



GWL-REA: A highly optimized numerical method for classifying European Grosswetterlagen based on circulation and air mass considerations

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Abstract. Grosswetterlagen (GWL) are a well-known classification of synoptic weather types that connect regional weather impacts over Central Europe to the large-scale circulation over the wider European and N.E. Atlantic regions. GWL-REA is a new algorithmic method for classifying the GWL from reanalysis, climate and/or forecast model data. The method is based initially on pattern correlations using multiple target patterns for each GWL. Further optimisations ensure an equitable classification covering three key aspects of these synoptic types: consistency of the large-scale circulation, regional circulation constraints introduced by each GWL's nomenclature and regional areal-mean precipitation. For the latter, a neural network is deployed to improve discrimination quality between respective anticyclonic and cyclonic GWL types. Temporal filtering is applied to remove noise on short timescales to make it easier for a person studying the output to assimilate the key aspects. A comprehensive verification of the GWL-REA outputs shows that the new method, when used with ERA5 reanalyses, is of a much higher quality than the original manual Hess-Brezowsky GWL series and to other comparable weather type classifications, in terms of both large-scale circulation consistency and in its applicability for regional weather impacts.

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1 Introduction

Synoptic weather types describe the relationships between large-scale circulation patterns over a specified area and their impacts on weather conditions on smaller-scales within this area. These circulation patterns are three-dimensional structures associated with high- and low-pressure systems that form in connection with troughs, ridges and jets in the upper flow. The prevailing flow patterns in a general weather situation can often remain similar for several days and are a primary determining factor for typical regional weather conditions. For example, strong links are found between large-scale circulation patterns and extreme weather events related to temperature and precipitation such as cold spells or heatwaves (Faranda et al. 2023; Rouges et al., 2023;), heavy and persistent rain (Hoy et al. 2014; Palarz et al., 2024), or drought (Savary et al., 2026; Neimry et al., 2026). Wind and radiative conditions can also vary considerably across different synoptic patterns, thus also affecting the production of renewable energies (Grams et al., 2017; Bloomfield et al., 2019; Drücke et al., 2021). Meanwhile synoptic conditions have wide-ranging societal impacts, such as on agricultural production, transport, outdoor activities and energy consumption.

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30 Various methods for classifying weather types are available. These can be divided fundamentally into two classes: those that derive types by finding structures in the input data objectively and those that use pre-defined types (Philipp et al., 2016; Huth et al., 2016). In the former case, the goal is to find a small number of representative patterns in pressure or geopotential height fields algorithmically (Huth 1996), such as via principal component analysis (PCA) or cluster analysis. This paper, however, focusses on the latter case: a specific weather typing scheme that uses pre-defined types based on synoptic experience.

35 The first definitions of synoptic weather types for the Central European region can be traced back to Baur, Hess, and Nagel (1944). One of the best-known and most frequently used classifications of large-scale weather patterns for Central Europe, which followed on from that early work, is that of Hess and Brezowsky (1952). That work was a first major attempt at encapsulating the regional synoptic aspects of the large-scale circulation, breaking them down onto a set of meaningfully named and, therefore, relatable patterns. The classification was further refined and updated during the following decades and
40 subsequently contained 29 pre-defined large-scale weather patterns (German: Grosswetterlagen, GWL). These distinguish between zonal, meridional, and mixed circulation patterns, while also accounting for differences in cyclonicity over Central Europe, i.e., separating cyclonic types that exhibit frequent frontal passages with widespread precipitation from anticyclonic types associated with settled, dry weather.

The Hess-Brezowsky GWL classification (HBGWL) has been a very popular dataset for synoptic climatologists for many
45 decades, primarily because the names of the types - referring to the location of the centres of action (high- and low-pressure areas and troughs) and the local cyclonicity over Central Europe - are easy to grasp intuitively. Furthermore, a minimum duration of three days is set for any GWL event within the series, thus filtering out short-lived transient features, making the series easier to read and assimilate. Hence, the series is not only useful scientifically, but is also accessible and inspirational for weather enthusiasts more generally. Essentially, the GWLs attach synoptic and weather-related meaning to their types – in
50 contrast to many algorithmically-derived pattern sets that rarely discuss the meaning or impacts of the individual types within the set and rarely give the derived patterns names.

A manually produced GWL catalogue is available in daily resolution from 1881 onwards. Following on from the original work of Hess and Brezowsky, the catalogue has been regularly updated, most recently by Werner and Gerstengarbe (2010) and in monthly updates by the German Weather Service (DWD).

55 Such a long GWL time series could be a valuable resource for studies on trends in synoptic weather due to climate change. However, the catalogue is far from ideal, since it is fundamentally a subjective one that has been created by manual assessments of daily synoptic charts across many decades. Even if one overlooks the fact that the 29 reference patterns are themselves, to a certain extent, subjective and have not been formally optimized in terms of their spread across some synoptic phase-space, the manual assignment of any current situation to the reference patterns is also highly dependent on the synoptic meteorologists
60 doing the classification. Since different people have been involved in this work over the decades, inconsistencies or even jumps/shifts in the manual time series have occurred (Cahynová and Huth, 2009; Kučerová et al., 2017). Hence, in order to be useful and robust for studying trends in the frequency and persistence of synoptic weather patterns, a homogeneous and objective time series is clearly needed.



Due to the broad, qualitative nature of the GWL type definitions and the somewhat subjective approach to their temporal filtering, there have been only a few attempts at producing an objective, algorithmic GWL classification. Indeed, the only method that has been deployed in several different studies in the literature is that of James (2006, 2007), which was based on an empirical pattern correlation method. However, even this method was not especially optimized in terms of ensuring that specific GWLs correlated as best as possible with expected rainfall patterns, for example, or that the circulation properties correspond optimally to the nomenclature of the GWLs in question.

In a more recent development, Mittermeier et al. (2022) have used a deep learning approach to develop a GWL classification using the original manual HBGWL series to train the method. In the current age of Artificial Intelligence (AI), such approaches have considerable potential. However, a fundamental problem remains that the HBGWL dataset is itself not of a sufficiently high quality to be an optimal training base for an AI, being inhomogeneous over time and not formally optimized to address specific correlations, e.g., with rainfall. Mittermeier et al. did not require their GWL series to be optimized with respect to nomenclature or properties of individual synoptic events, which would have been difficult given these weaknesses of HBGWL. Instead, they only compared its statistical properties to the HBGWL series in a climatological sense. Hence, if an additional focus is to be placed on the optimal classification of specific synoptic events, then it would be necessary to first create an optimized GWL method within the scope of traditional algorithmic concepts, which can then form a solid data basis for training future AI classifiers.

In this paper, a new algorithmic method for classifying daily synoptic weather types, with its primary focus on Central Europe, is presented. The method - called GWL-REA to indicate that its core task is to classify reanalysis data - is based broadly on the earlier method of James (2006, 2007), but with considerable improvements and expansions. GWL-REA delivers the first highly optimized homogeneous algorithmic classification of Central European GWLs.

The primary goal of this work, therefore, is to create a quality synoptic type classification that accurately places regional weather patterns and impacts over Central Europe, focussing on precipitation in particular, into the context of the larger scale circulation. This then allows users of the resulting reanalysed GWL catalogue to understand regional weather events and statistics more completely and derive conclusions with a higher statistical quality than has previously been possible.

The methods used in GWL-REA are first detailed in Section 2. Particular focus is given here to the specific improvements to the original method that add value in GWL-REA, including multi-target pattern correlations and the use of AI to improve type separation with respect to cyclonicity. In Section 3 a new 12-type grouping of the GWLs is introduced. In Section 4 a first comprehensive verification of the GWL classification quality is carried out, comparing GWL-REA with earlier methods and the original manual series. Furthermore, a new spatial verification method is deployed, which demonstrates how well the GWL series can discriminate precipitation classes as a function of distance from Central Europe. A discussion is given in Section 5, placing the new GWL series into a wider context by comparing it with another recent classification of the large-scale Atlantic-European circulation (Grams, 2026) and presenting outlooks for possible future developments within GWL-REA.



2 Input Data and Methodology

2.1 Input data and domain

GWL-REA has been designed to be used primarily with ECMWF ERA5 reanalyses (Hersbach et al., 2020), which are currently available going back to 1940 and up to near real-time (ERA5T). It can be also used to analyse and interpret other comparable datasets, such as from climate model simulations or NWP model (ensemble) forecasts.

The data are extracted onto a $2^\circ \times 2^\circ$ latitude-longitude grid covering the N. E. Atlantic and Europe (20°N to 80°N , 30°W to 60°E). Daily means of four fields are used: mean sea-level pressure (MSLP), 500 hPa geopotential heights (Z500), 500-1000 hPa geopotential thickness (ZTH) and total column precipitable water (PPW). The first three fields are used for pattern correlations and the PPW field is used for further optimisations, as discussed later. The Z500 and ZTH fields contribute equally to the total correlation, while the MSLP field's contribution is weighted to be around 27% higher.

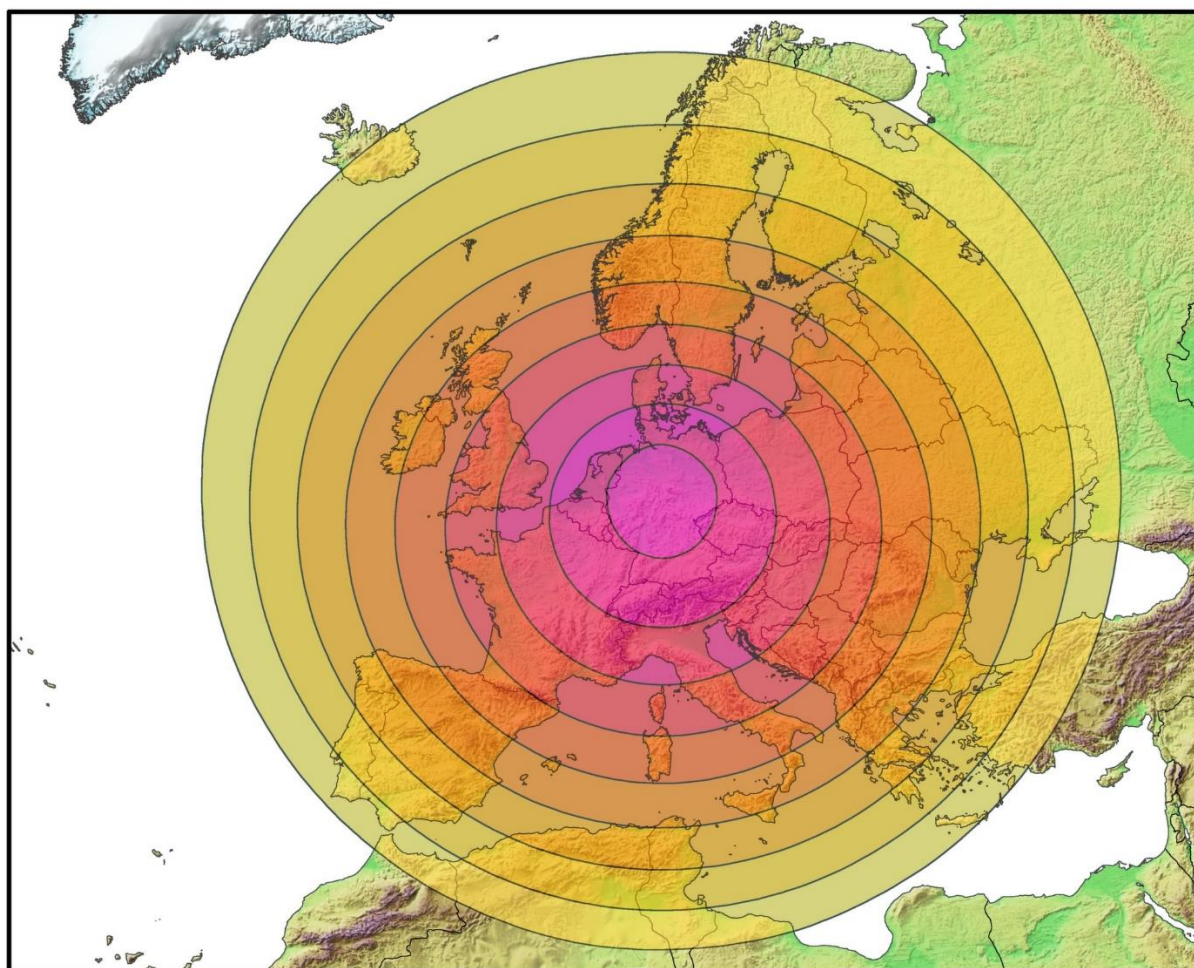


Figure 1. GWL-REA domain weighting for pattern correlations as fraction of maximum weight at centre (52.5°N , 10°E). Outermost contour 0.1, contour interval 0.1.



The daily means are typically formed by averaging the 00, 06, 12 and 18 UTC analyses, respectively. This centres the daily mean onto 09 UTC, rather than 12 UTC, but makes data preparation from six-hourly source analyses easier, especially with regards to extending the ERA5 period with the latest monthly updates. 12 UTC analyses could be used on their own, but daily means are preferred, since these smooth out small-scale transient effects, which may introduce undesirable noise into the classification system.

Although the domain described above covers quite a large geographical area, a circular weighting factor is used to increase the main focus onto Central Europe for the pattern correlations, as shown in Fig. 1. This is centred on 52.5°N / 10°E and is proportional to the inverse of the great-circle distances from this point. The weights are centred slightly to the north-west of the geographical centre of Germany and even more so relative to Central Europe as a whole. The northward bias counters the effect of the cosine weighting for grid-box areas, which on a sphere become smaller and closer together towards the north. The effective centre of the circular weighting scheme therefore becomes closer to 50°N as a result. The westward bias is deployed to prevent weather systems over the easternmost Mediterranean, Turkey and the eastern Black Sea regions, which are largely irrelevant for classifying Central European weather types, from significantly influencing the correlations. On the other hand, weather systems to the west of the British Isles and towards Iceland are more relevant on the whole and this is taken into account in this way.

2.2 Multi-target pattern correlations to address within-type variability

The GWL-REA classification method is based on pattern correlations with daily MSLP, Z500 and ZTH fields. While this is initially similar to the original empirical GWL method of James (2007), that older method used only one set of GWL climatological mean fields to base the correlations on, only distinguishing between the winter and summer half-years. For an empirical method this was a sensible approach, but had the disadvantage that the MSLP and Z500 fields were always coupled for each respective GWL, i.e., their relative phases were fixed.

In reality, for each GWL - named according to a specific meteorological state - there are potentially several differing MSLP, Z500 and ZTH field combinations that could correspond to that GWL. This fact is related not only to the significant within-type variability that each GWL exhibits, but also to the different air mass structures that can be part of each GWL.

Figure 2 shows some examples of within-type variability for specific GWLs to illustrate this point, showing composites of typical warm and cold variants, respectively. These are derived by grouping specific GWL base patterns (see further below) to create GWL subtypes, which separate the different upper flow structures and air mass situations that can occur within each GWL. For each GWL pair shown, the surface flow patterns are very similar to each other and have the typical characteristics of the GWL in question. Yet, the mid-tropospheric flows are clearly different, indicative of different air mass structures.

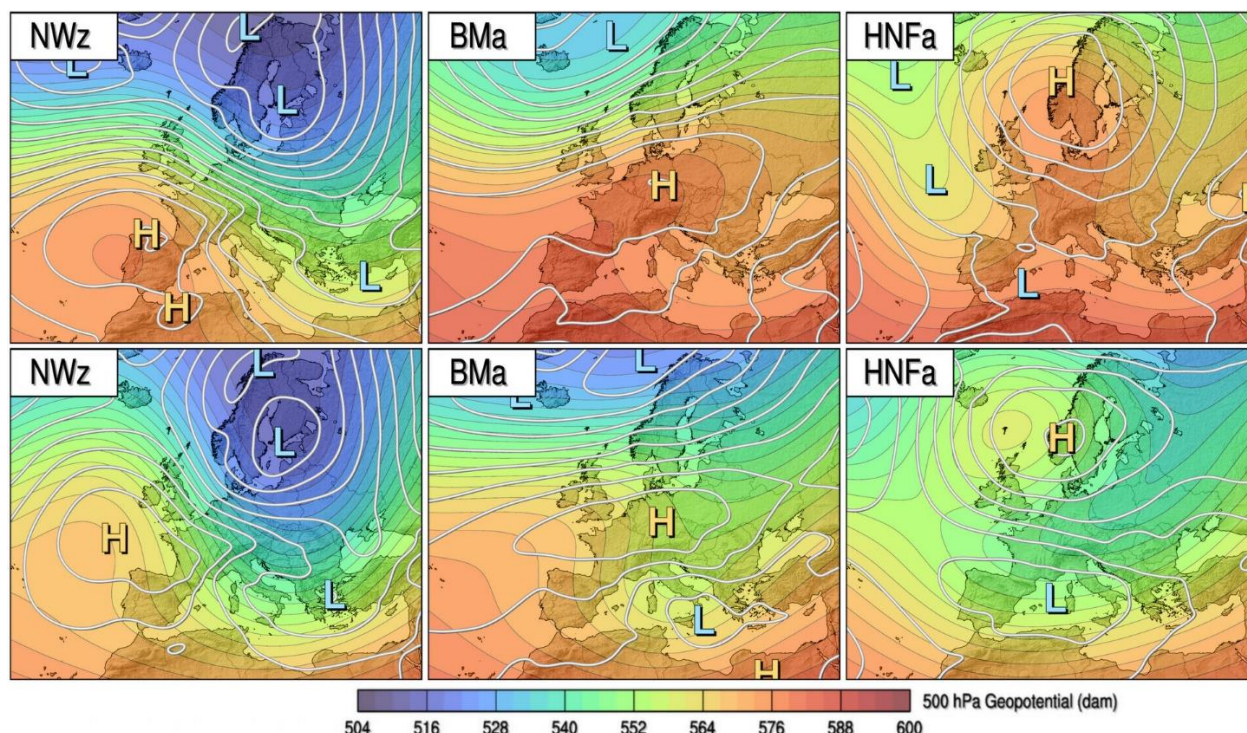


Figure 2. Climatological mean composites for selected GWL-REA Grosswetterlagen air mass variants, based on ECMWF ERA5 reanalyses, 1950-2024. Shown are MSLP contours (white), interval 3 hPa, and 500 hPa geopotential colour-filled contours, interval 3 dam, colour scale as shown at bottom of figure. Surface high (low) pressure centres are indicated with labels H (L). The upper row shows warm variants, the lower row shows cold variants, for the GWLs as indicated in the top-left panels of each composite. The composites are for all times of the year, except for NWz, which are for the winter half-year only.

The cyclonic north-westerly type (NWz) can vary between relatively mild and moist Atlantic air masses returning in a nearly straight upper flow, to cyclonically curved flow of cold polar maritime air. Although Hess and Brezowsky considered varying air mass characteristics to be a fundamental property of progressive cyclonic types, such as NWz, an examination of many years of synoptic charts shows that colder or warmer variants are often persistent enough to warrant being considered as different synoptic regimes.

In the case of an anticyclonic bridge over C. Europe (BMa), the surface high pressure zone can exist under a broad upper ridge with very warm air masses dominant. On the other hand, such a surface structure can develop after the influx of cold air masses, more especially in winter, underneath an upper trough.

Another example is that of the easterly type, HNFa, which exhibits anticyclonic, dry surface conditions. In typical winter cases, very cold polar continental air (very low ZTH) may be advected in depth from the east, with a pronounced trough over Central Europe at 500 hPa. By contrast, especially in spring or summer, it is quite common for the surface high to exist on the northern edge of a strong C. European ridge at 500 hPa, with very warm conditions at the surface and high ZTH.

To address this issue, GWL-REA has introduced a major improvement compared to James (2007). Now, for each GWL, several different patterns are used to span the typical range of synoptic situations associated with the GWL, with varying



surface and mid-tropospheric flow couplings. In total 312 base patterns are available, i.e., more than 10 per GWL on average, each containing the three fields required for correlations, Z500, ZTH and MSLP. These patterns are manually or algorithmically generated composites that have been created over a period of over a decade. This pattern database has been gradually expanded whenever synoptic situations were noted that were not being sufficiently well captured by earlier classification algorithms. To aid this work, a comprehensive set of 3-hourly synoptic charts were created for reference purposes, going back to the 1960s and forward to the present day.

GWL-REA correlates each daily synoptic pattern with all 312 base patterns. Then a look-up table is consulted to map the results onto the final set of GWLs. For each GWL, the highest few correlation coefficients of its base patterns are combined as a weighted average. The actual number of base pattern correlations varies with GWL, typically in the range 2 to 5, which gives an opportunity for tuning the system.

2.3 Solving the GWL-nomenclature problem with Lamb Weather Types

A major classification problem, specific to the GWL system, is that of nomenclature. Each GWL has a descriptive name that refers to a specific aspect of the circulation in each case. Some GWLs are described by a flow direction and cyclonicity over Central Europe, while some others are described by the position of a surface low- or high-pressure system over different locations. Further GWLs still are described according to the location of a mid-tropospheric trough. Hence, the naming convention is highly inconsistent, both in terms of spatial locations and in terms of the meteorological fields that are most important.

Automatic weather type classification systems elsewhere in the scientific literature are typically based on a fixed domain and a fixed and small set of input fields (often just one). The resulting type catalogues require a naming convention that is consistent across all weather types and takes the limitations of the specific method into account. This is usually a trivial exercise since such classifications are usually new and do not have pre-requirements in terms of type expectations.

By contrast, the inconsistency of the GWL nomenclature presents a major problem for an algorithmic classification system. Typical methods such as Principal Component analyses, k-means clustering or pattern correlations (including James' (2007) early GWL method) produce a spatially unbiased view of the circulation and cannot know that certain types require a different spatial focus than other ones, for example. This is the primary reason why empirical algorithmic GWL methods often do not work very well, even when the classification of the broad circulation characteristics is captured accurately and homogeneously. The key problem is that the resulting GWL catalogue immediately appears unacceptably poor whenever a specific day is classified as a type whose name is inconsistent with the local circulation at hand. The GWL concept indeed sets the bar very high for any algorithmic method to achieve an acceptable classification, especially when viewing single days, unless the user accepts a very broad spatial and temporal view of the GWL's naming convention in advance. Since users often may not be aware of this problem, the perception of the method's quality remains an important aspect of its acceptance or not.

To address this problem GWL-REA deploys the well-known Lamb Weather Types (LWT, Lamb, 1972) concept. A well-known automatized method of determining LWTs, in which pressure patterns are classified in terms of flow direction and



vorticity, has been reviewed for example by Jones et al. (2012). In GWL-REA, specific LWT statistics derived from this method are calculated with daily mean MSLP and Z500 over six different locations, as shown in Fig. 3, chosen to help address the nomenclature aspects of specific GWLs. The primary outputs used are the vorticity (curvature) and the flow direction at the respective domain centres. The resulting LWT classifications are not used explicitly, however. A look-up table is then used to determine exactly which aspects of the flow are important for each GWL.

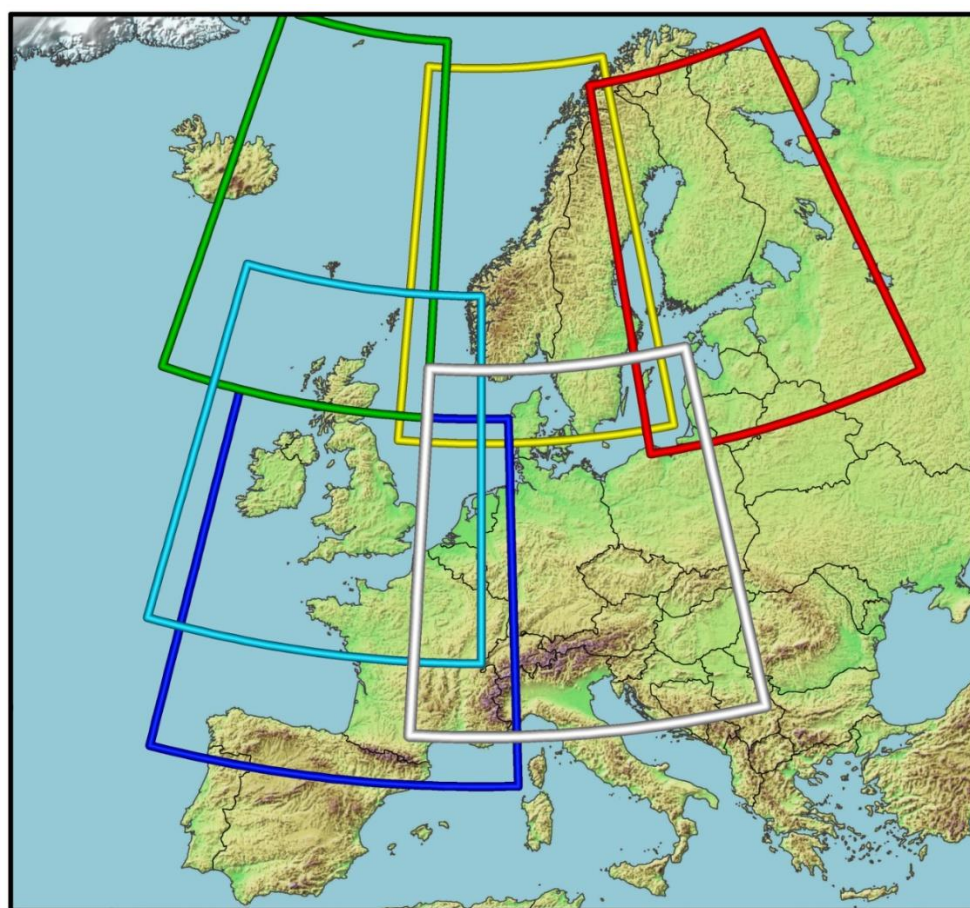


Figure 3. The six regions over which Lamb Weather Types statistics are calculated: C. Europe [white], British Isles [sky blue], Norwegian Sea [green], W. Scandinavia [yellow], Fennoscandia [red] and W. Europe [blue]. The edges of the boxes shown here are placed halfway between the respective outermost longitude (latitude) coordinates used in the LWT computations in each case.

The LWT statistics are deployed in the form of weighted penalties applied to the raw pattern correlation coefficients whenever the synoptic pattern is inconsistent with the respective GWL. The adjusted correlation coefficients then provide a more balanced account of both the broader scale circulation as well as its nomenclature-related local aspects. Following successful tuning this method has strongly improved the perceived quality of the resulting GWL classification, compared to previous methods, by strongly reducing the frequency of days with inconsistent local circulation characteristics. An objective verification of this aspect will be discussed in Section 4 of this paper.



2.4 Use of AI to improve correlations between GWLs and precipitation

Many of the original GWLs, with only a few exceptions, were named according to whether they refer to anticyclonic or cyclonic conditions over Central Europe. Nevertheless, it has not been entirely clear as to what precisely was meant by “cyclonicity”: whether it refers to the curvature of the mid-tropospheric flow (i.e., ridged or troughed), or to the surface flow, or to some combination of the two, or to the presence or lack of rain-bearing frontal systems.

To clear up this ambiguity, GWL-REA defines cyclonicity practically in terms of the synoptic situation’s ability to produce widespread precipitation, since this is the most relevant quantity typically correlated with cyclonicity. Hence, anticyclonic types produce predominantly dry weather across much of Central Europe, while cyclonic types produce widespread precipitation across this region. Furthermore, all GWLs are grouped definitively into one or the other cyclonicity class, adding HB to the anticyclonic set and TrM and TrW to the cyclonic set.

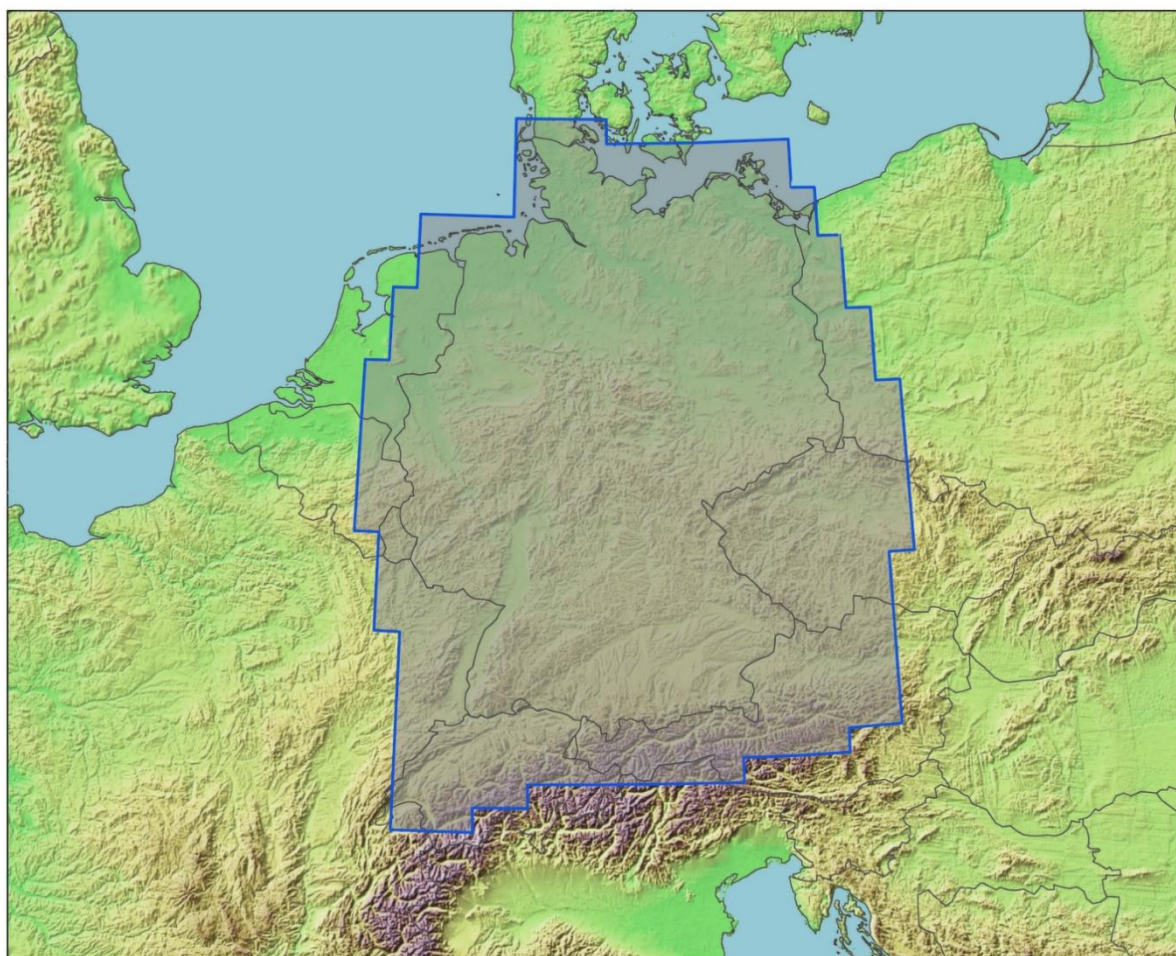


Figure 4. Geographical area over and around Germany used for forming daily means of ERA5 precipitation and 2m-temperature anomalies for AI module training and verification purposes, as indicated by the shaded area bounded by blue edges. Country boundaries and surface topography are also indicated.



220 In order to achieve an optimal correlation between precipitation and GWL-related cyclonicity, an AI module has been developed, based on a distributional regression network within the PyTorch framework, with two hidden layers. This module has been trained on ERA5 daily precipitation covering the period from 1950 to 2023, averaged across a specific geographical region, shown in Fig. 4, covering Germany and its bordering regions, including the eastern edges of the Netherlands and Belgium, Luxembourg, (north)easternmost France, the western Czech Republic, westernmost Poland and much of Austria and
225 Switzerland (down to the central Alpine axis). Note that this region has its primary focus on Germany, since the DWD, as a publicly-funded national weather service, requires a strong regional focus in its primary intended deployment of GWL-REA in climate science and forecasting. Nevertheless, in shown later in section 4, the resulting GWL classification is still very useful more widely across the eastern regions of Central Europe that lie outside of the area specified in Fig. 4.

To choose which features to use for this AI, one would expect precipitation generation to correlate with factors such as available
230 moisture, seasonality, flow direction and the presence of active frontal systems along air mass boundaries. After some experimentation the best results were found using a basic 3x3 grid over Germany (48°N - 54°N; 6°E - 14°E) containing ZTH, MSLP and PPW fields, as well as each of their gradients in both zonal and meridional directions. All fields are normalized to be in the range 0 to 1. Such an array can capture typical frontal situations in which ZTH and PPW gradients of the same sign (i. e. cold-dry to warm-moist) are found in conjunction with an MSLP gradient at a different angle, representing cold or warm
235 advection. The raw MSLP values also implicitly contain flow direction information, which correlates with precipitation enhancement on the wind facing slopes of mountain ranges (e. g. the Alps) or reduction in the lee of such ranges (e. g. Föhn effects).

It was found that the gradients of ZTH and PPW at 54°N were less useful and these were not used, leaving 69 out of 81 meteorological values in the AI feature set. A sine and cosine pair were included to represent the seasonal cycle. In total 71
240 features were used in the AI. To capture frontal structures as accurately as possible, six-hourly ERA5 input fields are used to run this AI. The AI-predicted precipitation total for any day, summed from the four six-hourly estimates, is then converted into a weighted penalty against wet GWLs for precipitation below a certain threshold, or against dry GWLs for precipitation above this threshold. This is then subtracted from the respective correlation coefficients, similarly to the LWT penalties for the nomenclature improvements discussed earlier. This improves the catalogue's overall quality still further and strongly
245 improves the quality of the GWL catalogue for any studies involving precipitation in this broad geographical region.

2.5 Temporal filtering

After creating a table of modified daily GWL correlation coefficients, the final task is to undertake temporal filtering to help reduce short-timescale noise in the series, thus making it easier for a person studying it to assimilate its content – an aspect that we refer to as readability. Without any filtering, there would be many short-lived single day GWLs, whose correlation
250 coefficients may be only slightly higher than other GWLs in some cases. This would lead to a noisy time series that would be difficult to assimilate, with no easy way to know how relevant any specific GWL is. Because of this generic problem, Hess and Brezowsky set a minimum GWL length of 3 days, assuming that any short-lived event that disturbs the broader picture is



a transient feature that can be ignored. In other words, the HBGWL series was specifically designed to group similar synoptic events on broad timescales of a few days rather than trying to resolve all individual synoptic systems on daily timescales separately – an approach that GWL-REA attempts to emulate.

GWL-REA's temporal filtering makes use of a bespoke numerical block optimisation algorithm. This examines periods of up to 25 days at a time and tests the mean correlation coefficients that would result from every single possible permutation (usually a few thousand) of GWL event lengths, within the given period. Event length sequences of between 3 and 7 days are all fully permuted. Within each event block, the top correlating GWL is determined by averaging the correlation coefficients. After finding the optimal set of GWL events in the period (i.e., that which yields the highest mean correlation coefficient), the window is shifted forward a few days to the start of the second GWL event, leaving the first GWL event finalized. This process continues until the entire time series has been fully classified.

In principle GWL-REA applies the same 3-day minimum event length as in the HBGWL series. However, the block optimisation method in its raw form has a tendency to produce very many events with the shortest possible length (3 days) – typically around 50% of all events. This happens because the method maximizes the block mean correlations, irrespective of gain magnitude, and because transient events lasting for just one or two days cause an information cascade onto the shortest available block length of 3 days, effectively introducing noise into the classification. Hence, many of these short events may yield only a fractionally higher mean correlation than if they were substituted by longer GWL events extending across them, or may not be a representative choice of GWL if the noise component dominates over the longer timescale circulation transitions. A high short event rate also comes at the cost of readability and raises the question of how to account for event relevance and how to set the threshold for defining transient events.

In order to provide a method of tuning the magnitude of the temporal filter and reduce the effect of noise, GWL-REA applies short-event penalties to the mean correlation calculations during the block optimisation process. 3-day events have a penalty applied, weighted so that the total number of such short events is reduced by a half, compared to the results of an unrestricted optimisation. Hence, those 3-day events that remain are the most strongly defined half: i.e., the ones that stand out most in terms of their effect on the mean correlation coefficients of the final GWL series. Using this approach, it is also much more likely that the remaining 3-day events represent events that do actually last for around 3 days, rather than being the residual effects of shorter-lived transients.

Although this approach is somewhat arbitrary, it reduces the mean event length from 3.75 days to around 4.4 days, making it more comparable to the HBGWL series (near 5 days). As a result, the filtered GWL series is effectively a highly optimized, objective version of HBGWL and could be considered as the former's replacement. The only difference is that GWL-REA GWLs do not have any "undefined" single day events that have been inserted in the HBGWL series to represent brief transitional states that are not easy to classify. Attempts have been made to find ways of adding such undefined days objectively, but with limited success, since there is considerable arbitrariness in doing so. Indeed, the mean annual number of such undefined days per year in the HBGWL series has varied massively, being typically around 5 before 1990, falling to only



around 2 in the following three decades, but increasing to over 24 from 2022 onwards - demonstrating an unacceptably large inhomogeneity. Hence, undefined days are not part of the GWL-REA output and all days have a definite classification.

Finally, it must also be recognized that there are at least two different user groups for a GWL series. For some data-driven scientific research where correlations with other meteorological factors are a core aspect, the need for a time series that is as accurate as possible on a daily time scale is paramount. On the other hand, weather history enthusiasts and climate researchers more interested in longer time scales will prefer a broader and more readable time series, in which the GWLs do not change as frequently.

While the aforementioned filtered GWLs provide for the latter, GWL-REA also provides a completely unfiltered daily GWL version. Here, each daily GWL is calculated independently of the neighbouring days, based simply on the type showing the highest correlation value, while accounting for the LWT- and AI-based precipitation modifications.

2.6 Extending the classification: adding a 30th GWL

The Hess-Brezowsky GWLs have remained an integral part of Central European synoptic meteorology for many decades because their nomenclature is easy to grasp and the original 29 patterns span a large part of the total phase-space, albeit with a high within-type variability. However, during the development of GWL-REA a specific synoptic pattern was frequently observed, most often during the summer months, which was difficult to classify and typically mapped onto a diverse range of GWLs, none of whom were ideal matches.

The pattern in question looks similar to BM or sometimes NWa near the surface, but it is disrupted by having an active embedded quasi-stationary air mass boundary over Central Europe, with the air mass gradient typically oriented along a west-south-westerly axis, i.e., with colder air to the north or northwest and warm, humid air to the south and southeast. As such, the pattern resembles Wz or SWz in the mid-troposphere, contrasting with its BM- or NWa-like appearance at low-levels. In some cases, shallow surface low pressure troughs can develop along the frontal boundary, enhancing precipitation. The surface pressure pattern can also resemble a col pattern at times, with a locally weak and indistinct flow. Nevertheless, averaged over the whole event period, these events usually exhibit anticyclonically curved surface pressure patterns across Central Europe, despite the locally enhanced precipitation, contrary to typical expectations.

Given its closest similarity to BM, it was decided to give the new pattern the label BMz, indicating that this is a disrupted BM-like state with cyclonicity in the form of embedded precipitation enhancement. Meanwhile the original anticyclonic pattern BM is now labelled BMa. Following this split, it is found that many difficult synoptic events, which had been hard to classify, are now much easier to recognize and define clearly.

The BMz type is in fact highly relevant in relation to climate change. BMz typically involves a quasi-stationary mass of warm-humid air just to the south or south-east of an air mass boundary. This leads to widespread, slow-moving areas of rain and/or thunderstorms, most commonly across the Alpine regions and Southern Germany. This can even generate local flooding, despite the ambient surface pressure being relatively high. Since global warming is increasing the warmth and humidity of the air masses in these regions in summer, the impacts of BMz events are likely to increase. Indeed, it is found that the annual

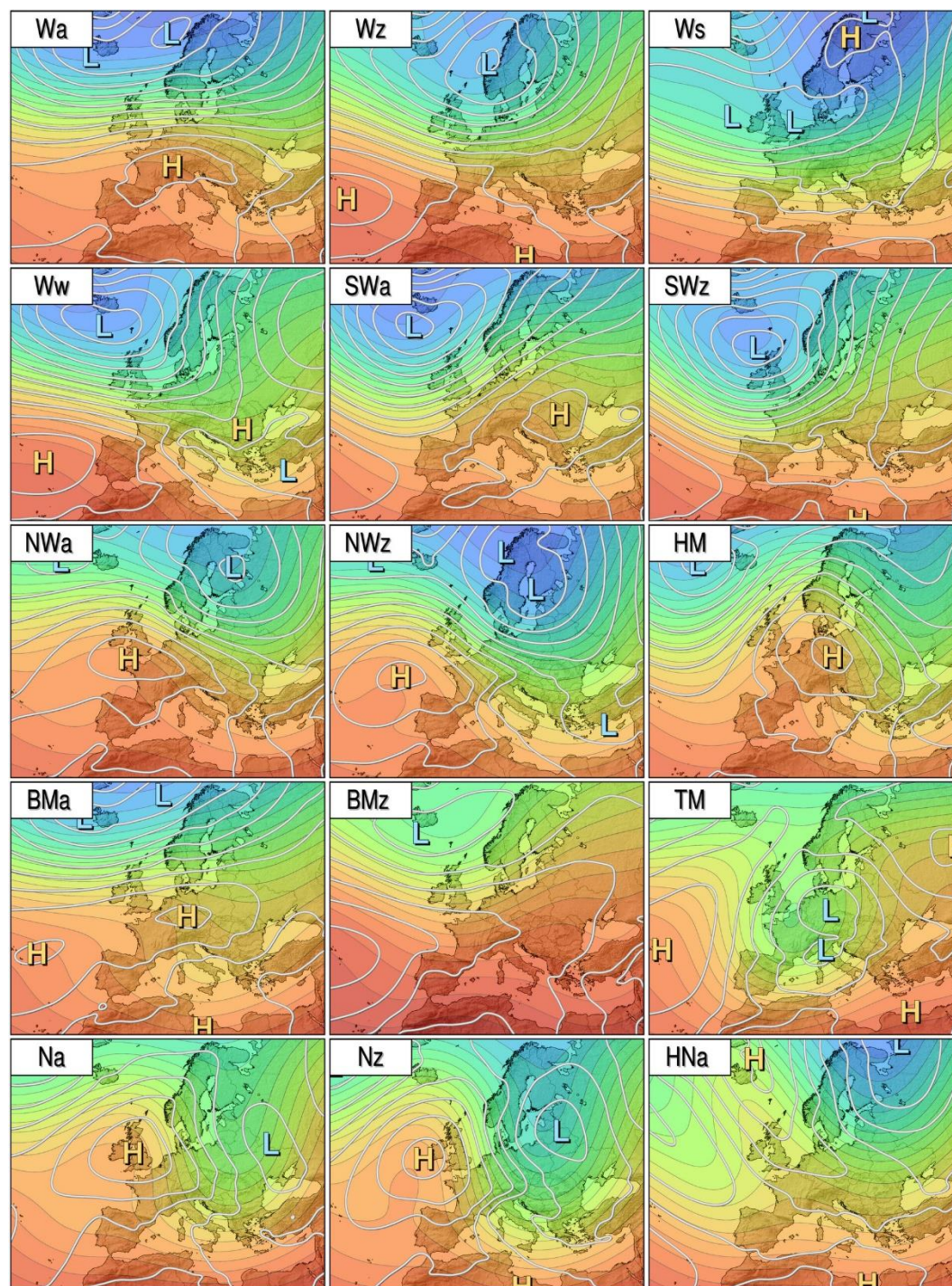


frequency of BMz exhibits a strong trend, increasing from 3.2% during 1951-1987 to 4.2% during the 1988-2024 period. In
320 fact, the summer of 2024 was unusually dominated by the BMz type, which occurred on 37 days: a record in the entire ERA5
period by a large margin. The next highest total was 27 days in 2022, while no other summer exceeded 23 days. Without this
type being explicitly defined, positive trends of such synoptic conditions may have gone undetected.
Although the new GWL type represents an extension to the Hess-Brezowsky concept, its relevance justifies the change.
Furthermore, allowing the type to be part of a BMa-BMz pair keeps the change to the nomenclature as small as possible.
325 A list of all 30 GWLs, together with an indication of their respective cyclonicity and frequency can be found in Table 1.
Climatological mean composites for each of the 30 GWL patterns, showing the surface and mid-tropospheric flow in each
case, are illustrated in Fig. 5 for reference, based on GWL-REA's low-pass filter classification of ECMWF ERA5 reanalyses.



GWL		Description (German)	Description (English)	Cycl.	Freq.
01	Wa	Westlage, antizyklonal	Anticyclonic Westerly	A	4.5
02	Wz	Westlage, zyklonal	Cyclonic Westerly	Z	9.5
03	Ws	Südliche Westlage	South-Shifted Westerly	Z	2.0
04	Ww	Winkelförmige Westlage	Angular (Diffluent) Westerly	Z	3.3
05	SWa	Südwestlage, antizyklonal	Anticyclonic South-Westerly	A	5.7
06	SWz	Südwestlage, zyklonal	Cyclonic South-Westerly	Z	4.3
07	NWa	Nordwestlage, antizyklonal	Anticyclonic North-Westerly	A	3.5
08	NWz	Nordwestlage, zyklonal	Cyclonic North-Westerly	Z	5.7
09	HM	Hoch Mitteleuropa	High over Central Europe	A	3.7
10	BMa	Brücke Mitteleuropa, antizyklonal	Anticyclonic Bridge across C. Europe	A	7.4
11	BMz	Unterbrochene Brücke Mitteleuropa	Disrupted Bridge across Central Europe	Z	3.6
12	TM	Tief Mitteleuropa	Low over Central Europe	Z	1.6
13	Na	Nordlage, antizyklonal	Anticyclonic Northerly	A	1.6
14	Nz	Nordlage, zyklonal	Cyclonic Northerly	Z	1.7
15	HNa	Hoch Nordmeer, antizyklonal	High Norwegian Sea, anticyclonic	A	2.1
16	HNz	Hoch Nordmeer, zyklonal	High Norwegian Sea, cyclonic	Z	3.1
17	HB	Hoch Britische Inseln	High over the British Isles	A	2.8
18	TrM	Trog Mitteleuropa	Trough over Central Europe	Z	4.1
19	NEa	Nordostlage, antizyklonal	Anticyclonic North-Easterly	A	2.2
20	NEz	Nordostlage, zyklonal	Cyclonic North-Easterly	Z	1.9
21	HFa	Hoch Fennoskandien, antizyklonal	High over Fennoscandia, anticyclonic	A	2.8
22	HFz	Hoch Fennoskandien, zyklonal	High over Fennoscandia, cyclonic	Z	2.7
23	HNFa	Hoch Nordmeer-Fennosk., antizykl.	High Norwegian.Sea-Fennosc., anticyc.	A	2.2
24	HNFz	Hoch Nordmeer-Fennosk., zyklonal	High Norwegian Sea-Fennosc., cyclonic	Z	1.9
25	SEa	Südostlage, antizyklonal	Anticyclonic South-Easterly	A	4.2
26	SEz	Südostlage, zyklonal	Cyclonic South-Easterly	Z	1.5
27	Sa	Südlage, antizyklonal	Anticyclonic Southerly	A	3.9
28	Sz	Südlage, zyklonal	Cyclonic Southerly	Z	1.5
29	TB	Tief Britische Inseln	Low over the British Isles	Z	2.0
30	TrW	Trog Westeuropa	Trough over Western Europe	Z	3.3

330 **Table 1: List of the 30 GWLs classified by GWL-REA with German and English names. The respective precipitation class over C. Europe is indicated in the column labelled “cycl.”: (A) anticyclonic/dry, (Z) cyclonic/wet. The climatological mean frequency of the GWLs during the period 1940 to 2025 is shown in percent in the right-hand column, based on the low-pass filtered GWL series using ERA5 reanalyses.**



335 **Figure 5(a).** Climatological mean composites for GWL-REA Grosswetterlagen Nos. 1-15, based on ECMWF ERA5 reanalyses, 1950-2024. Shown are MSLP contours (white), interval 3 hPa, and 500 hPa geopotential colour-filled contours, interval 3 dam, colour scale as Fig. 2. Surface high (low) pressure centres are indicated with labels H (L).

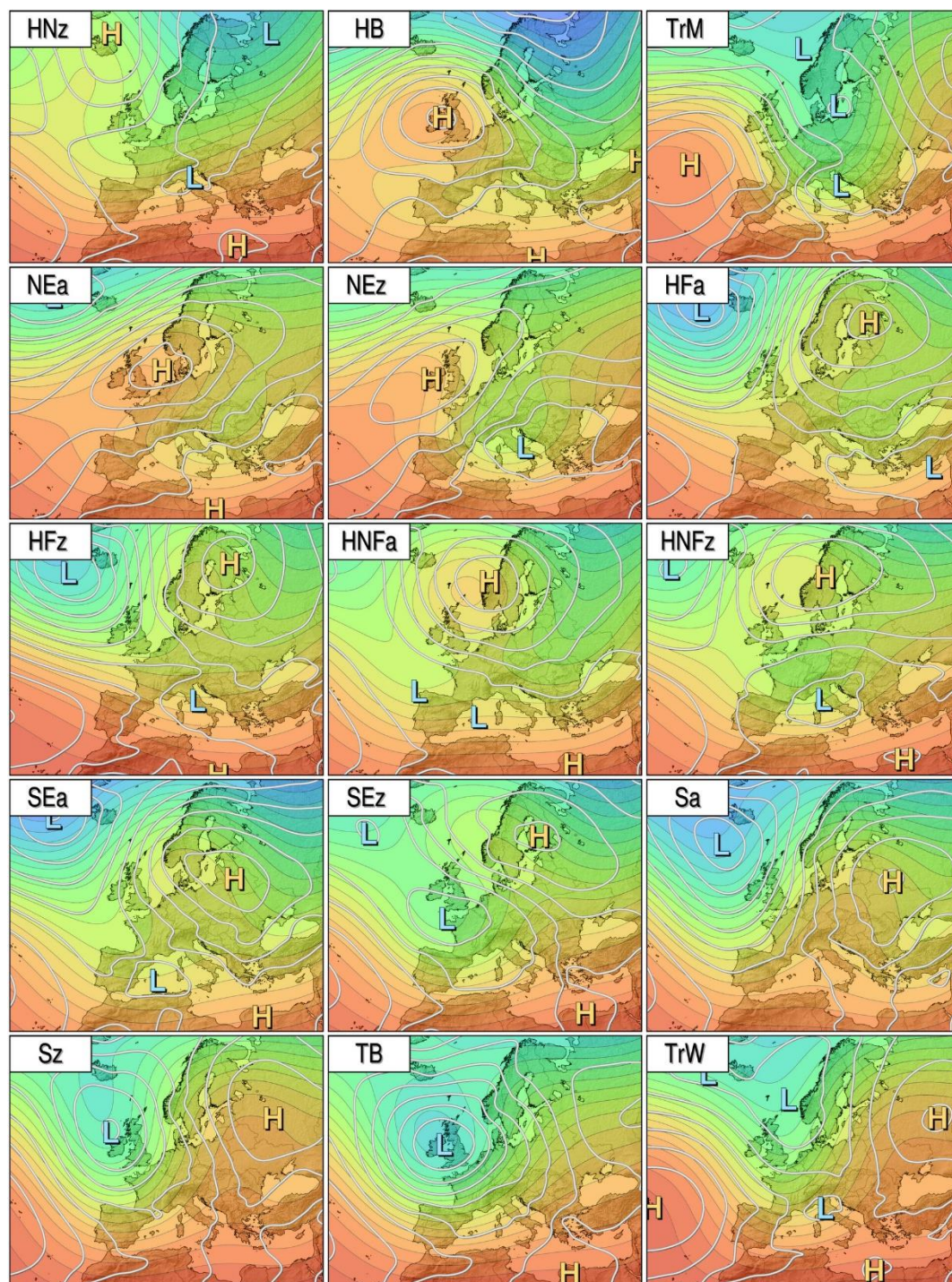


Figure 5(b). Climatological mean composites for GWL-REA Grosswetterlagen Nos. 16-30, based on ECMWF ERA5 reanalyses, 1950-2024. Shown are MSLP contours (white), interval 3 hPa, and 500 hPa geopotential colour-filled contours, interval 3 dam, colour scale as Fig. 2. Surface high (low) pressure centres are indicated with labels H (L).

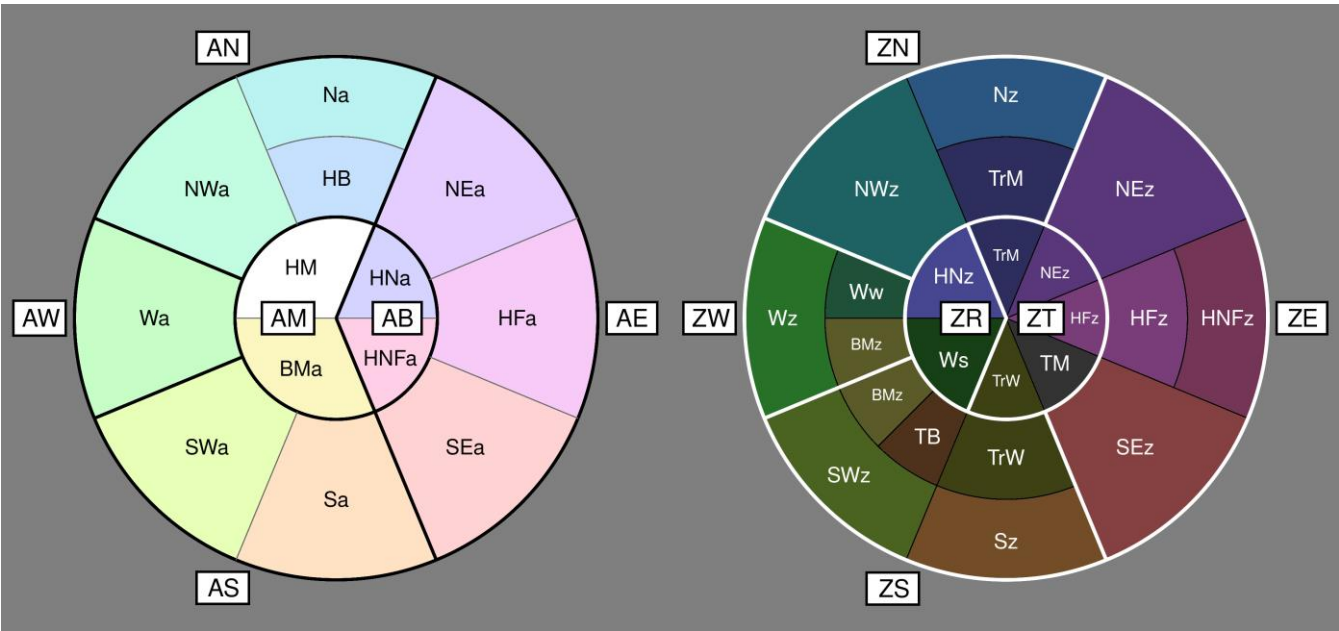


3. Grouping the GWLs by circulation form: GWL-Groups (GWG)

The original Hess-Brezowsky GWL concept included a concatenation of the GWLs into 8 basic circulation groups, called *Großwettertypen*. These groups gathered GWLs together, whose large-scale circulation properties were largely similar, with
345 flow direction being the main criterion. While it is useful to have a small set of circulation-based groups, many of these groups mixed anticyclonic and cyclonic types together, thus removing the most powerful aspect of the GWL system: its ability to discriminate between dry and wet regimes.

In GWL-REA a new concept for grouping the GWLs has been developed that maintains a clear separation of anticyclonic and cyclonic types, while still concatenating similar GWLs together in a systematic fashion. The new set has 12 groups - 6
350 anticyclonic and 6 cyclonic ones - and is designed to provide users with a simpler system that nevertheless still maintains a strong discrimination of Central European rainfall and a meaningful separation of basic circulation characteristics. The new grouping is called GWL-Groups (German: *Großwettergruppen*) and labelled GWG. The grouping has been carefully developed after examining mean correlation coefficient differences between all possible GWL pairs and selecting the groups that minimize the largest correlation differences of the various specific GWL pairs within each group.

355



**Fig. 6: Schematic diagram showing how the GWLs are concatenated into the GWL-Groups (GWG). The two-letter GWG labels are shown in white text-boxes, while the GWGs are delineated by thicker lines. Standard GWL colours are used in the background of each GWL, which are located in relation to their corresponding GWG. Anticyclonic types are shown on the left, cyclonic types on
360 the right. While most GWLs map onto a single GWG, some cyclonic GWLs map onto two GWGs (see text).**



As shown in Fig. 6, all anticyclonic GWLs and many cyclonic GWLs have a straightforward one-to-one mapping onto specific GWGs. The GWG labels are kept simple with just two letters. The first letter describes whether the group is anticyclonic (A) or cyclonic (Z). The second letter refers to a broad flow direction or indicates a centred or regional circulation state.

The most common flow direction, westerly, is given its own respective pair of groups (AW / ZW), while the neighbouring groups (AS / ZS and AN / ZN) have a wider compass, covering meridional and mixed circulation types (i. e. south-westerly together with southerly; north-westerly together with northerly), respectively. While most GWLs within these groups have a one-to-one assignment, the GWL BMz is characterized by a mid-tropospheric flow that typically lies near the boundary between westerly and south-westerly flow regimes. As such, it is split between the corresponding groups, ZW and ZS, and the assignment is made by examining the correlations of the available BMz subtypes and finding the most appropriate match.

The easterly circulation groups (AE / ZE) gather a broad range of GWLs together that exhibit continental flow structures, ranging from north-easterly to south-easterly. The remaining two anticyclonic groups are those for high pressure zones centred over C. Europe (AM, *Mitteleuropa*) and the group AB featuring blocking high pressure over the Norwegian Sea (*Nordmeer*), a characteristic of HNa and HNFa. The latter is needed because the HNa type does not correlate well with any of the neighbouring GWLs in the AN or AE groups, except for HNFa, which would otherwise be in the AE group.

The remaining two cyclonic groups are those for surface troughs across C. Europe, either predominantly zonal in orientation (ZR) or predominantly meridional (ZT). The ZR group is characterized by having a quasi-zonal air mass boundary parallel to westerly or west-south-westerly mid-tropospheric flow somewhere over or near to C. Europe. Underneath this boundary an active surface trough typically forms. The R suffix is derived from the German word for an elongated surface trough, *Rinne*, i. e. *Tiefdruckrinne*.

The ZT group (T for Trough, *Trog*) exhibits a quasi-meridional surface trough on the edge of an upper trough, which is usually located over the western half of Europe and usually extends over at least the western half of C. Europe. This is an important synoptic type, but one which is not mapped uniquely onto a single GWL. The ZT group represents synoptic situations that are often associated with the development of so-called “Vb”-track low pressure situations (Mudelsee et al., 2004), which lead to heavy precipitation and sometimes flooding events somewhere over Central Europe, and are discussed in more detail in this paper’s supplement. Since the standard GWL scheme does not uniquely capture Vb-situations, the ZT group represents an important contribution to synoptic climatology in Central Europe.

While the TM type is always mapped onto the ZT group, four other GWLs map onto it in part: TrM, NEz, HFz and TrW. GWL-REA determines whether specific cases of these GWLs are ZT-like or not by examining the GWL subtype correlations. In each case, if the highest correlating GWL subtype is a ZT-like subtype, then the GWL is mapped onto the ZT group, but otherwise not. For longer GWL sequences, or for consecutive GWLs that each have a ZT component, a GWL sequence can be split into a part belonging to one group and another part to the other group.

The GWG series is based on the low-pass filter GWL series and must also obey the temporal restriction of a 3-day minimum sequence length. Hence, GWL sequences splitting into two or more GWG sequences can only occur when the GWL sequence is sufficiently long.



395 The mean frequencies and descriptions of the GWGs are shown for the ERA5 period, 1940-2025, in Table 2, for reference. The ordering of the GWGs follows that of the GWLs as determined by the dominant or most representative GWL within each respective GWG. Climatological mean composites for each of the GWG patterns, showing the surface and mid-tropospheric flow in each case, are illustrated in Fig. 7 for reference, based on ECMWF ERA5 reanalyses.

GWG		GWG Description	Corresponding GWLs	Freq.
01	AW	Anticyclonic Westerly types <i>Antizyklonale Westlagen</i>	Wa	4.5
02	AS	Anticyclonic South-Westerly or Southerly types <i>Antizyklonale Südwest- bis Südlagen</i>	SWa, Sa	9.5
03	AN	Anticyclonic North-Westerly or Northerly types <i>Antizyklonale Nordwest- bis Nordlagen</i>	NWa, Na, HB	7.8
04	AM	Anticyclonic types with central High or Bridge <i>Antizyklonale Lagen, Hoch / Brücke Mitteleuropa</i>	HM, BMa	11.1
05	AB	Anticyclonic, Blocking High over Norwegian Sea <i>Antizyklonale Lagen mit einem Nordmeerhoch</i>	HNa, HNFa	4.3
06	AE	Anticyclonic Easterly types <i>Antizyklonale Ostlagen</i>	NEa, HFa, SEa	9.1
07	ZW	Cyclonic Westerly types <i>Zyklonale Westlagen</i>	Wz, Ww, BMz	15.0
08	ZS	Cyclonic South-Westerly or Southerly types <i>Zyklonale Südwest- bis Südlagen</i>	SWz, BMz, Sz, TB, TrW	11.1
09	ZN	Cyclonic North-Westerly or Northerly types <i>Zyklonale Nordwest- bis Nordlagen</i>	NWz, Nz, TrM	9.5
10	ZT	Cyclonic types with a meridional surface trough <i>Zyklonale Lagen mit einer merid. Tiefdruckrinne</i>	TM, TrM, NEz, HFz, TrW	6.4
11	ZR	Cyclonic types with a zonal surface trough <i>Zyklonale Lagen mit einer zonalen Tiefdruckrinne</i>	Ws, HNz	5.1
12	ZE	Cyclonic Easterly types <i>Zyklonale Ostlagen</i>	NEz, HFz, HNFz, SEz	6.5

400

Table 2: Frequency distributions of the GWL-Groups (GWG) in GWL-REA over the period 1940 to 2025 in percent, based on ERA5 reanalyses, with descriptions in English and German and lists of GWLs corresponding to each group. GWLs shown in italics map onto two different groups.

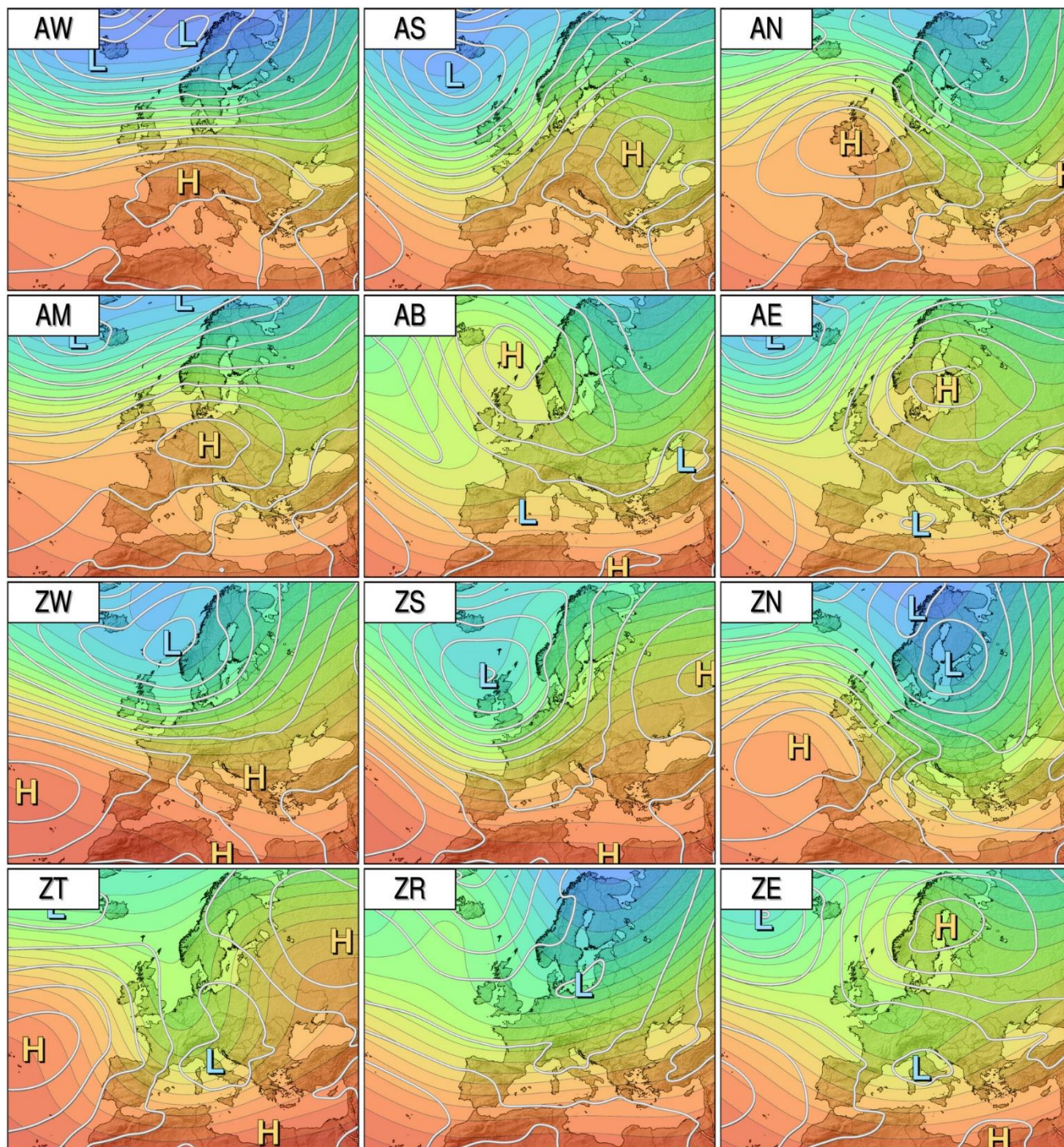


Figure 7. Climatological mean composites for GWL-REA GWL-Groups (GWG), based on ECMWF ERA5 reanalyses, 1950-2024. Shown are MSLP contours (white), interval 3 hPa, and 500 hPa geopotential colour-filled contours, interval 3 dam, colour scale as Fig. 2. Surface high (low) pressure centres are indicated with labels H (L).



4 Verification

4.1 Four-axis verification scores

One of the biggest potential criticisms of GWLs in general is that they are not easily verifiable. One could say that the manual HBGWL series is essentially a list of expert opinions about what each synoptic situation was considered to be at the time. Since the series was created by several different synoptic meteorologists over the decades, it is in fact highly inhomogeneous. For example, the number of GWL events per year in the manual series has varied widely from around 80 before 1985, to nearer
415 60 during the period 1986-2005 following an abrupt change (Cahynová and Huth, 2009). Meanwhile, over the last two decades this number has steadily increased again, reaching over 100 very recently. This has nothing to do with the real weather – GWL-REA's event lengths have no significant trends over the years – but reflects subjective decisions about whether shorter events should be shown explicitly as GWL events or be ignored as transients. Inconsistencies in the GWL determination itself are also apparent, as will be shown below.

420 Now, for the first time, a comprehensive four-axis verification of the GWL series will be described and its results shown, comparing GWL-REA with older methods and the HBGWL series. The four aspects to be addressed by the verification are now discussed.

The first problem is that the GWL nomenclature is inconsistent across the different types, such that it has been difficult to find a way of defining objectively whether a classification is correct or not. Now, for the first time, the LWT penalty scheme
425 embedded in GWL-REA provides a concrete method of verifying GWL classifications, since the LWT penalties essentially measure whether or not a synoptic type agrees with the nomenclature of a given GWL. There is still a certain level of subjectivity and arbitrariness about exactly how this penalty scheme is set up, especially with respect to the relative weights given to different aspects of the circulation (flow direction, curvature and proximity of high- or low-pressure centres). Nevertheless, it is definitely the only available method for verifying the GWL nomenclatures and the results need to be
430 discussed. The nomenclature verification score is defined as:

$$S_N = \frac{(\rho_r - \rho)}{(\rho_r - \rho_{min})} \quad (1)$$

Here, ρ is the mean daily accumulated penalty points over the whole time series, ρ_r is the mean penalty points that would be accumulated by a random time series and ρ_{min} is the lowest possible mean penalty point value that could be achieved if every day was classified optimally. This latter value is close to zero, but is still slightly positive, since some rare synoptic situations
435 exist, which do not fit with the nomenclature of any GWL.

In a second verification, the large-scale circulation should also look like typical climatological examples of GWLs, independent of the question of nomenclature. This can be verified by taking the correlation coefficients of the GWLs from the GWL-REA calculations. Here there is also a certain level of subjectivity regarding the choice of GWL base patterns that form the basis of the correlation results. However, there is no better alternative available to carry out this kind of verification and it is important
440 to show and discuss these unique results. The circulation score is defined as follows:



$$S_c = \frac{(C - C_r)}{(C_{max} - C_r)} \quad (2)$$

Here, C is the daily correlation coefficient of the chosen set of GWLs averaged over the whole time series, C_r is the mean correlation coefficient of a random time series and C_{max} is the highest possible mean correlation coefficient that could be achieved if every day was classified optimally.

445 The above two verification scores are normalized to fall into a range of zero (random classes with no skill) to one (perfection). There are two further scores to consider. Probably the most important verification is that of precipitation discrimination. The precipitation score is specifically defined as:

$$S_p = 0.1785 \left[(P_z - P_a) + \left(\sqrt{\frac{P_z}{P_a}} - 1 \right) - 17.51 \sum_{i=1}^2 (f_i - 1/2)^2 \right] \quad (3)$$

450 Here P_z and P_a are the mean precipitation totals, based on ERA5 areal averages, for days classified as cyclonic and anticyclonic, respectively, and f_i are the respective mean frequencies of these two classes. The score is highest when the mean precipitation difference and/or ratio are as high as possible (cyclonic days should be relatively wet, anticyclonic days should be relatively dry) and the number of days in each of the two classes should be balanced, i.e., close to 50% each. Note that a purely random classification, with 50% of days in each class, would have a score of zero, since P_z and P_a would be approximately equal. The factor 0.1785 ensures that a “perfect” classification of ERA5 data, which correctly classifies the
455 wettest 50% of all days into the wet class, would achieve a score of 1.0. The second factor 17.51 for the frequency bias is scaled so that a perfect forecast of evenly distributed precipitation classes would then see its score reduced to zero on average if the total frequency bias reached 0.8, i.e., with frequencies of 10% and 90%.

One final aspect of a GWL series that needs to be considered is that of readability. Although it is a somewhat subjective concept, GWLs are meant to be seen as a set of synoptic regimes that overlook short-lived transients. Hence, a GWL time
460 series should be readable in the sense that the GWL should not change too frequently and certainly not every one or two days. If they did change so often, the data could still be used in a technical sense of course, but the time series’ use as a descriptive tool would be diminished from a human perspective. Hence, an optimum needs to be found between readability and accuracy. For the purposes of verification, a mean event length (E) of one (i.e., changing to a different GWL every day) is given a score of zero and a “perfect” score of 1.0 is set (somewhat arbitrarily) when the mean event length of 7 days is reached. The score
465 here can be written as:

$$S_R = \frac{7}{6} \left[1 - \frac{1}{E} \right] \quad (4)$$

The four-axis verification has been applied to several GWL series, including the HBGWL series and an earlier objective scheme based closely on James (2007) known as “SynopVis GWL” (e.g., Fleig et al., 2015). These are compared in Table 3 to GWL-REA: both to its unfiltered GWL series and to its low-pass filtered GWLs. For reference, comparable scores are also
470 shown for the well-known LWT method, when centred over Germany, and the DWD’s other objective typing scheme, the 40-type objective weather type classification WLK (Bissolli and Dittmann, 2001). Since these last two classifications do not have



an explicit precipitation expectation for many types, the best possible assignment is made by assuming that the half of types with the highest mean precipitation belong to the cyclonic class, and vice-versa for the anticyclonic class.

475 GWL-REA, even in its low-pass filter version, shows a huge improvement compared to all other series, with the AI module having the largest impact. As one would expect, the unfiltered GWL series performs best in terms of precipitation, nomenclature and circulation accuracy, but at the cost of very poor readability. The HBGWL series performs the worst, despite the GWL nomenclature allowing a precipitation discrimination in principle. The LWT series performs quite well for precipitation, due to the strong intrinsic correlation between low-level cyclonicity and precipitation, but has the disadvantage of very poor readability. The WLK series has a similarly poor readability, but also has a worse precipitation performance than
480 LWT.

Synoptic Type Classification	Precip.	Nomencl.	LS-Circ.	Read.	Wt. Mean
	S _P	S _N	S _C	S _R	
GWL-REA: GWL (unfiltered)	0.95	0.94	0.93	0.38	0.83
GWL-REA: GWL (low-pass filter)	0.83	0.85	0.89	0.90	0.86
SynopVis GWL	0.59	0.82	0.90	0.82	0.77
Hess-Brezowsky manual GWL	0.57	0.73	0.78	0.93	0.73
LWT (Germany)	0.70	-	-	0.27	-
WLK	0.63	-	-	0.27	-

490

Table 3. Verification scores for various GWL and other weather type classifications for comparison. The scores and their weightings for the mean score (GWL only) are precipitation (0.30), nomenclature correspondence (0.26), large-scale circulation (0.24) and readability (0.20). Scores shown in italics are those where the classification does not have an explicit discrimination for a specific quantity. In these cases, optimal groupings are utilized, based on seasonal climatological means of the quantity for each synoptic type.

495

4.2 Spatial verification: Quantile Entropy Reduction

The verification scores presented in the previous section are designed to assess the quality of GWL-REA's GWL classification from the point of view of a region within Central Europe, specifically focussing on Germany. However, there is also the important question of the method's applicability further afield. In other words, is it possible to quantify how far outside of
500 Germany the GWLs are still meaningful or applicable? Furthermore, how does the reduction of applicability with distance compare between different classifications? To address these questions a spatial verification method is required.

To achieve this, a new methodology has been developed called Quantile Entropy Reduction (QER). For parallel time series of a weather type classification (WTC) and a specified meteorological parameter at some location, the QER is defined as the magnitude of the reduction of the total Shannon Entropy (Shannon, 1948) that is achieved when quantiles of the parameter
505 (e.g., terciles, quartiles, quintiles etc.) are summed up into bins corresponding to the different weather types, relative to the average entropy level resulting from reading the same WTC series in a random order.



To illustrate this, consider the following. If a purely random WTC is deployed, with no intrinsic skill, the distribution of the quantiles within each weather type would be approximately even and the entropy would be close to a maximum, i.e., 1. Strictly speaking, random noise effects typically lead to slightly uneven distributions and, hence, to an entropy value slightly below 1 for random WTCs. This noise level is a function of the number of weather types in the WTC and must be taken into account. By comparison, if a more skilful WTC is deployed, the distribution of quantiles should ideally have strong biases in many of the types, leading to a notable reduction in the total entropy value. For example, if precipitation over Germany with respect to a GWL time series is under consideration, some GWLs are primarily dry types while others are primarily wet types. Hence, skewed distributions of precipitation can be expected across many of the different types.

Formally, the QER (e.g., for precipitation) is calculated as follows:

$$QER = \frac{1}{N_r} \sum_{j=1}^{N_r} \sum_{i=1}^{N_{wt}} f_i \cdot S_{r_i} - \sum_{i=1}^{N_{wt}} f_i \cdot S_i \quad (5)$$

where N_{wt} is the number of weather types in the classification, f_i is the relative frequency of a specific weather type (i), S_i is the Shannon entropy of the precipitation quantile distribution for the respective weather type and S_{r_i} is the equivalent entropy of a randomized version of the WTC series, i.e., reading the individual elements of the time series in a completely random order. Typically, several different random series are averaged for extra accuracy. Hence, an extra summation loop is required over N_r , the number of randomisations, which was set to 10 for the results shown below. The Shannon entropy itself is defined as:

$$S = \frac{-1}{\log(N_q)} \sum_{q=1}^{N_q} f_q \cdot \log(f_q) \quad (6)$$

where N_q is the number of classes (quantiles) and f_q is the relative frequency of observed events in a specific class. The product is set to zero in cases where f_q equals zero.

The QER is primarily useful as a comparative measure of WTC quality for discriminating meteorological parameters across their value ranges. Whether it is possible to develop absolute QER thresholds to define possible significance levels for WTCs is beyond the scope of this initial study, but could be the focus of a future paper.

Figure 8 presents comparative spatial maps over Europe of the QER values for various different WTCs, based on quartiles of daily gridded precipitation totals from ECMWF ERA5 reanalyses over the period 1981-2020. Here, it must be noted that precipitation represents a special case with regards to dividing into quantiles, since there are typically many cases with exactly zero precipitation. Indeed, the number of zero precipitation values in a time series could even considerably exceed the expected size of the first quantile. Hence, to avoid this problem, zero precipitation values are all bundled automatically into the first quantile, irrespective of its eventual resulting size. The remaining quantiles are then divided up equally in size. For example, the quartiles shown here represent a zero-precipitation class followed by positive precipitation values divided into terciles.

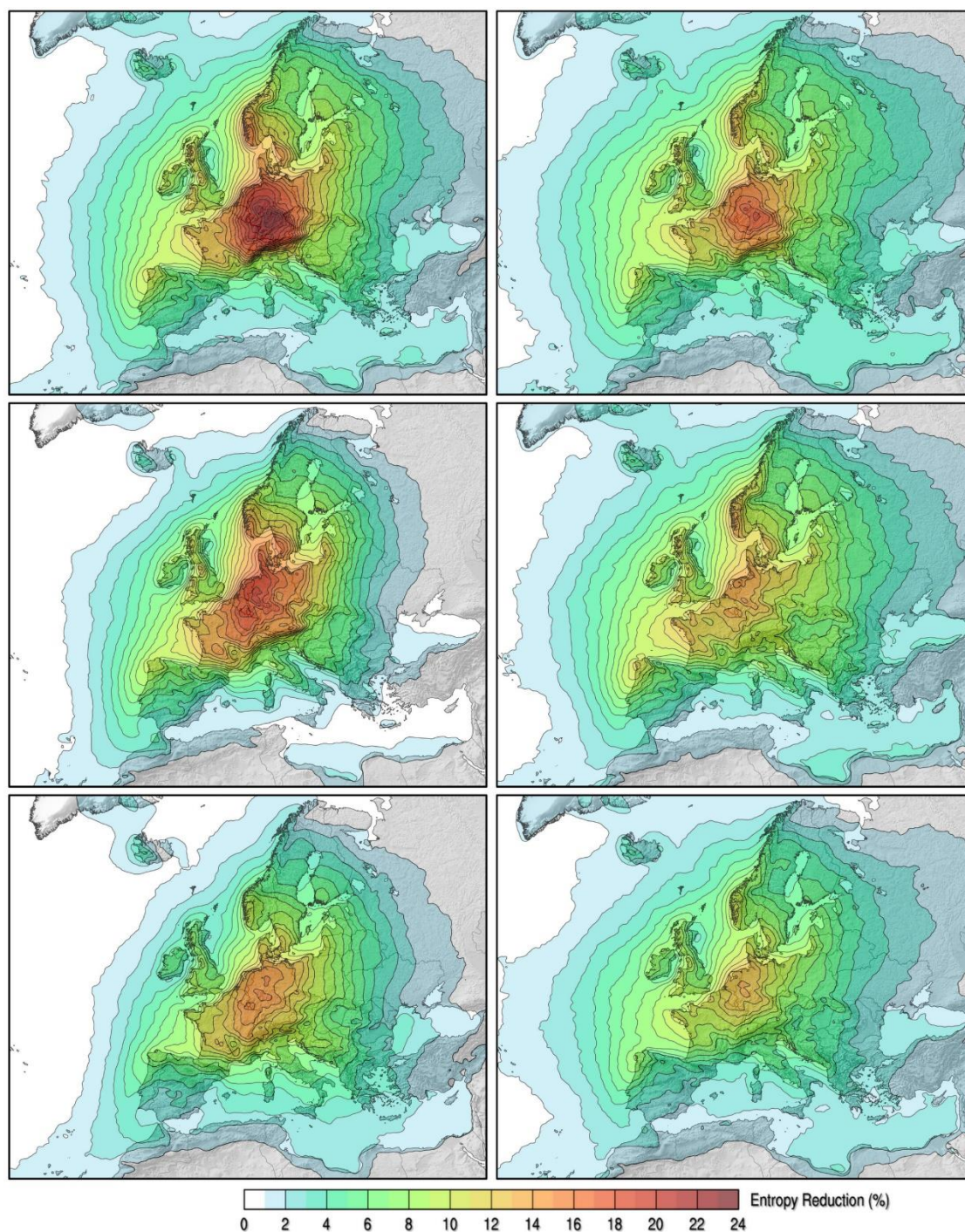


Figure 8. Quantile Entropy Reduction (%) for precipitation quartiles, based on ECMWF ERA5 reanalysed total daily precipitation, 1981-2020, comparing different weather type classifications. [Left side: daily classifications, no temporal filter] (top) GWL-REA
540 GWL, (centre) LWTs centred over Germany, (bottom) WLK. [Right side: classifications with low-pass filters] (top) GWL-REA
GWL, (centre) SynopVis GWL, (bottom) Hess-Brezowsky manual GWL.



In general, QER values decrease when a low-pass temporal filter is applied to a WTC time series, since high-frequency variability in precipitation cannot be accounted for as accurately. Hence, it is important only to compare WTCs with others whose temporal properties are broadly similar. In Fig. 8 the left-hand side compares three unfiltered daily classifications, while the right-hand side compares three low-pass filtered classifications.

545 In general, the highest QERs are located over Germany, as expected given that all of the WTCs being compared are Germany-centric. The values decay quasi-circularly with distance, while exhibiting some geographical traits. In many cases, the decay is slowest towards the west-south-west, with moderately high values still seen over the western Iberian Peninsula. On the other hand, the decay is much faster to the south, especially over eastern Spain and the western Mediterranean. Local minima are also seen elsewhere, notably to the east of Scotland and to a lesser extent over the Gulf of Bothnia. Hence, there seems to be a
550 rain shadow effect with the prevailing westerly winds, where precipitation amounts become much less predictable from the perspective of a Central European WTC. By contrast, locally higher QERs are seen in regions more exposed to the prevailing winds, with frequent orographic precipitation enhancement.

Comparing the unfiltered daily WTCs, the temporally unfiltered version of GWL-REA's GWL series performs very strongly over Germany, with the QERs decaying slowly with distance. The LWT method performs almost as well over Germany itself,
555 albeit with the maximum values further north, but with a more rapid decay with distance. The inherent correlation between local precipitation and low-level vorticity is a clear beneficial factor in the LWT method. Indeed, the QERs are actually similar to GWL-REA over parts of northern Germany, while being notably lower over southern Germany and the adjacent Alps. The WLK series does not perform well in comparison, despite having 40 types, and cannot be recommended for precipitation-based assessments.

560 The comparison of the low-pass filtered GWL series shows that GWL-REA outperforms the older SynopVis GWL method (which lacked any precipitation optimisations, e.g., with AI) over Germany. However, the precipitation enhancements tighten the spatial scale of GWL-REA, whose QERs decay initially more quickly with distance.

Most importantly, the comparison between GWL-REA and HBGWL shows a strong improvement relative to the original manual series. Despite a slightly faster decay with distance, GWL-REA stays ahead of HBGWL throughout a large part of
565 Europe. This result confirms that GWL-REA represents a major improvement for synoptic precipitation studies compared to the former manual series, even well outside of Germany.

To underline these results, Table 4 shows the areal-mean average QER values over Germany and immediate surroundings, i.e., the shaded area in Fig. 4, for the six classifications.

570



Temporal Properties	Synoptic Type Classification	Mean QER (%)	Peak QER (%)
Daily (Unfiltered)	GWL-REA: GWL	18.1	24.6
	LWT (Germany)	14.8	20.5
	WLK	12.8	15.7
Low-Pass Filter	GWL-REA: GWL	14.0	18.9
	SynopVis GWL	10.9	15.0
	Hess-Brezowsky manual GWL	9.8	14.3

Table 4. Areal mean and peak Quantile Entropy Reductions (%) over Germany for various weather type classifications, based on quartiles of daily ERA5 precipitation, 1981-2020. The peak QER values are the respective maximum values seen at any grid-point within the Germany region, based on a grid-box size of 0.3125° latitude x 0.5° longitude.

585 **5 Discussion**

5.1 GWL-REA summary and comparison to Atlantic-European Regimes

In this paper, a new algorithmic method for classifying daily Central European Grosswetterlagen from reanalysis, climate and/or forecast model data, known as GWL-REA, has been introduced. This represents the first time that an automatized, objective GWL classification has been developed that has been highly optimized based on a systematic verification suite.

590 GWL-REA finds a near-optimal balance between the different aspects of a GWL classification, addressing the large-scale circulation, the type nomenclatures, the readability of the time series via temporal filtering and the accuracy of its separation of cyclonic and anticyclonic types via an AI-based precipitation estimation.

As a result, the low-pass filtered series of GWL-REA based on ERA5 reanalyses can be considered a successor to the original Hess-Brezowsky series. Verifications show clearly that GWL-REA is objectively strongly superior to the manual catalogue

595 and should lead to significant quality improvements when applied in climatology and weather impact studies. Furthermore, its algorithmic nature means that GWL-REA can also be used more widely, for example to interpret climate model outputs or ensemble forecasts in the medium- and seasonal-ranges, something that was beyond the scope of the HBGWL series. Indeed, GWL-REA has already been deployed in recent studies of heavy rain events in Germany (Palarz et al., 2024) and of low renewable energy production episodes caused by so-called “Dunkelflauten” events - wind lulls in gloomy conditions, often in

600 winter anticyclones (Kaspar et al., 2024). Furthermore, GWL-REA is used operationally at DWD to summarize and interpret the 15-day ensemble forecasts of ECMWF, which will be the subject of a future paper.

Despite these advantages, the potential limitations of GWL-REA must also be discussed. The optimizations give it a special regional focus on Germany and immediate surroundings, especially on precipitation discrimination there. This somewhat reduces its usefulness for more distant regions towards the edges of Europe, as indicated by the gradual reduction of QER

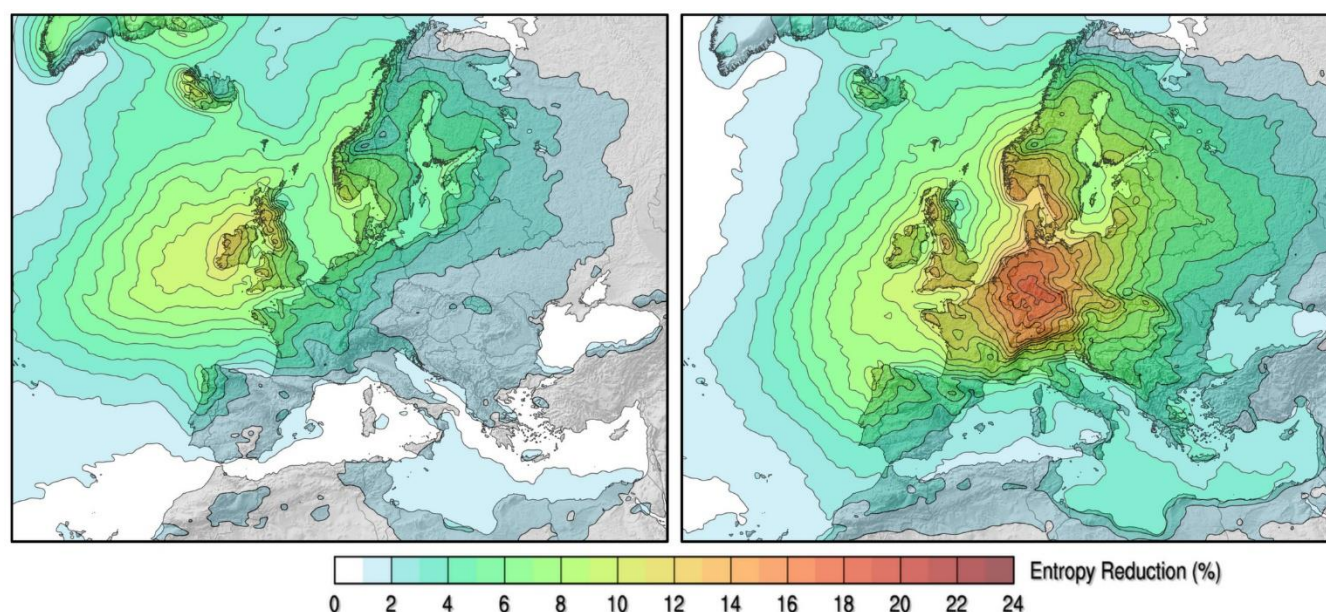


605 scores with distance from Germany shown in Fig. 8. Notwithstanding this limitation, GWLs also have a descriptive quality that can be useful for discussing the larger-scale circulation across the N.E. Atlantic and Europe as a whole.

In this context, the GWLs can be compared to a recent, widely discussed classification developed by Grams (2017, 2026). This 7-type scheme, referred to as Atlantic-European Weather Regimes (here AER), is based on an EOF analysis and k-means clustering of low-pass filtered 500 hPa geopotential anomaly fields. As such, the AERs focus only on large-scale drivers of synoptic variability, for which it is certainly a very useful method. However, surface pressure patterns are not addressed directly and, as a result, the AERs have only a weak correlation with some meteorological quantities such as regional daily precipitation. Furthermore, the AER method allows some days to remain unclassified whenever the large-scale flow does not correspond to any of the 7 patterns sufficiently well. Nearly 30% of all days fall into this “no regime” state, which further reduces the method’s applicability for regional impact studies.

615 It is particularly interesting to compare precipitation QER values between the AERs and outputs from GWL-REA. To make this comparison more equitable, given the relatively heavy temporal filtering of the AERs and their limited number of types, daily precipitation is replaced by centred 5-day running mean precipitation and the 12 GWL-Groups (GWG) are used instead of the 30 GWLs. The mean QER values of the AERs for precipitation discrimination have maxima of around 12% over western Ireland, but fall to just 2-6% over Germany – much lower values than are typical of regionalized type classifications. Indeed, despite its C. European focus, the 5-day mean precipitation QER values of the GWG remain higher than the AERs across most of Europe and only become comparable or even slightly lower from the west of Ireland into the Atlantic and near Iceland and Greenland, as shown in Fig. 9.

620



625 **Figure 9. Quantile Entropy Reduction (%) for precipitation quartiles, based on ECMWF ERA5 reanalysed 5-day centred running mean precipitation, 1981-2020. (Left) Atlantic-European Weather Regimes, (Right) GWL-REA GWL-Groups.**



This result suggests strongly that an optimized regional weather type classification can have advantages over and above a broad, large-scale classification method, even well outside of the region it is meant to serve. The key requirements that lead to this advantage are having a consistent, meaningful set of large-scale circulation patterns and appropriate optimization methods for gaining a useful regional focus within these patterns. Hence, there is a solid case for the need to develop regionally-focussed and -optimized classifications such as in the case of GWL-REA. Such methods can then provide a high level of applicability and quality in their designated region, exceeding that of broader methods considerably.

5.2 Applicability to temperature and other weather parameters

A further general weakness of the GWL series is that it is less useful for temperature-focussed studies, since the GWLs do not separate different air mass situations within any specific GWL type and their definitions largely ignore air mass considerations. To illustrate this point, the QERs for 5-day running mean 2m-temperature terciles have been calculated and compared between the AERs and the GWG in Fig. 10. Note that a one-day time lag is applied to each synoptic type series for this comparison, since this improves their correlations with temperature (i. e. today's circulation type correlates best with tomorrow's temperature). Compared to precipitation, the poor temperature performance of the GWG is apparent. The AERs perform relatively strongly over parts of the North Atlantic, especially over the Norwegian Sea and far to the south-west of Iceland, although the practical relevance of surface temperature correlations over oceanic regions is surely rather limited. Indeed, over most of the European landmass, except Scandinavia, the GWG still perform slightly better than the AERs for temperature.

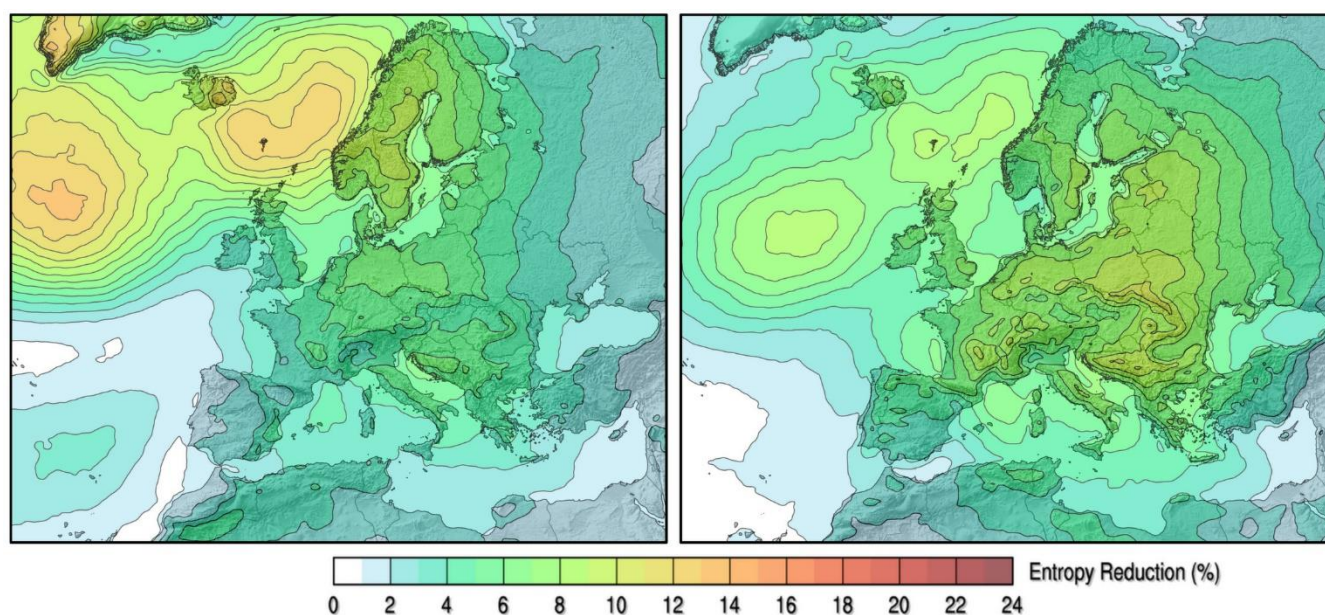


Figure 10. Quantile Entropy Reduction (%) for 2m-temperature terciles, based on ECMWF ERA5 reanalysed 5-day centred running mean 2m-temperature, 1981-2020. (Left) Atlantic-European Weather Regimes, (Right) GWL-REA GWL-Groups. In both cases, the synoptic type catalogues are lagged by one-day to improve temperature discrimination.



To focus on temperature in GWL-REA more effectively a further neural network could be developed, for example using ERA5 detrended seasonal 2m-temperature anomalies as the target. This has been done experimentally with GWL-REA to create a new time series in which the GWG are split into cold and warm variants, respectively, leading to a 24-type scheme. While further details are beyond the scope of this paper, the great advantage of such a series is that it discriminates precipitation, circulation and temperature classes, while still having less types than the original GWLs that only discriminate precipitation and circulation.

It should also be noted that the method of adding a further meteorological dimension to the GWGs could easily be modified to introduce a dependency on a different parameter. For example, temperature could be replaced by the 10m-wind speed, which could be estimated by an appropriately developed neural network, or indeed any other weather parameter. This idea, which bears some similarity to the “Targeted Circulation Types” concept of Bloomfield et al. (2019), has considerable scope for the development of bespoke and flexible weather type time series that are optimized for specific users concerned with specific elements of the weather and their relationship to the large-scale circulation.

5.3 Philosophical aspects of synoptic type classifications, Outlook

No automatized classification scheme that is optimized to account for a number of different aspects simultaneously can achieve absolute perfection for any of the individual aspects alone, no matter how well it is optimized. In a manual classification the rules are effectively being changed continually, since synoptic meteorologists set different priorities for each sequence of weather charts they examine. During one event the large-scale circulation may seem to be the most important feature, during another it is the regional rainfall or temperature patterns, during another it is the local circulation over a specific region, and so on. Furthermore, the manual approximation of temporal filtering (i. e. the 3-day minimum event length rule) is also highly subjective, since it will vary according to whether certain transient events are regarded as important or not. Hence, in an automatic classification, there will inevitably be some individual sequences where a meteorologist may think that the results are sub-optimal – but only because they are changing priorities for each specific case subjectively.

Ultimately, there is no such thing as a “correct” or “perfect” classification. Neither is it possible to create an automatized version of the HBGWL catalogue that will satisfy subjective expectations on every single day of the catalogue. The best that one can achieve is to set up objective and balanced rules, apply them homogeneously and optimize according to a verification that addresses all relevant aspects. This is exactly what GWL-REA has done.

Having reached this point, one could keep trying to optimize the method with small tweaks, whenever a specific case is found that doesn’t appear subjectively to be optimally classified. This approach was indeed undertaken during the early stages of the GWL-REA development, since such sub-optimal event classifications were frequent at that time and it was necessary to tune the various parameters in the algorithm. However, once an acceptable level of tuning has been achieved, such tweaks are no longer beneficial, since they only improve the classification on the specified days, but then often lead to new problems materializing elsewhere in the series. Such efforts soon become futile and a form of chasing after the wind.



680 In terms of the further development of GWL-REA, there seems to be little scope for further meaningful improvements to the method within the context of traditional algorithmic approaches. While specific aspects of the classification could be tuned further or weighted more highly, this usually comes at the cost of slight reductions in quality in the other aspects. The current GWL-REA version achieves a balance across different aspects, as confirmed by the four-axis verification, showing that a high quality has been reached, especially compared to earlier methods.

685 During the latter stages of GWL-REA's development, a significant general quality improvement was only possible after an AI module was introduced to improve the precipitation correlations. This suggests that the final goal could be the development of a generic AI-based method that replaces GWL-REA in its entirety. Such a method would be trained on the current GWL-REA outputs and use only the small set of original daily (or six-hourly) meteorological fields and the time of year as input features, without any of the complex algorithmic calculations that GWL-REA must perform.

690 This would then provide a further reason for the development of GWL-REA – to generate a GWL classification of a sufficiently high quality, which no previous method has been able to achieve, to serve as features to train an AI classifier. Once this has been built, the problem of needing to justify using a highly complex non-reproducible ad hoc expert system to create GWL catalogues will become irrelevant.

695 **Code and data availability**

The code and datasets required to run GWL-REA are the property of DWD and are not currently available to the general public. The input reanalysis data, ERA5 and ERA5T, are provided by ECMWF and were extracted from the MARS data archive. The low-pass filtered GWL catalogues of GWL-REA, based on ERA5 (http://dx.doi.org/10.5676/DWD/GWL-REA_V1.6_ERA5_GLP) and ERA5T, are available via the Climate Data Center of the Deutscher Wetterdienst

700 (https://opendata.dwd.de/climate_environment/CDC/event_catalogues/europe/weather_types/GWL-REA/).

Supplement link

In parallel with the publication of this paper, a supplementary document is also being made available with additional information. This contains detailed descriptions of the GWL types and their typical variants, a discussion about seasonality and additional climatological type composites.

705 **Author contributions**

Paul James developed the concept of GWL-REA as well as code and its input datasets, including tuning and verification, and created the graphical outputs shown in this paper. Paul James wrote the original draft of the manuscript. Jennifer Ostermüller



developed test environments, performed experiments with reanalyses and other climate datasets and researched relevant scientific literature. Both authors contributed to the editing and finalization of the manuscript.

710 **Competing interests**

The authors declare that they have no conflict of interest.

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720 patterns. This work has been an inspiration and been the core motivation for the desire to build an algorithmic method to model the task of synoptic classification and broaden its applicability. Data provision and updates of the GWL-REA catalogues via DWD Opendata environment are carried out as part of DAS-Basisdienst (German Strategy for Adaption to Climate Change Core Service).

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