over the depth of the sounding were also excluded. It was required that each considered level have u and v wind components, temperature, moisture, height and pressure data available. If any variable was missing, such levels were not considered. Only missing moisture observations higher than 6000 m AGL were acceptable as that was often the case for soundings from the 1980s and 1990s, and was not necessary for calculation of metrics considered in this study. Soundings with unrealistic vertical changes of air temperature, moisture or wind conditions were also removed. Temperature gradients between any pair of levels exceeding 12 K km^{-1} in 0–2 km AGL layer, and 10 K km^{-1} above 2 km AGL resulted in those soundings also being removed. We also did not consider non-physical levels where air was saturated and dry-adiabatic at the same time. Mean dew point depression lower than 2°C for the entire profile also resulted in

sounding removal. Quality-control also extended to correction of the lowest 500 m AGL, where gradients of temperature exceeding 12 K km^{-1} were changed to 12 K km^{-1} by adjusting values of air temperature (to reduce any potential negative effect on the parcel calculations). Using selected temperature, wind and moisture parameters, soundings that had values higher than 0.99999th and lower than 0.00001th percentiles (considering the whole dataset) were removed.

Even though the applied quality-control techniques may remove a small fraction of good-quality profiles, they notably increase the overall quality of the sounding dataset. After quality control, we considered only those stations that contained at least 20,000 observations (512 per year) and a ratio between 0000 and 1200 UTC measurements ranging from 0.85–1.15 (to avoid thermodynamic biases resulting from higher number of profiles during day or night). This filter was aimed at focusing only on locations where trends were unlikely to be impacted by other factors. Nevertheless, the mean number of soundings per station was still usually slightly higher for observations from 0000 UTC, which should be taken into account when comparing results with climatological records from ERA5 and MERRA2 (Fig. 1b). In total, 2.07 million atmospheric soundings were obtained following filtering for use in this analysis, including ~1 million from 40 stations in the European domain, and another million from 44 stations situated in the United States domain. The number of available profiles was comparable among seasons, and the missing data accounted for around 15% of the total record equally distributed throughout the year (Fig. 1b).

Despite applied quality-control techniques, we note that there are a number of possible data inhomogeneities which may be caused by the relocation of sounding stations, instrument changes or measurement practices. Because of that, the assumption that rawinsondes provide real long-term trends may be misleading. However, it has been a common practice in recent studies to consider rawinsonde observations as the reference to reanalysis evaluation (Bao and

Zhang 2019; King and Kennedy 2019; Li et al. 2020; Varga and Breuer 2021; Wang et al. 2021).

b. Reanalyses and evaluated variables

ERA5 is the fifth generation atmospheric reanalysis produced by ECMWF (Hersbach et al. 2020) available through the Copernicus Climate Change Service (2017). It has a regular latitude-longitude grid at $0.25^{\circ} \times 0.25^{\circ}$ resolution and 137 hybrid-sigma model levels up to 0.01 hPa. The density of levels in the lower troposphere (e.g. 28 levels in the layer of 0–2 km AGL), allows for detailed representation of conditions in the lower atmosphere that are crucial for thermodynamic metrics such as convective inhibition. ERA5 reanalysis is based around a 4D-Var assimilation method, and provides hourly data with 12-h assimilation windows (at 0900 and 2100 UTC).

The second reanalysis is the Modern-Era Retrospective analysis for Research and Applications version 2 (MERRA2; Gelaro et al. 2017) developed by NASA's Global Modeling and Assimilation Office and based on a period of regular conventional and satellite observations starting in the 1980s. MERRA2 has a $0.5^{\circ} \times 0.625^{\circ}$ horizontal grid spacing with 72 hybrid-sigma model levels, where in contrast to ERA5, only 14 are included in the layer 0–2 km AGL. The reanalysis relies on a 3D-Var algorithm for assimilation based on the gridpoint statistical interpolation (GSI) with 6-h update cycle and so-called first-guess-at-appropriate-time (FGAT) procedure and a temporal resolution of 3 hours (Gelaro et al. 2017).

Both reanalyses were obtained for a period equivalent to the sounding data to match the nearest proximal grid to the selected sounding sites across Europe and the United States for all 0000 and 1200 UTC steps (Fig. 1a). As reanalyses do not suffer from the same quality control issues as observations, we used complete datasets for the profiles while, for soundings only the number of available measurements were used. Vertical profiles of temperature,

humidity, height, pressure, u and v wind components in all three datasets were processed with the ‘*thundeR*’ R language package (Taszarek et al. 2021b). To match surface conditions between soundings, ERA5 and MERRA2, an interpolated level of 10 m AGL was chosen as a starting point for computations in all three datasets. Parameters evaluated in this study (Table 1) were chosen based on prior studies focusing on various aspects of severe convective storms across Europe and the United States (Craven and Brooks 2004; Gensini and Ashley 2011; Mohr and Kunz 2013; King and Kennedy 2019; Rädler et al. 2019; Chen et al. 2020; Liu et al. 2020; Taszarek et al. 2020b, 2021b). For calculation of mixing ratio (MIXR), lifted index (LI) and CIN a mixed layer of 0–500 m AGL was used. Following Púčik et al. (2017), we use LI instead of CAPE as it is a continuous quantifier even if the atmosphere is stable whereas CAPE by its nature only represents buoyant atmosphere. Bulk wind shear parameters were computed as a magnitude between surface (10 m AGL) and heights of 1 km AGL (BS01) and 6 km AGL (BS06). Downdraft CAPE (DCAPE; Gilmore and Wicker 1998) was computed by calculating the lowest θ (theta-e) value in the layer of 0–4 km AGL and descended moist adiabatically to the surface. In this study we also present trends in a vertical profile of temperature interpolated every 100 m relative to the height above ground level. We do not evaluate trends in vertical profiles of dew point temperature, due to frequent gaps in rawinsondes data before 1990 and reliability of moisture measurements, especially in higher parts of the troposphere.

One of the most significant limitations of using reanalysis when compared to observed profiles, is the horizontal grid spacing ($0.25^\circ \times 0.25^\circ$ for ERA5 and $0.5^\circ \times 0.625^\circ$ for MERRA2), which results in vertical profiles reflecting an average over that grid at any individual level. Thus, reanalyses struggle with representation of local processes, most commonly seen along sharp boundaries such as mountains or coastal zones. Convective parameterization schemes applied in ERA5 and MERRA2 can also lead to errors in the

vertical profile of temperature and moisture as compared to rawinsonde observations (Allen et al. 2014; King and Kennedy 2019; Taszarek et al. 2021b; Varga and Breuer 2021; Wang et al. 2021). However, in this study these issues are of lower importance, as we focus on the magnitude and sign of the temporal change and any single-profile differences are reduced by the large sample size and climatological averaging. Although local biases with respect to absolute values of specific variables are still possible, we expect a slope of the trends to be consistent between all three datasets if the signal is credible and physically-based.

c. Regionalization and trend computation

Long-term changes in selected convective parameters are considered for individual stations across Europe (40) and the United States (44; Fig. 1a). Based on annual means, trends are calculated for each dataset using the non-parametric Sen's slope estimator (Wilcox 2010). This method of trend calculation is non-parametric, more robust to outliers, and thanks to these properties, it is commonly applied in atmospheric sciences, especially extreme events (e.g. Gensini and Brooks 2018; Tang et al. 2019; Masroor et al. 2020). In this research, a non-parametric Mann-Kendall two-tailed test and Sen's slope estimator was used to ascertain significant trends, at the $\alpha = 0.05$ level. Resulting trends are normalized to show changes per decade to improve interpretation. Calculations were provided using the '*trend*' R package (Sen 1968; Hipel and McLeod 1994).

In addition to individual station analysis, a regional aggregation of data was also considered, allowing us to minimize negative aspects arising from analysis of single-station data. For Europe this focused on four regions: Northwest, Central, Southeast, and East, while for the United States: Northern Great Plains, Southern Great Plains, Midwest, and Southeast (as defined on Fig. 1a). Each region was chosen to consist of 3–7 stations. The slope of the trend was also computed for the mean values across meteorological seasons (MAM, JJA,

SON, DJF).

3. Results

a. Moisture and lapse rate parameters

Trends in near-surface moisture represented by observations indicate decreases over the western United States and significant increases over the eastern part of the country (Fig. 2, Fig. 3). Results from ERA5 are in agreement with observations, but MERRA2 provides increases over the entire United States, primarily during spring and summer (Fig. 3). The discrepancy in trends of MIXR between MERRA2 and observations is surprising, as this variable is generally well represented by MERRA2 with high correlations and small mean errors (Taszarek et al. 2021b). This suggests that the primary source of error in MERRA2 for the United States is most likely related to the quantity and quality of assimilated data over time (McCarty et al. 2016).

Across Europe, changes in low-level moisture are in much better agreement between the three datasets, with significant positive trends over the entire continent except the southwest and east. The largest trends exceed $+0.2 \text{ g kg}^{-1}$ per decade, and are observed for stations located in central and southern Europe (Fig. 2a). Seasonally, all datasets are consistent with increases of around $+0.1 \text{ g kg}^{-1}$ per decade, except spring and summer in eastern Europe where small insignificant decreases are indicated by soundings and ERA5 (Fig. 3). Considering absolute differences between reanalyses and soundings, MIXR is typically underestimated by reanalyses across the United States through time, while in contrast it is slightly overestimated for Europe (Fig. 3).

For 0–3 km AGL lapse rates (LR03), mostly positive tendencies are observed for sounding sites across the United States, but in contrast the reanalyses show downward and insignificant trends (Fig. 2b). Lapse rates trends notably vary in space, especially over areas

with complex terrain, which was also demonstrated for other parts of the world by Minder et al. (2010) and Kattel et al. (2012). A disparity in trends of LR03 is also observed among seasons. During spring and summer decreasing trends are observed across the Northern Great Plains while increases occur during winter (Fig. 4). In the Midwest, there is a good agreement in terms of increases between reanalyses and soundings during summer, autumn and winter. Southern Great Plains and Southeast feature mixed trends.

In Europe, similar to MIXR, reanalyses and observations are in agreement and indicate significant increases to LR03 of around $+0.06 \text{ K km}^{-1}$ per decade across almost the entire continent except Mediterranean area (Fig. 2b). The best agreement is found in central Europe where significant increases in LR03 occur all year round (Fig. 4). Over northwestern and southern Europe there are similar patterns, with the exception of spring where only modest changes take place (Fig. 4). For eastern Europe, the trend is inconsistent among the datasets during autumn and winter where MERRA2 indicates strong decreases in contrast to ERA5 and soundings. Over both domains ERA5 provides overall similarity to soundings for LR03 compared to MERRA2, which is mostly underestimated. Although the biggest differences among datasets are observed over Southern Europe, the slope of the trend is very similar.

Consistent decreases in the mean 0–4 km AGL relative humidity (RH04) are observed for both continents and each dataset (Fig. 2c). This result is in line with prior studies suggesting that pronounced decreases in the land surface relative humidity are an expected outcome of a warming climate as temperature rises outpace available moisture (Frick et al. 2014; Byrne and O’Gorman 2016, 2018; Vicente-Serrano et al. 2018; Chen et al. 2020; Taszarek et al. 2021a). Across the southern Great Plains all datasets suggest reductions in RH04 of around -1% per decade during spring and winter, while over other regions in the United States only modest and insignificant signals are observed (Fig. 5).

In Europe, trends in RH04 are more mixed depending on the region and season evaluated. Significant decreases in all seasons are found across the datasets for central, eastern and northwestern Europe. Annual rates of change exceed -0.5% per decade, and the strongest decreases above -2% per decade are in spring summer (Fig. 5). The most significant changes can be observed especially in Eastern Europe, where all datasets are in agreement with downward trends. In contrast, changes over southern Europe indicate increases, mainly during autumn and winter, but these signals are mostly insignificant.

b. Buoyancy parameters

Spatial patterns in trends of LI are similar to MIXR with all datasets having a consistent signal across Europe, and different signals in the United States. While changes to instability based on sounding data seems to be mostly insignificant, ERA5 indicates significant decreases in buoyancy (increases in LI) over the western mountainous part of the United States (Fig. 6a). MERRA2 has a differing pattern with robust increases to buoyancy (decreases in LI) observed over eastern portion of the United States. Seasonally, trends among the datasets and seasons are mixed with the most consistent changes over the Midwest where increases in buoyancy are observed in summer and autumn (Fig. 7). In comparison to these results, DeRubertis (2006) using rawinsonde observations over the period 1973–1997 found an increase in instability during summer, particularly over the southern states.

In Europe, the atmosphere has become significantly more unstable across all datasets, with the most notable decreases in LI over parts of central and southern Europe, especially in the Alpine region where the rate of change exceeds -0.5 K per decade (Fig. 6a). Seasonal changes in Europe are also consistent between datasets and indicate consistent increases in instability in every season and region (except spring and summer in eastern Europe; Fig 7). Another important aspect is that over the entire evaluated 39-year period mean errors between

reanalyses and soundings are small, despite inconsistency in dew points caused by changes in the instrumentation around the year 1990 (Mohr and Kunz 2013). These cross-dataset findings for LI increases our confidence in the result of consistently increasing atmospheric instability across Europe, mainly driven by rising near surface temperature and moisture (Kunz et al. 2009; Riemann-Campe et al. 2009; Púčik et al. 2017; Rädler et al. 2019; Taszarek et al. 2021a). However, as noted in prior research, increases to moisture provide more near-surface moist static energy and thus deliver a greater contribution to rising instability (Agard and Emanuel 2017; Li and Chavas 2021).

Despite differences among moisture and instability parameters between reanalyses and observations over the United States, there is robust agreement for changes in CIN. CIN is a very important variable, which when large in magnitude, is indicative of resistance of the atmosphere to storm initiation, despite availability of ample instability (Wilson and Roberts 2006; Bunkers et al. 2010; Gensini and Ashley 2011; Hoogewind et al. 2017; Westermayer et al. 2017; Taszarek et al. 2020b). Over both domains each of the datasets shows robust decreases in CIN (increasing inhibition) (Fig. 6b). Across the United States, the highest decreases in CIN occur over the Great Plains (around -3.5 J kg^{-1} per decade) where climatologically CIN reaches the highest values (Gensini and Ashley 2011; Taszarek et al. 2020b). However, significant decreases in CIN are found at almost every station east of the Rocky Mountains, suggesting increasing resistance to convection and greater stability (Fig. 6b and 8). Decreases in CIN are found for all seasons, but the strongest rate of change of around -5 J kg^{-1} per decade is during spring and summer across the Great Plains. Although the slope of the trend is generally in good agreement with observations, reanalyses still underestimate the absolute value of CIN (Fig. 8). Results also indicate that consistent increases in convective inhibition seem to be advancing faster than changes to instability, which may lead to less effective convective initiation in future - a result broadly consistent with prior studies

(Hoogewind et al. 2017; Chen et al. 2020; Rasmussen et al. 2020; Taszarek et al. 2021a).

In Europe, changes to CIN are less pronounced, partly as a result of overall smaller climatological CIN (Siedlecki 2009), but the rate and sign of change remains consistent between reanalyses and soundings (Fig. 6b). Trends for Europe generally do not fall below -1 J kg^{-1} per decade, although the majority of these signals are still significant. Seasonally, the largest decreases in CIN (increasing inhibition) occur during both spring and summer over southern Europe, while changes elsewhere during the remainder part of the year are very small and not significant (Fig. 8). Similar to the United States, both ERA5 and MERRA2 demonstrate a consistent underestimation of CIN through time for Europe. However, in contrast to LI, reanalyses successfully reconstruct the rate of the change and sign over both domains, and regardless of the analyzed region, the largest changes are typically during spring and summer (Fig. 8).

Another parameter of interest is DCAPE - a proxy of atmospheric potential for producing strong convective winds originating from evaporative cooling of downdrafts (Gilmore and Wicker 1998). Values of DCAPE are generally large when the mid-troposphere is dry and low-level lapse rates are steep. Thus, previously discussed decreases in RH04 (Fig. 6c) and increases in LR03 (Fig. 6b) should lead to higher DCAPE over time. Although large instability environments are typically accompanied also by high DCAPE, as evidenced in our study, trends in these parameters are not consistent. Despite mixed trends in LI across the United States (Fig. 6a), reanalyses and soundings are in better agreement in terms of significant increases to DCAPE over the United States (Fig. 6c). Positive trends are also found for every season and region with the most significant changes during spring and summer across the Great Plains of the United States (Fig. 9).

In Europe, robust increases in DCAPE can be found across the entire continent, each dataset, and every season (Fig. 6c and 9). The highest rate of change in the mean annual

DCAPE is observed over southern Europe with some of the sounding stations indicating increases as large as $+30 \text{ J kg}^{-1}$ per decade. Changes in central and western Europe are also pronounced with many stations exceeding $+25 \text{ J kg}^{-1}$ per decade. The highest contribution to these increases is mainly during summer in line with the annual cycle of convective activity, but also in spring (Fig. 9). These results indicate that the potential for severe convective winds resulting from evaporative cooling of the downdrafts is increasing across Europe. Whether this has manifested in observed downburst events is difficult to assess as there remain strong temporal and spatial limitations for wind reports in the European Severe Weather Database (Pacey et al. 2021). It is also important to highlight that over both domains, reanalyses mostly underestimate absolute values of DCAPE when compared to soundings (Fig. 9).

c. Wind parameters

Changes in the vertical profile of wind are an important aspect of convective environments, as availability of strong vertical wind shear and/or the presence of a low-level jet promotes better organized convective modes such as squall lines or supercells that are more capable of producing severe weather (Smith et al. 2012; Thompson et al. 2012; Guastini and Bosart 2016; Bagaglini et al. 2021; Pacey et al. 2021). Changes to BS06 over both domains are generally modest with most trends being insignificant (Fig. 10a). However, despite the low mean errors for wind parameters, the slope of the trend and sign is diversified among seasons and regions (Fig. 11). The most consistent signal among all datasets is observed over the Northern Great Plains and Midwest where a mean annual BS06 has been increasing with a rate of around $+0.2 \text{ m s}^{-1}$ per decade, mostly during spring and winter (Fig. 11). In Europe, a long-term decrease occurs in almost every season and in each dataset except northwest where increases in the sounding database (mostly during winter) are in contrast to modest decreases in ERA5 and MERRA2 (Fig. 10). Better overlap between absolute values of BS06 in soundings and reanalysis is observed in the United States as compared to Europe,

although both reanalyses typically underestimate BS06.

Considerable differences between observations and reanalyses are found for BS01, an important parameter in tornado prediction (Thompson et al. 2003; Grams et al. 2012; Gensini and Bravo de Guenni 2019; Ingrosso et al. 2020; Rodríguez and Bech 2020; Tochimoto et al. 2021). This is somewhat unsurprising given a known tendency for this parameter to be underestimated in numerical weather prediction datasets (Allen and Karoly 2014; Gensini et al. 2014; Taszarek et al. 2018; King and Kennedy 2019; Taszarek et al. 2021b). Our results not only indicate large differences in the absolute values of BS01 between the datasets, but differing signs of the trend for soundings (Fig. 10b and 12). The two reanalyses provide generally very similar signals, with local modest significant increases across the United States and decreases in Europe, while soundings over both continents feature increases, which are the largest over southwestern Europe (Fig. 10b and 12). For Europe, the mean error in BS01 between reanalyses and soundings has changed over time from overestimation in the 1980s to underestimation in recent years with respect to ERA5. This tendency may be connected with a changing quality of rawinsonde wind measurements over time, and an increasing number of available low-tropospheric levels in the 1990s for the area of Europe (Taszarek et al. 2021b). Using the Standard Normal Homogeneity Test (R ‘*trend*’ package), we found change-point in BS01 data in 1992 for all analyzed European regions. Because of that clear discontinuity, we present trends for soundings in Europe for the period of 1992–2018 (Fig. 10 and 12). For these years both reanalyses have similar trend slopes as sounding data across southern and eastern Europe but feature higher underestimation of BS01 absolute values when compared to the United States.

Considering a mean wind in the 1–3 km AGL layer (MW13) as proxy for the low-level jet (Rife et al. 2010; Shapiro et al. 2016), we find more consistent results between datasets as compared to BS01 (Fig. 10). Trends in MW13 across the United States are mixed

seasonally, but those stations that exhibit significant changes indicate small increases over Southeast (mainly during summer and winter; Fig. 13). Changes to MW13 across Europe are spatially very similar to those of BS06, with more widespread significant trends (Fig. 10c). Sounding trends are mixed, while reanalyses seem to only capture negative trends with the biggest differences relative to observations over southwestern Europe. Consistent significant decreases in MW13 are found for all datasets over central and eastern Europe in every season (Fig. 13). In contrast to BS01, MW13 features fairly small mean errors in magnitude between soundings and reanalyses, although errors are similarly larger over Europe (Fig. 13).

d. Vertical profiles

In order to better understand which processes are leading to specific changes in convective parameters, we evaluate trends in vertical profiles of temperature in all three datasets. In the United States (Fig. 14), positive trends in air temperature across the vertical profile can be observed during all seasons except winter. Temperature increases generally by around 0.2°C per decade, but this rate differs among regions and by AGL height (Fig. 14). The best agreement among datasets in terms of significance of the trend is observed across Southern Great Plains in spring, summer and autumn, where warming of the near-surface is lower compared to aloft. This pattern may be related to more intense drying and warming over the western United States, which through the advection of elevated-mixed layers, is displaced eastwards (Carlson and Ludlam 1968). As evidenced in the results of our study, this mechanism leads to increases in CIN, and in some situations may even cause stabilization and decreases in instability (Taszarek et al. 2021a). The biggest differences among the datasets are during winter, especially over Northern Great Plains and Midwest where sounding measurements indicate negative trends in low and mid troposphere as opposed to modest changes in ERA5 and MERRA2 (Fig. 14).

In Europe, we find a good agreement between datasets among all regions and seasons, except spring and summer over eastern Europe where sounding data indicate faster warming as compared to ERA5 and MERRA2 (Fig. 15). Increases in temperature of around $+0.5^{\circ}\text{C}$ per decade in almost the entire tropospheric profile are significant among datasets during spring and summer across northwestern, central and southern Europe, and summer and autumn in eastern Europe. In autumn and winter, trends across northwestern, central and southern Europe have typically smaller and insignificant rates with the highest values near-surface (Fig. 15). It can be also observed that for both Europe and the United States the rate of warming in the upper troposphere decreases with height and in some regions negative trend values occur, especially for the sounding data. This finding is in agreement with IPCC reports, where cooling of the upper troposphere and stratosphere over the last decades has also been indicated (IPCC, 2014).

4. Concluding remarks and discussion

In this study trends in convective parameters derived from ERA5 and MERRA2 reanalyses were compared with ~ 2.07 million proximal atmospheric soundings over the period of 39 years (1980–2018) across Europe and the United States. We examined which parameters commonly used in the operational prediction of severe thunderstorms and climatological evaluations feature consistent trends among datasets and which have differing signals. Results consistent among soundings, ERA5 and MERRA2 increase our confidence while differences raise uncertainties. Below, we highlight the most important findings:

- Differences in trends exist between Europe and the United States for common metrics including low-level moisture, lapse rates, instability, vertical wind shear and mean wind. These differences are robust whether using observations or reanalysis data.
- Trends seem to be more consistent among reanalyses and sounding datasets over

Europe as compared to the United States where bigger differences are observed for MERRA2 in low-level moisture and instability.

- All datasets are in a remarkable agreement for trends in CIN. This highlights robust strengthening of inhibition through differential mid-tropospheric warming, especially across the Great Plains during spring and summer despite only modest changes to instability.
- Robust increases in DCAPE are consistent among datasets and domains. These changes indicate that the potential for severe winds resulting from evaporative cooling is likely increasing in a warming climate as low-level lapse rates are becoming steeper and relative humidity decreases, thus contributing to higher DCAPE.
- Low-level wind shear features clear data inhomogeneities over time for sounding measurements. Reanalyses indicate modest increases over the United States and decreases in Europe, while soundings indicate increases over both domains. This disagreement indicates large uncertainties related to trends in BS01. Low correlations and enhanced mean errors for this parameter were also found in prior studies comparing reanalyses with observations (Allen and Karoly 2014; Gensini et al. 2014; Taszarek et al. 2018; King and Kennedy 2019; Taszarek et al. 2021b).
- Reanalyses are in a good agreement with observations for trends in deep-layer wind shear and low-level jet, although these trends are generally insignificant. Modest increases are observed across the United States while reductions occur in Europe. This result remains in contrast to future projections evaluated in Hoogewind et al. (2017) and Rädler et al. (2018) where opposite signals for the vertical wind shear were found. However, it is possible that projected trends may not have emerged from relatively larger interannual variability.

- Trends in vertical profiles of air temperature represented by soundings, ERA5 and MERRA2, show warming of the low and mid troposphere for almost all seasons and regions. Significant changes were found for all seasons in the Southern Great Plains, as also for spring and summer in all European regions. In Europe warming is the strongest typically near-surface while in the United States around 2–3 km AGL, which contributes to increases in CIN.

Results presented in this study suggest that while trends may vary depending on evaluated variable and region, reanalyses are generally capable of providing reasonable results for convective parameters when used with caution. While this differs from the overall aim of reanalysis products (Thorne and Vose 2010), these offer much better temporal and spatial record than observations for this application and thus can be used in more complex analyses. As recent reanalyses have become increasingly popular in studying convective environments (e.g. Gensini and Brooks 2018; Rädler et al. 2018; Mohr et al. 2019; Tang et al. 2019; Tippett et al. 2019; Li et al. 2020; Bagaglini et al. 2021; Sulik 2021), it is of great importance to test their performance and be aware of their limitations. However, given limitations of observational data, soundings should be also used with caution as a reference dataset. While ERA5 and MERRA2 differ in terms of spatial resolution or assimilation methods used in their production, trends evaluated in this study are similar for many variables and indicate a similar sign of change when compared to observations. This similarity is most prevalent for CIN, DCAPE, BS06, and MW13, where spatial variability, statistical significance, and the magnitude of trends is consistent between the datasets.

Near-ground wind and moisture parameters continue to present issues for credible trend evaluation, with notable discrepancies among datasets for parameters like MIXR over the United States and BS01 in Europe. This trend inconsistency is despite high correlations exceeding 0.97 for MIXR when ERA5 and MERRA2 are compared with soundings (Taszarek

et al. 2021b). This highlights that statistically significant correlations may not necessarily mean that a reanalysis has a credible representation of a long-term trend as the skill of reanalyses and reliability of rawinsonde measurements also changes over time. Not every dataset may be suitable for reliable sampling of trends in selected variables or geographical regions and thus any results considering temporal changes should be always interpreted with caution and compared with available datasets. As shown in our study, a good agreement among datasets for CIN and DCAPE increased our confidence for trends in these parameters, while differences for MIXR or BS01 raised uncertainties.

Acknowledgements

This research was supported by a grant from the Polish National Science Centre (2017/27/B/ST10/00297). J.T. Allen acknowledges support from the National Science Foundation under Grant No. AGS-1945286. Additional funding was provided by the Funding was provided by NOAA/Office of Oceanic and Atmospheric Research under NOAA-University of Oklahoma Cooperative Agreement #NA21OAR4320204, U.S. Department of Commerce.

Data availability statement

All datasets used in this study are openly available. ERA5 data was downloaded from the European Centre for Medium-Range Weather Forecasts (ECMWF), Copernicus Climate Change Service (C3S) available at <https://cds.climate.copernicus.eu/>. MERRA2 data was downloaded from the National Aeronautics and Space Administration (NASA), Goddard Earth Sciences Data and Information Services Center (GES DISC) available at <https://disc.gsfc.nasa.gov/>. Radiosonde data was downloaded from the University of Wyoming upper air database available at <http://weather.uwyo.edu/upperair/>.

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Table 1. Parameters evaluated in the study

Abbreviation	Full name	Units
MIXR	0-500 m mixed-layer mixing ratio	g kg^{-1}
CIN	0-500 m mixed-layer convective inhibition	J kg^{-1}
LI	0-500 m mixed-layer lifted index at 500 hPa	K
DCAPE	0-4000 m lowest theta-e downdraft convective available potential energy	J kg^{-1}
LR03	0-3000 m temperature lapse rate	K km^{-1}
BS06	0-6000 m bulk wind difference (wind shear)	m s^{-1}
BS01	0-1000 m bulk wind difference (wind shear)	m s^{-1}
RH04	0-4000 m mean relative humidity	%
MW13	1000-3000 m mean wind	m s^{-1}

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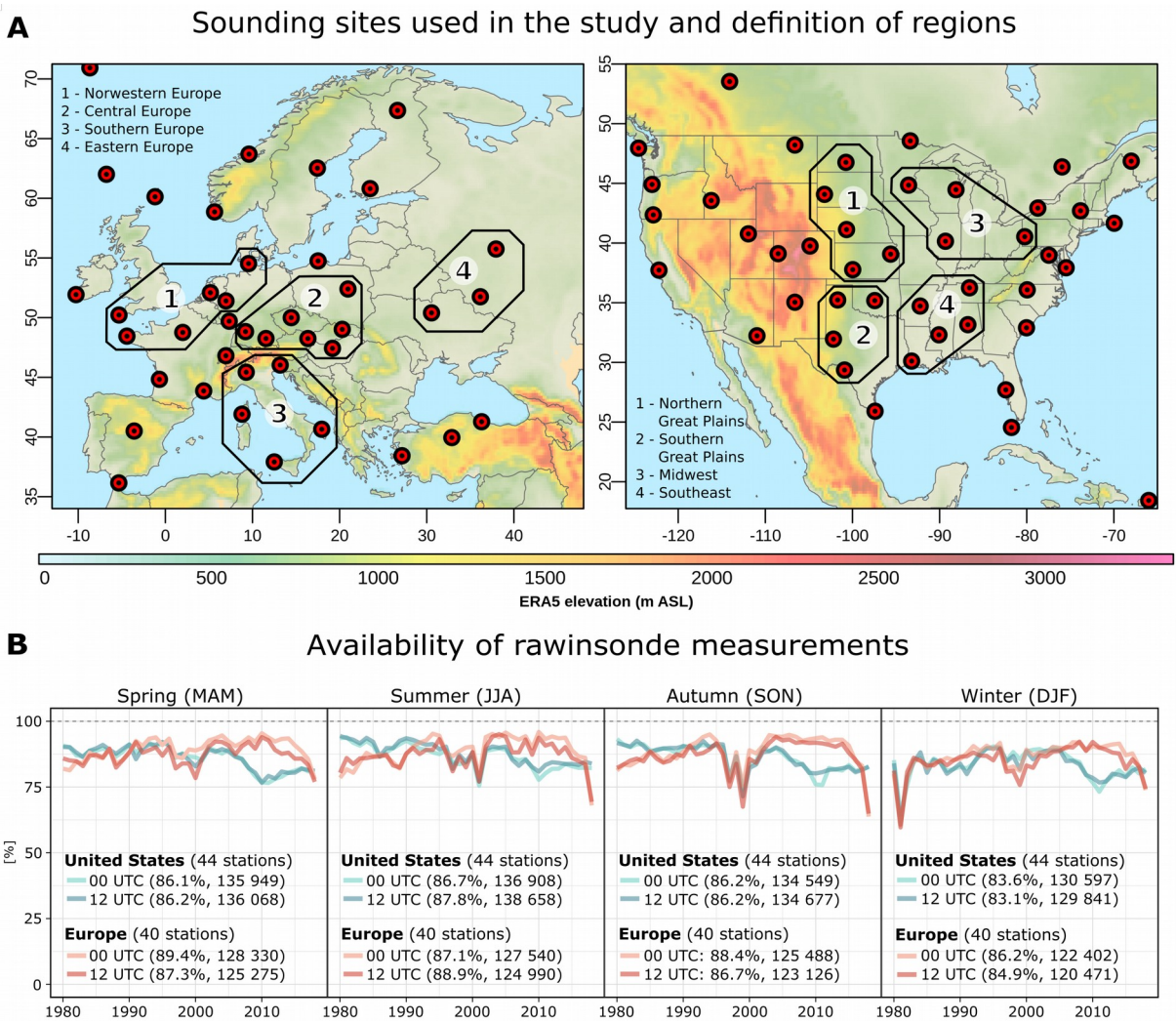


Figure 1. (a) Sounding stations used in the analysis and definition of regions, and (b) mean number of 0000 and 1200 UTC observations over the seasons.

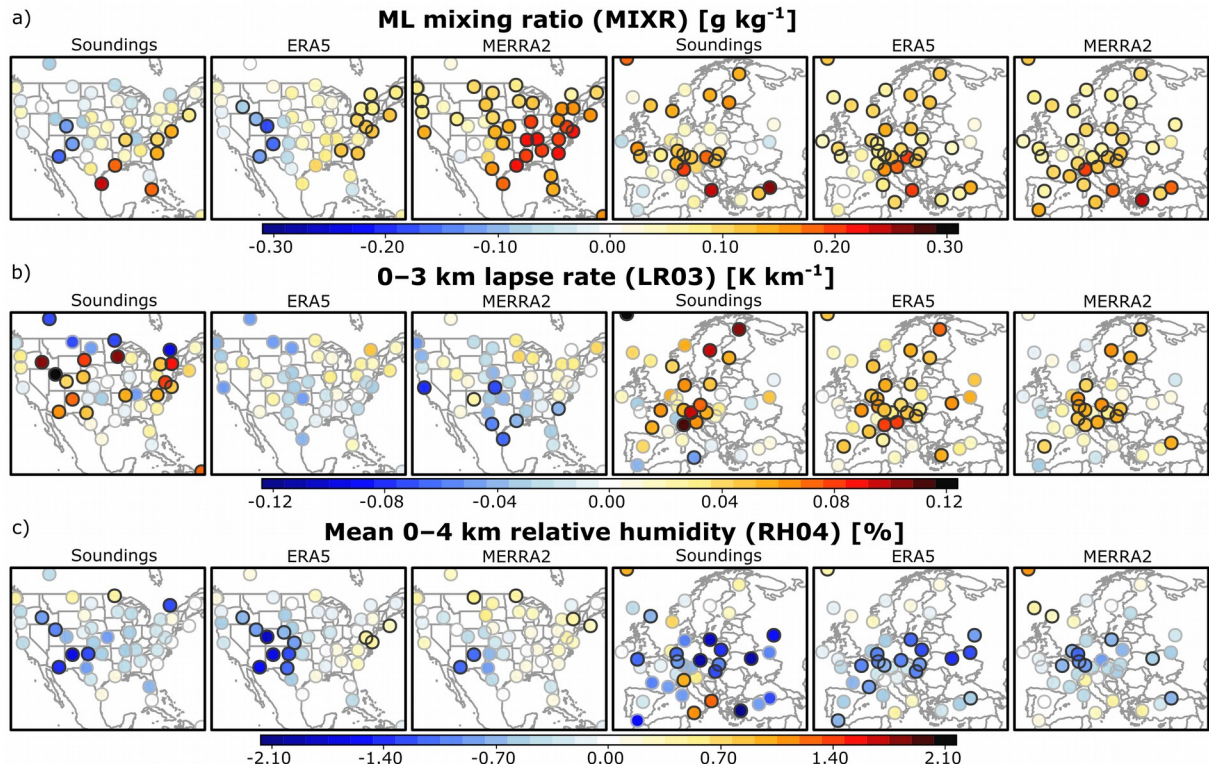


Figure 2. Long-term trend per decade for a) ML mixing ratio, b) 0–3 km lapse rate, and c) mean 0–4 km relative humidity, based on soundings, ERA5, and MERRA2. Trend is derived from Sen’s slope estimator. Black circles around each point denote p-value below 0.05. Only 00 and 12 UTC time steps are considered.

ML mixing ratio (MIXR) [g kg^{-1}]

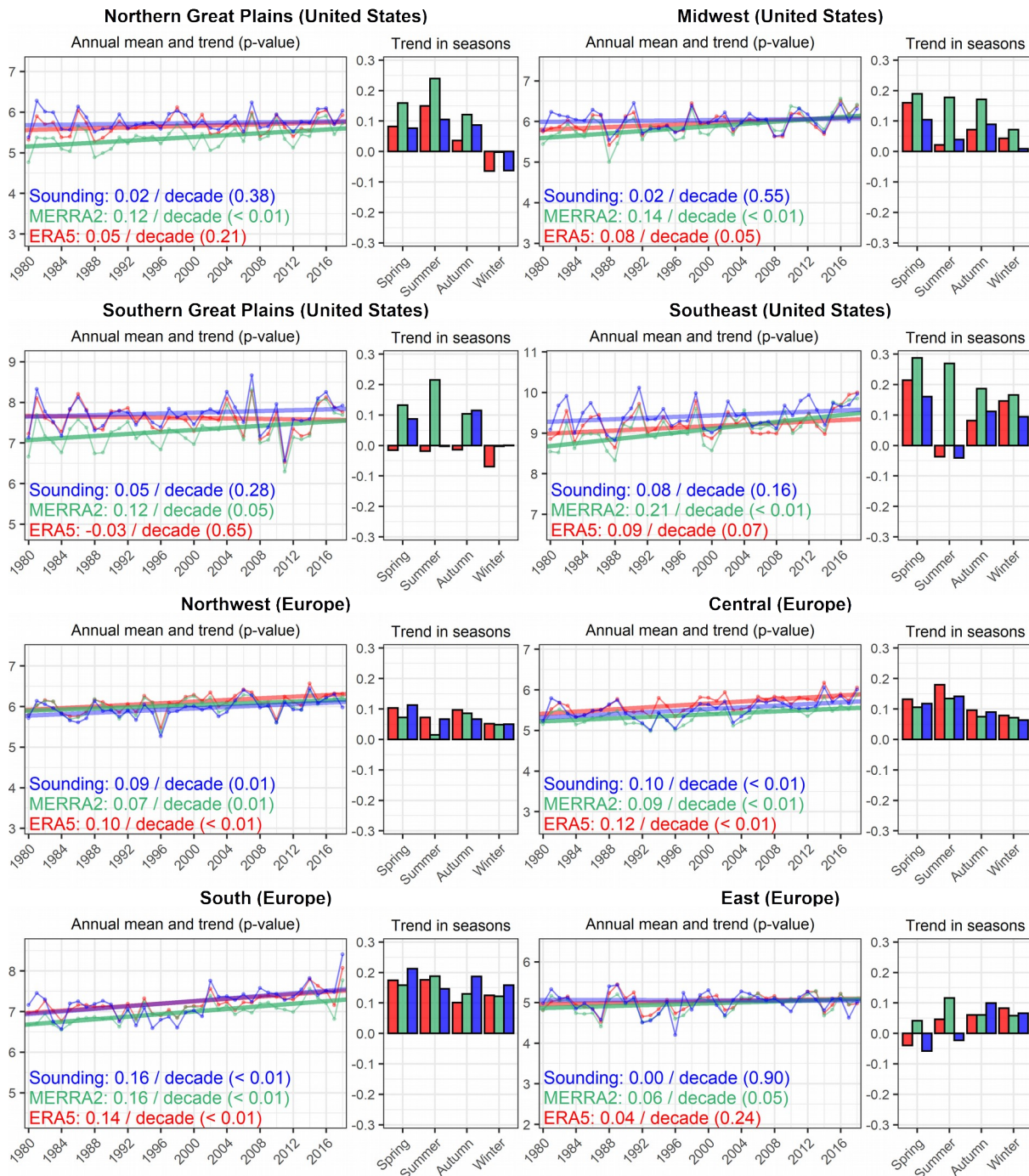


Figure 3. Annual mean and corresponding long-term trend for the period 1980-2019 among European and United States regions for ML mixing ratio (blue - soundings, green - MERRA2, red - ERA5). Trend is derived from Sen's slope, values in the brackets denote p-value. Bars indicate trend values per decade over seasons. Only 00 and 12 UTC time steps are considered.

0–3 km lapse rate (LR03) [K km^{-1}]

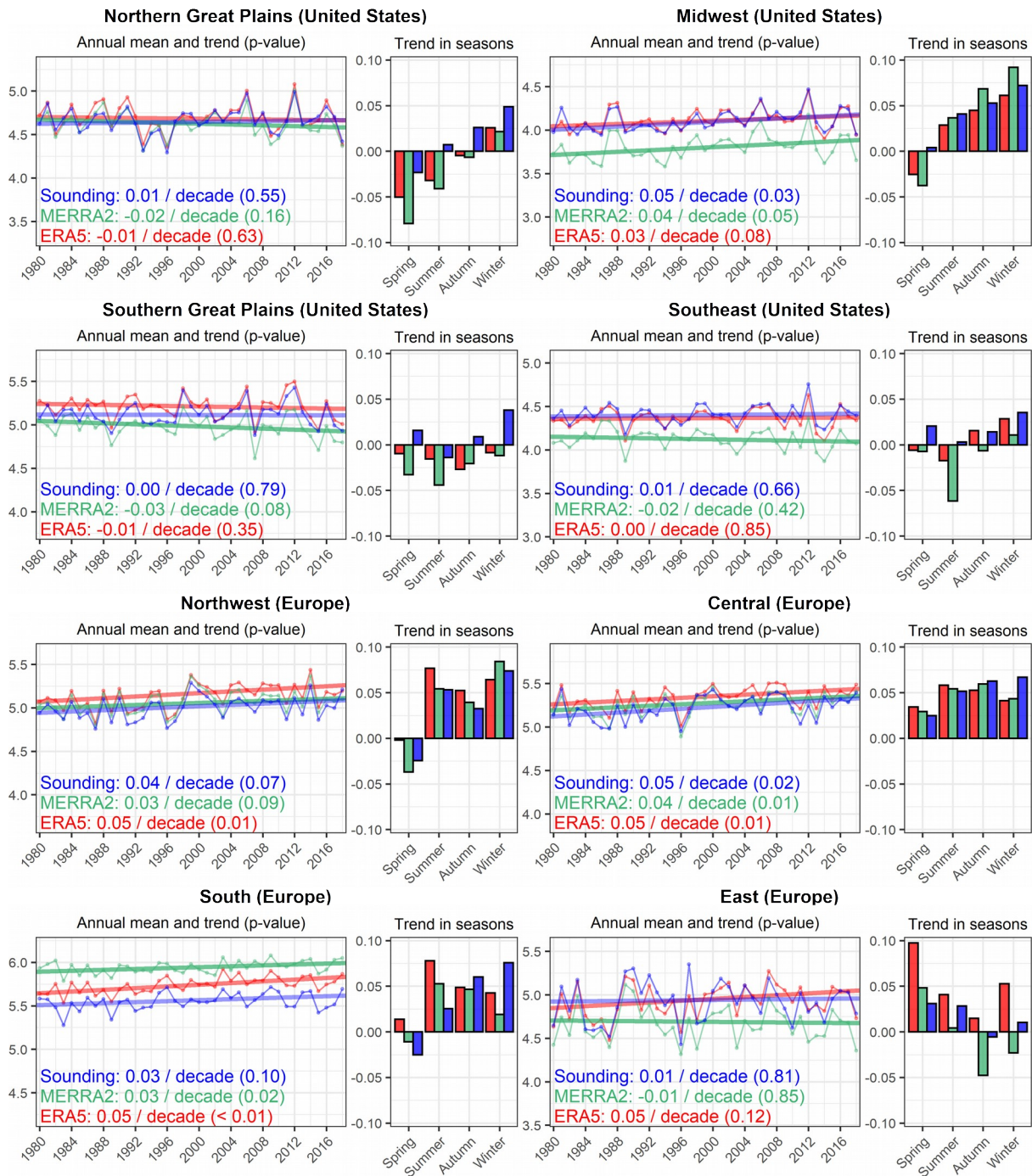


Figure 4. As in Fig. 3 but for 0–3 km lapse rate.

Mean 0–4 km relative humidity (RH04) [%]

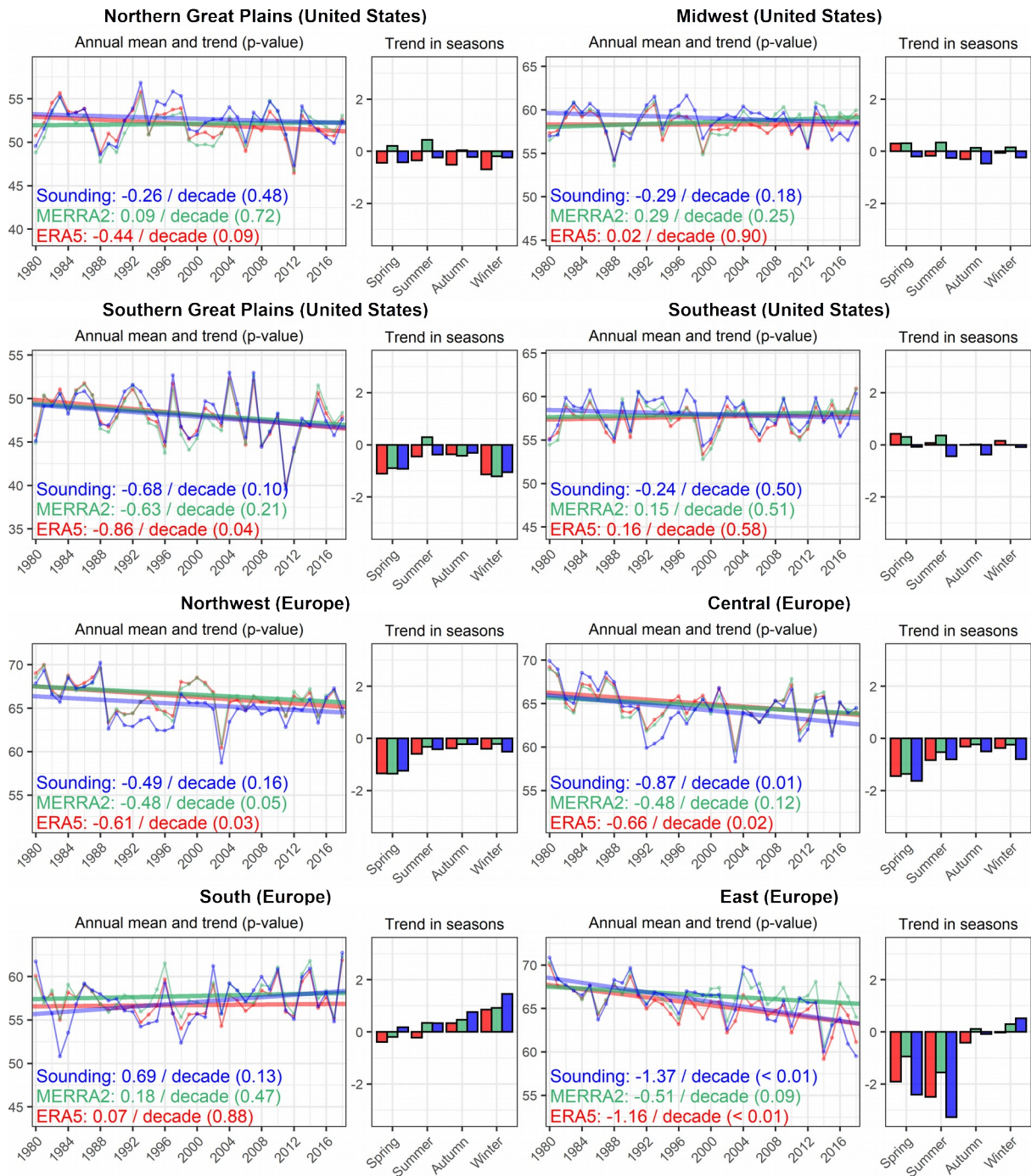


Figure 5. As in Fig. 3 but for mean 0–4 km relative humidity.

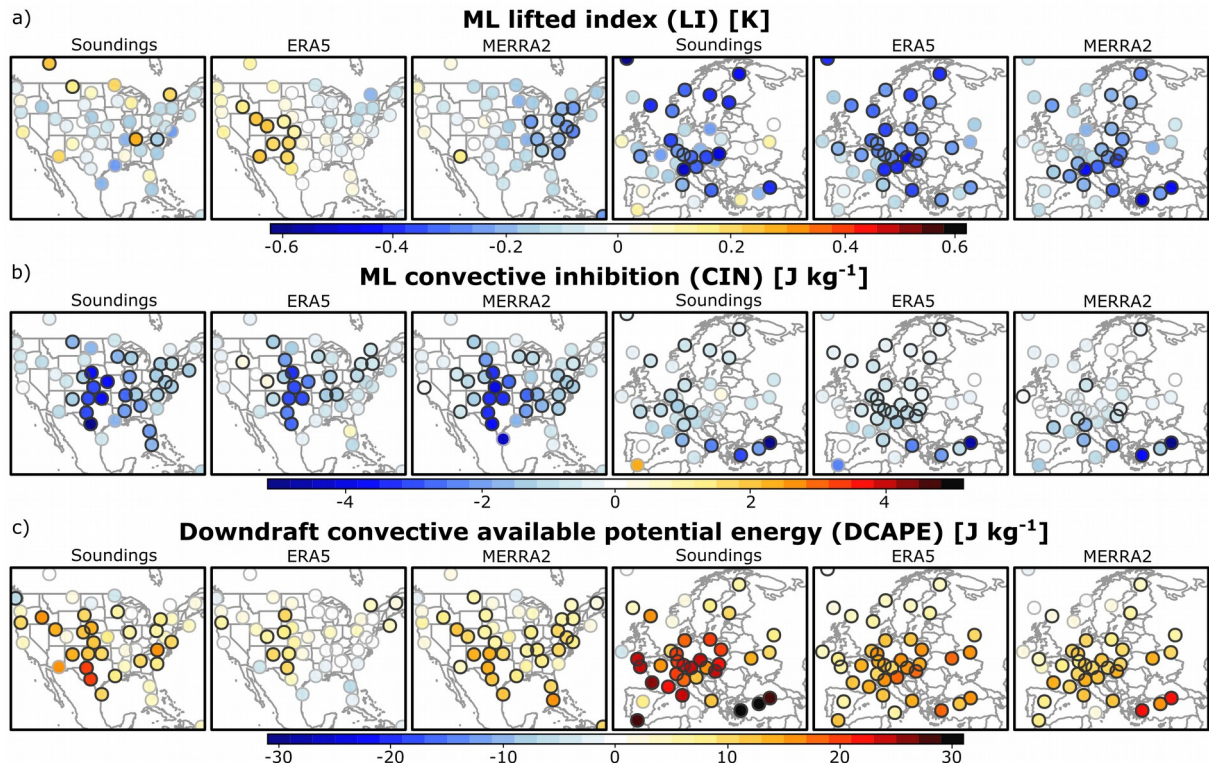


Figure 6. As in Fig. 2 but for (a) ML lifted index, (b) ML convective inhibition, and (c) downdraft convective available potential energy.

ML lifted index (LI) [K]

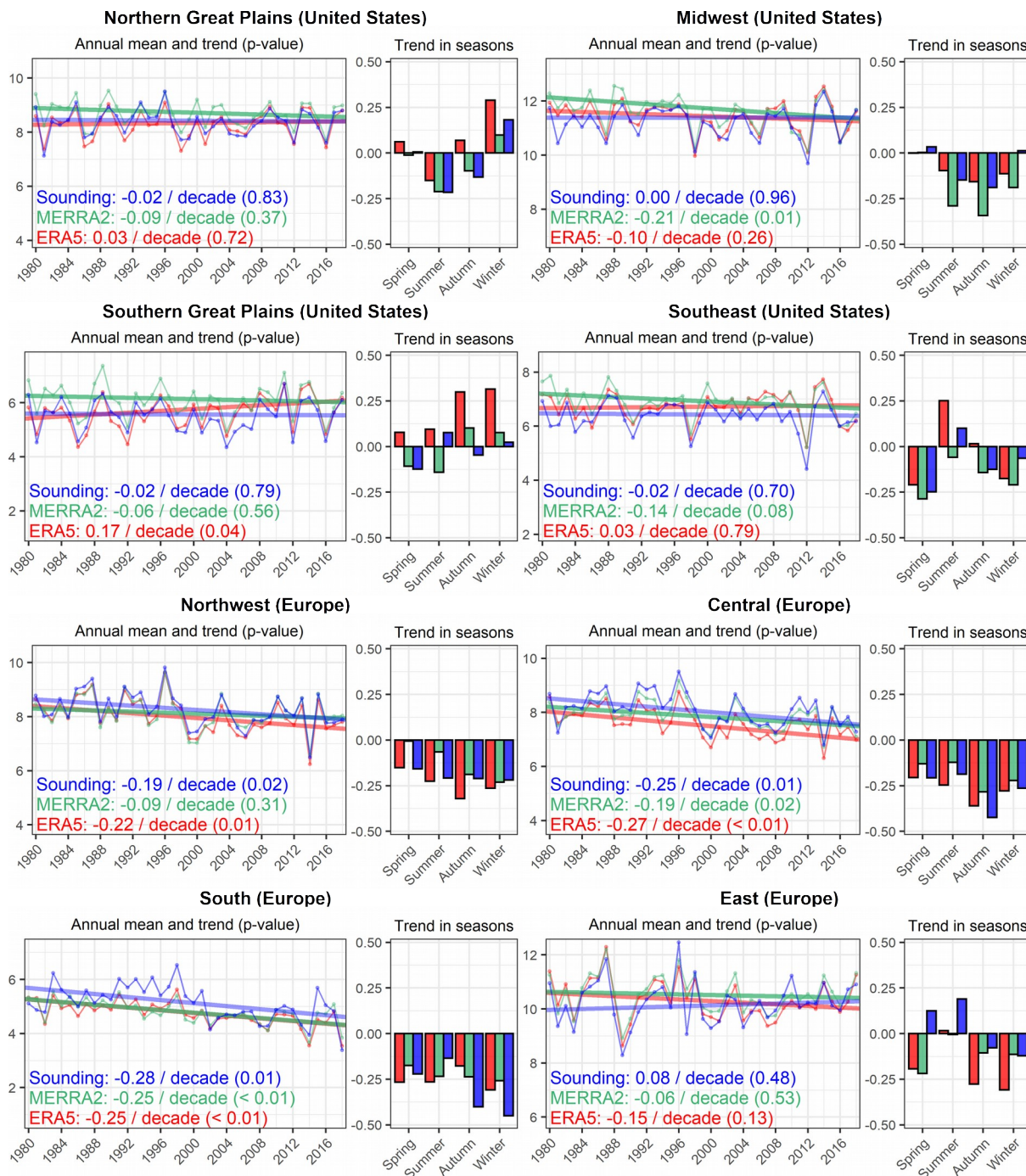


Figure 7. As in Fig. 3 but for ML lifted index.

ML convective inhibition (CIN) [J kg^{-1}]

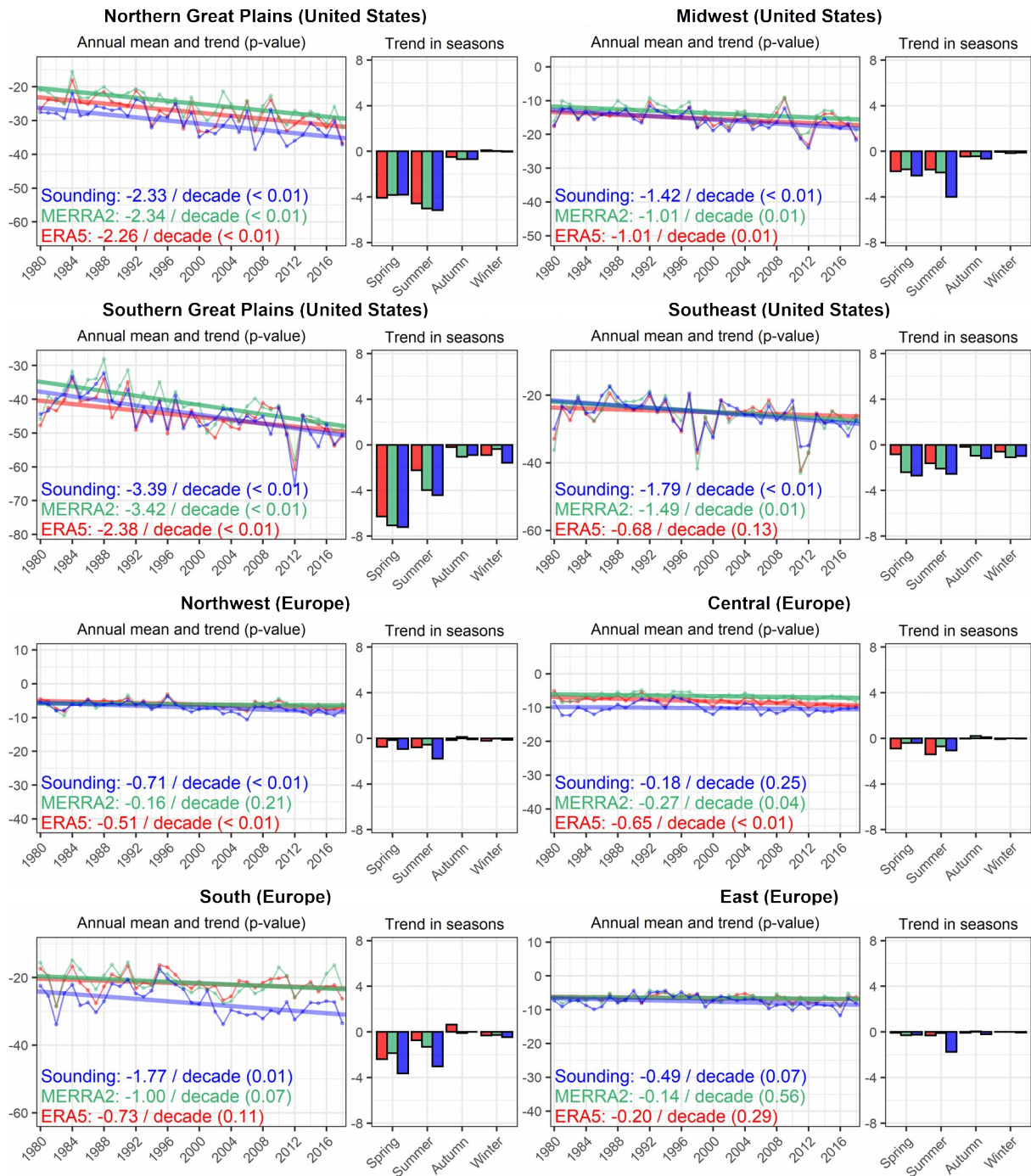


Figure 8. As in Fig. 3 but for ML convective inhibition.

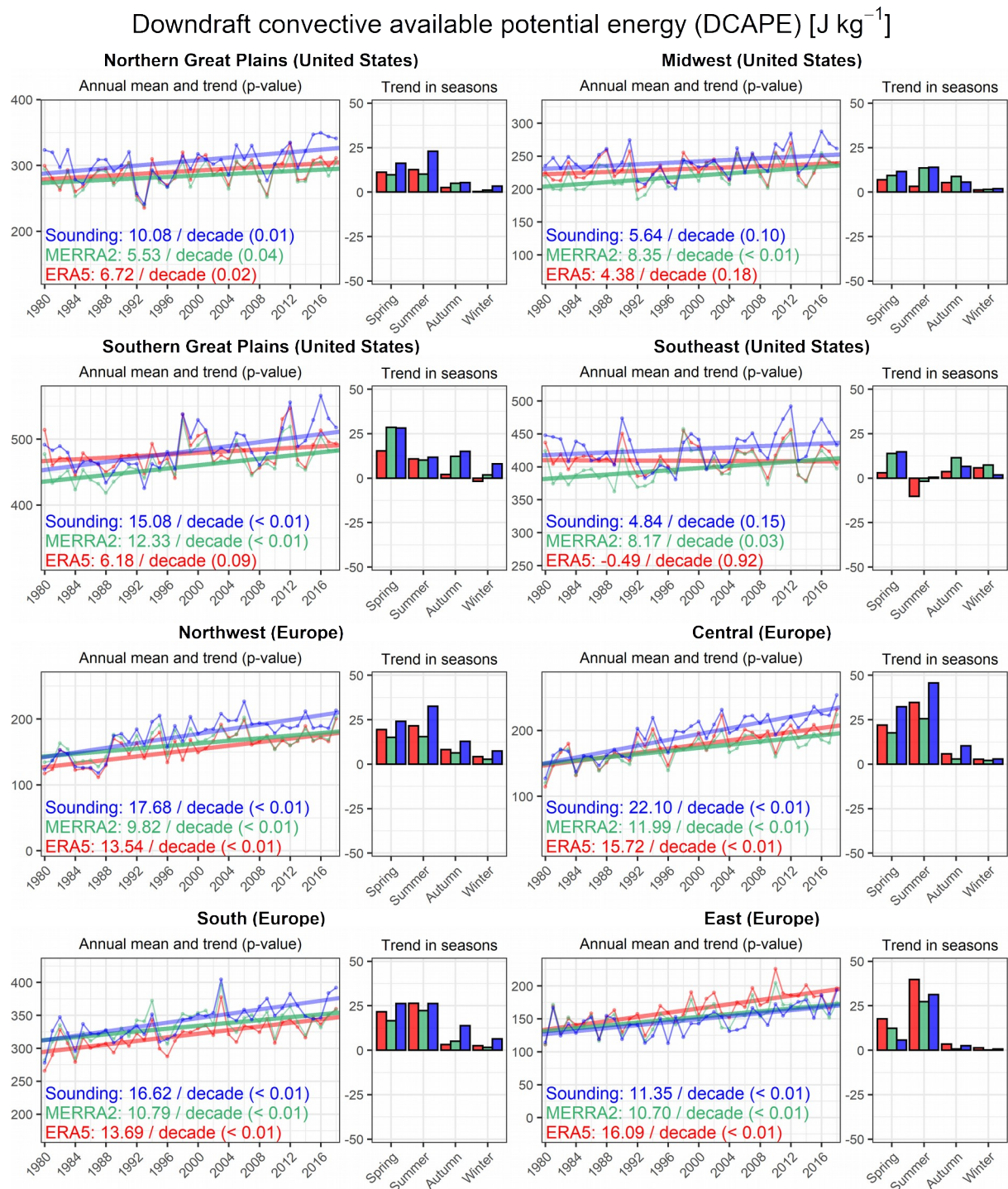


Figure 9. As in Fig. 3 but for downdraft convective available potential energy.

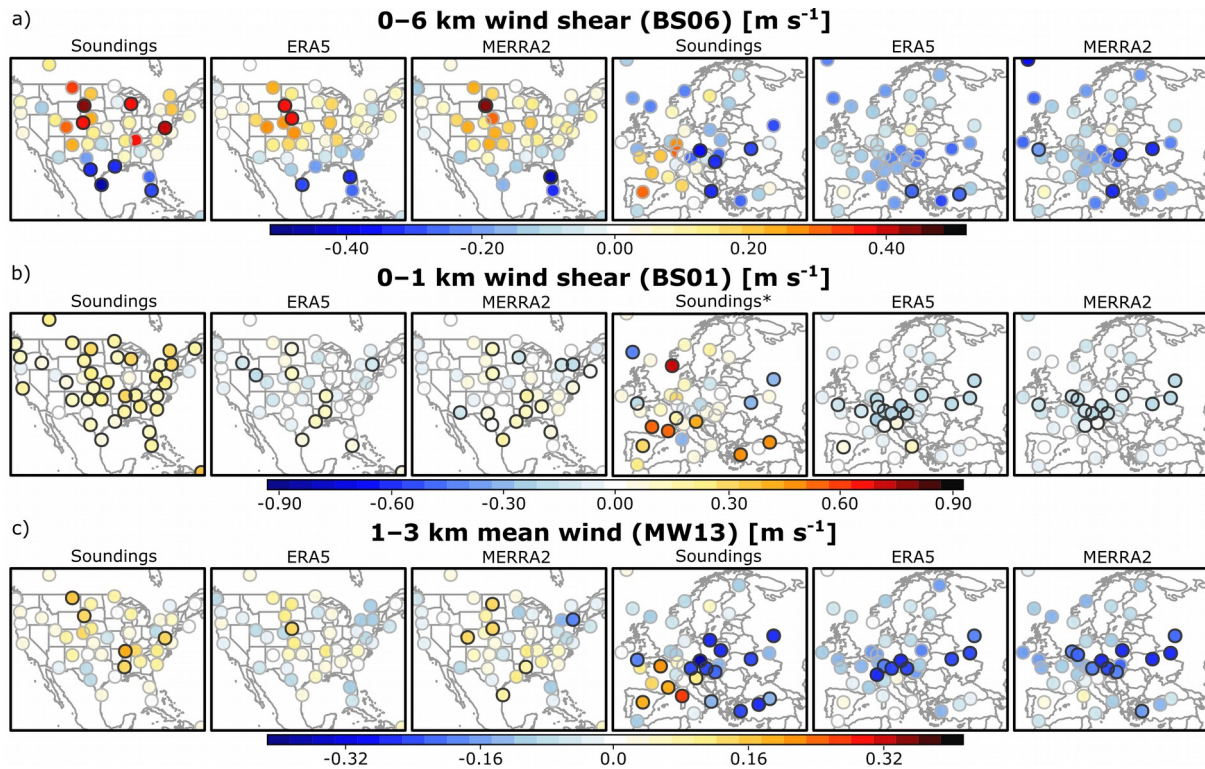


Figure 10. As in Fig. 2 but for (a) 0–6 km wind shear, (b) 0–1 km wind shear, (c) 1–3 km mean wind. Sounding trends for regions marked with * cover the period of 1992–2018 (see section 3c for further details).

0–6 km wind shear (BS06) [m s^{-1}]

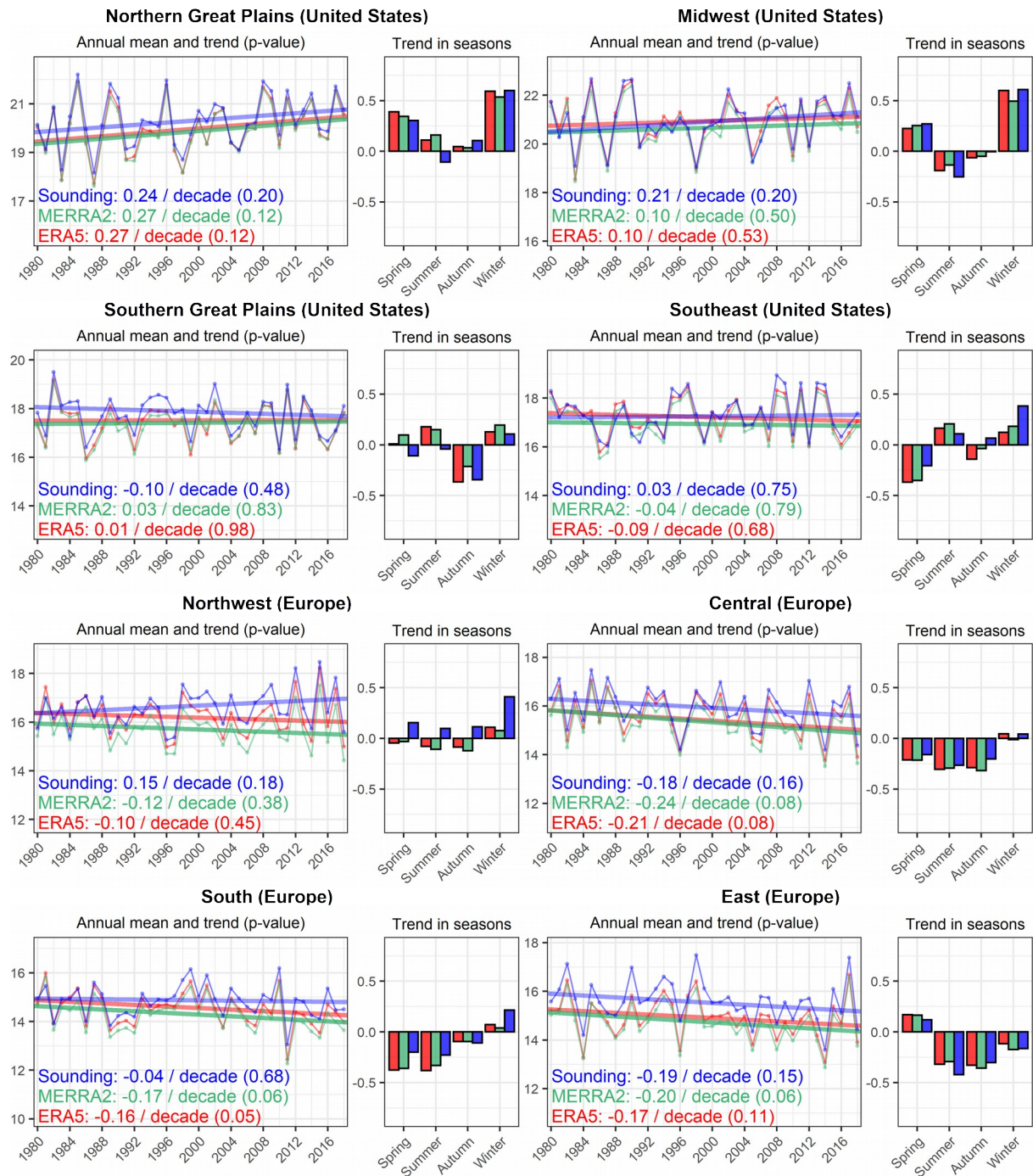


Figure 11. As in Fig. 3 but for 0–6 km wind shear.

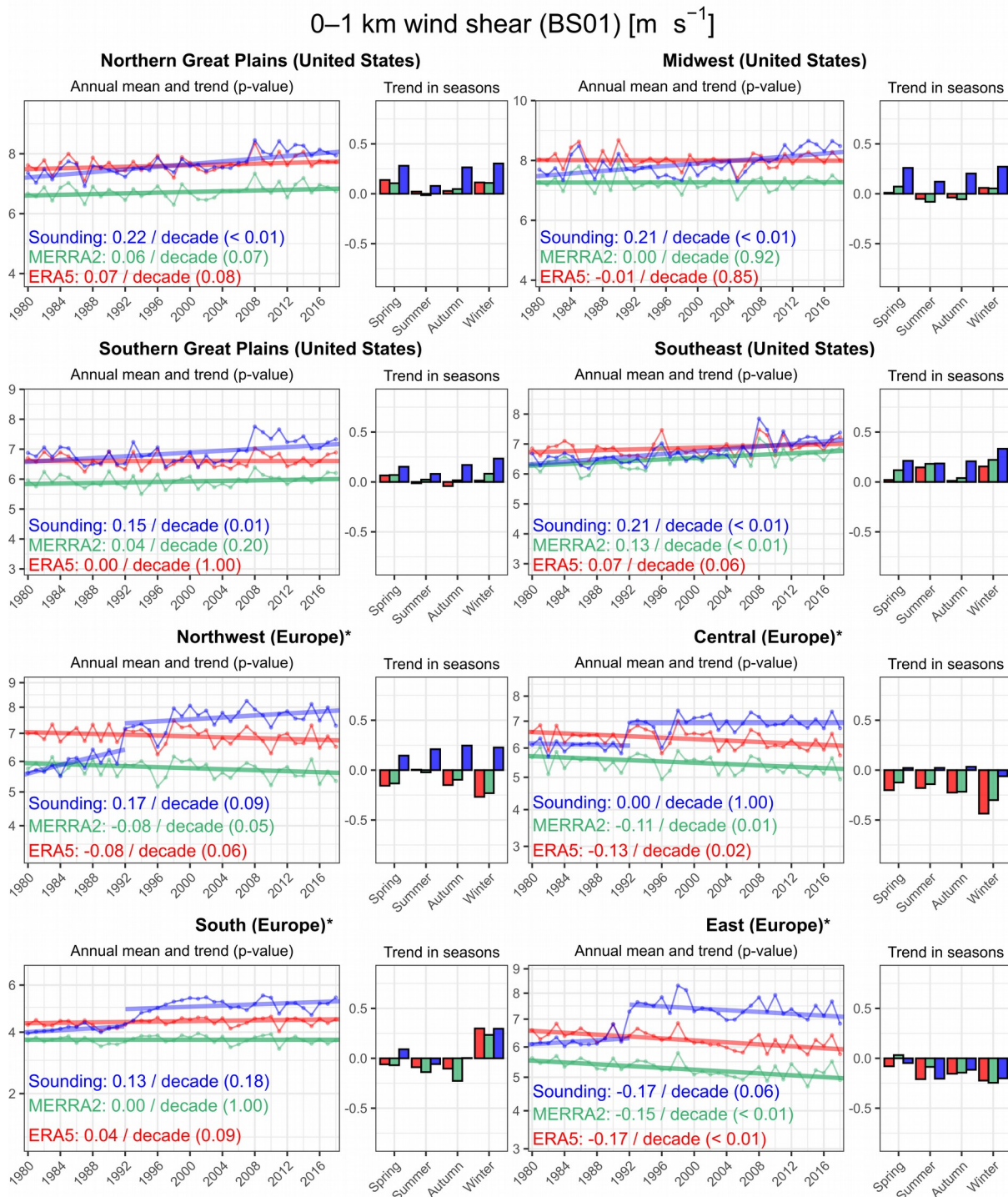


Figure 12. As in Fig. 3 but for 0–1 km wind shear. Sounding trends for regions marked with * cover the period of 1992–2018 (see section 3c for further details).

1–3 km mean wind (MW13) [m s^{-1}]

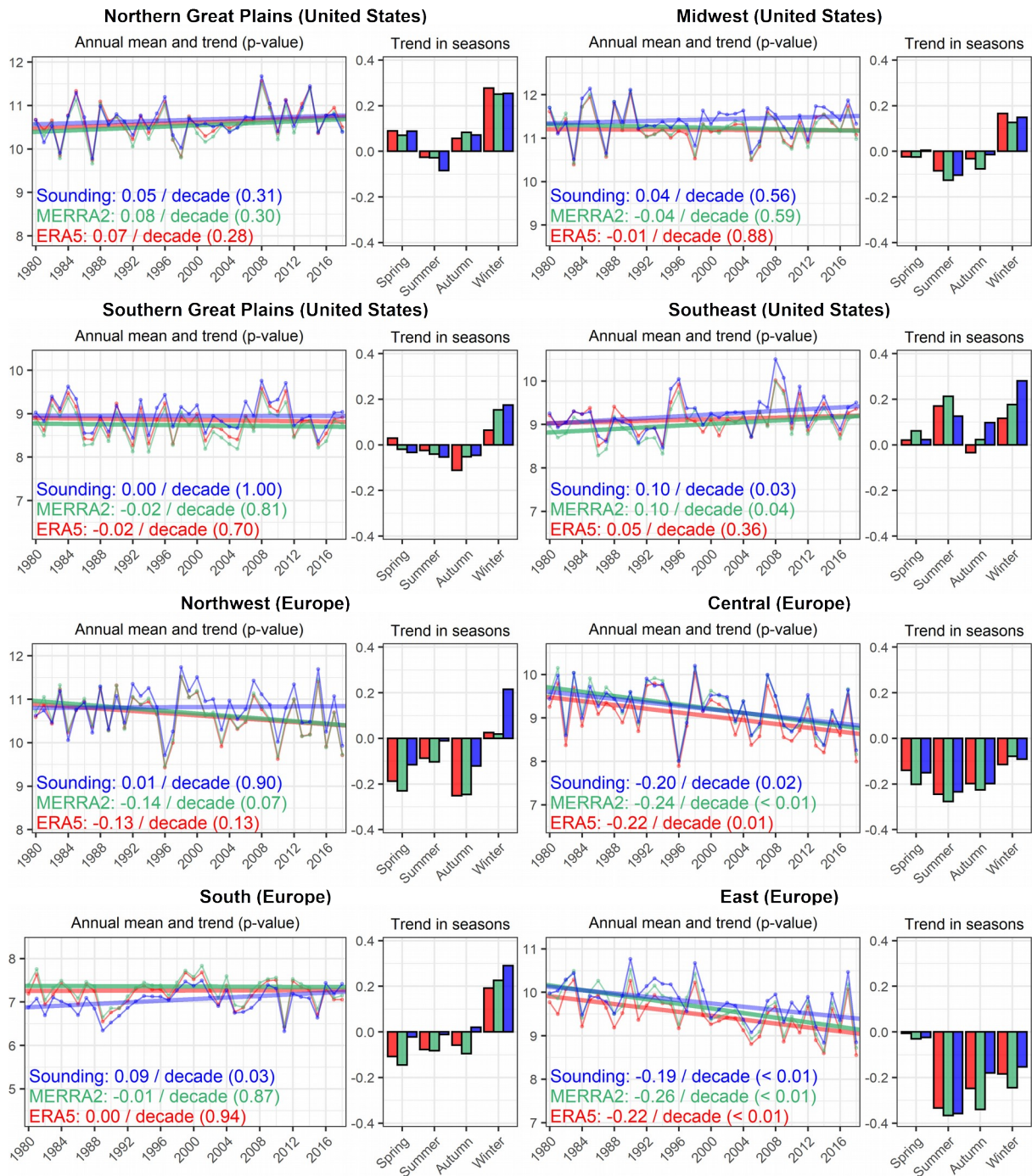


Figure 13. As in Fig. 3 but for 1–3 km mean wind.

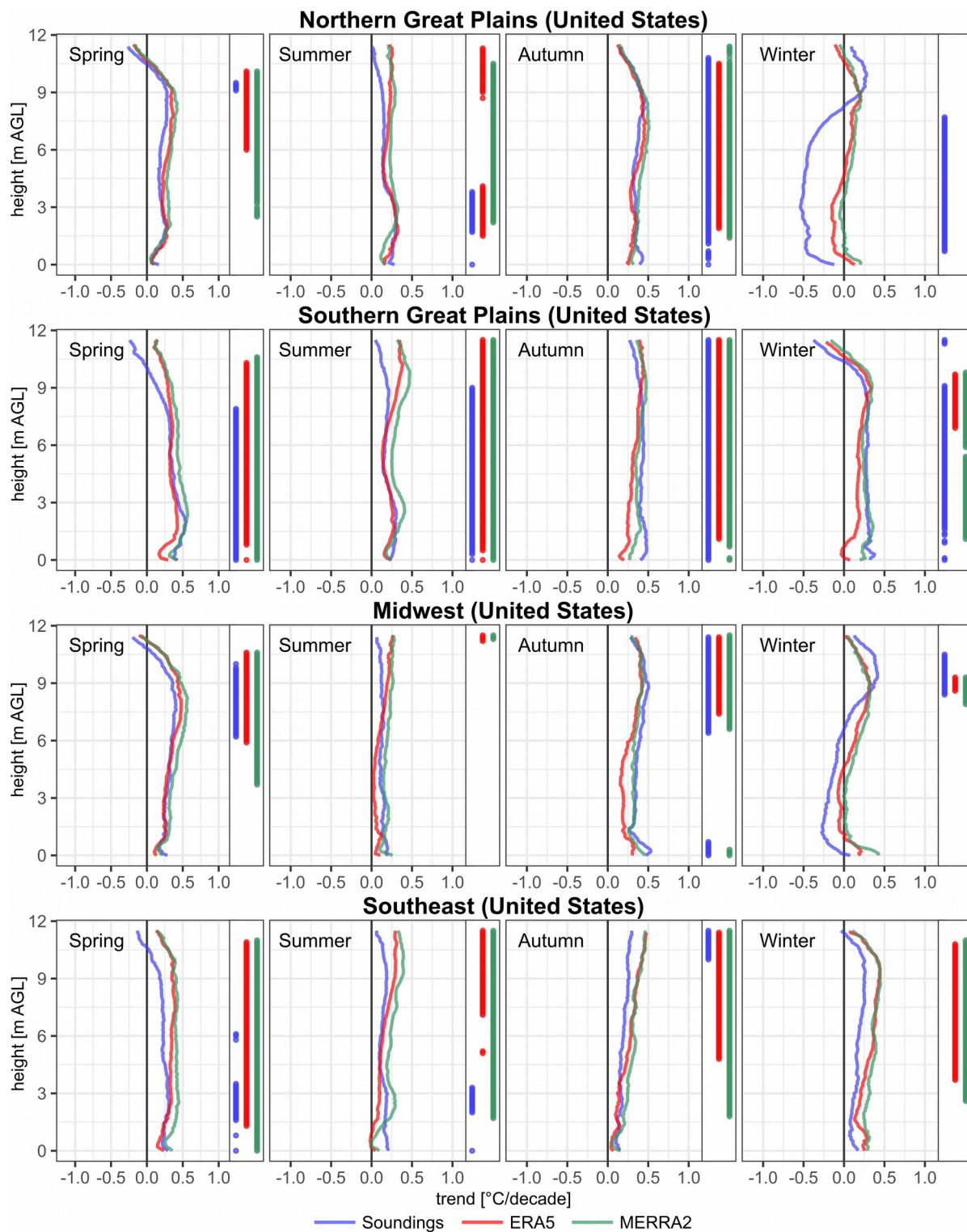


Figure 14. Long-term trends of air temperature at specific heights AGL based on the period 1980–2018 and across the United States. Trend is derived from Sen’s slope. Points on the right side of each plot denote layers with trends that have two-tailed p -values below 0.05.

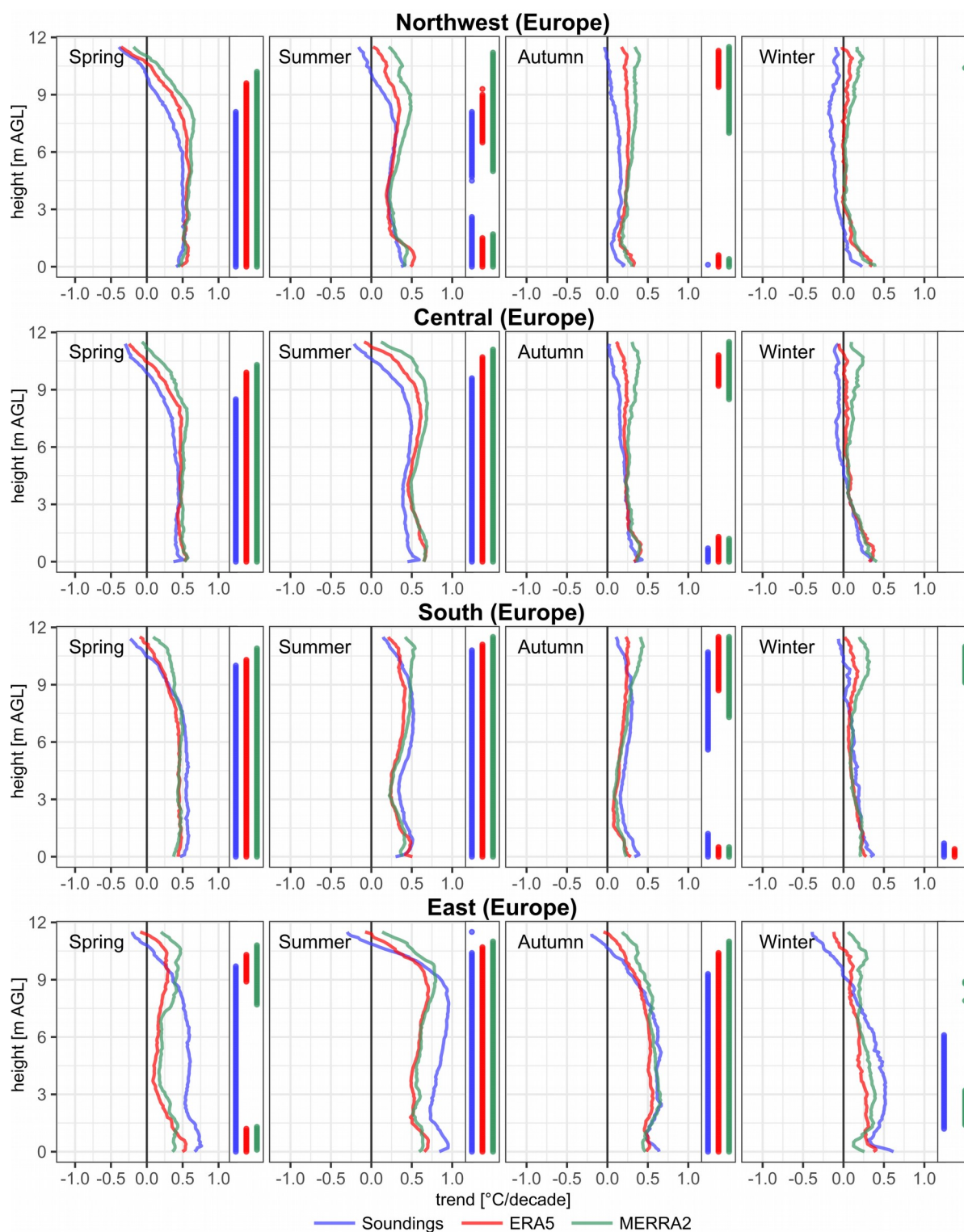


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