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Do Atlantic-European Weather Regimes Physically Exist?

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Key Points:

- We assess the physical grounding of Atlantic-European winter weather regimes (WR) using dynamical systems (DS) theory
- Most WR display distinct and predictable flow characteristics at their maximum stage, and unpredictable flow at onset and decay
- The agreement between the statistical classification and the DS analysis provides strong evidence for most WR being physically meaningful

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract The subseasonal variability of the extratropical large-scale atmospheric flow is characterized by recurrent or quasi-stationary circulation anomalies, termed weather regimes. Despite the usefulness of these regimes in numerous meteorological and socioeconomic applications, there is an ongoing debate as to whether they represent physical modes of the atmosphere, or are merely useful statistical categorizations. Here, we answer this question for wintertime Atlantic-European regimes. We argue that dynamical systems theory applied to a refined regime definition provides strong evidence in support of most weather regimes being physically meaningful. This finding underpins the broad relevance of weather regimes, for understanding the response of the atmosphere to external forcing, supporting subseasonal weather forecasting, and down scaling of climate projections.

Plain Language Summary The weather situation over the North Atlantic and Europe region is dominated by steady large-scale atmospheric circulation patterns that occur repeatedly, often termed weather regimes. Despite their usefulness in weather forecasting, it is questioned whether these regimes have a clear physical grounding, or are merely useful statistical classifications. By showing that the atmospheric circulation indeed settles down in a comparably steady state during certain regimes, we provide strong evidence in support of their physical foundation. This finding underpins the broad relevance of weather regimes in supporting weather forecasting several weeks ahead and, in addition, understanding the impacts of climate change on our atmosphere.

1. Introduction

The subseasonal atmospheric variability in the extratropics is a key research topic within atmospheric science and of broad socioeconomic relevance (White et al., 2017). A far-reaching paradigm is that a small number of states, termed "weather regimes," can describe this variability. These are defined as recurrent or quasi-stationary states of the large-scale circulation (Hannachi et al., 2017). Weather regimes have implications for extended-range weather forecasting and in the understanding of climate variability (Merryfield et al., 2020).

The concept of weather regimes was first introduced by weather forecasters in the late 1940s (Levick, 1949). A corresponding theory was developed by Charney and DeVore (1979), who hypothesized that the large-scale circulation transitions between multiple equilibria states, based on a spectral model. The multiple equilibria viewpoint has been later authenticated for the barotropic case (Legras & Ghil, 1985), and in two-layer models (Yoden, 1983), yet was criticized using models with higher spectral resolution (Cehelsky & Tung, 1987). Faranda et al. (2016) argued for linking blocked regimes to unstable fixed points rather than stable equilibria. Nowadays, there is little doubt that weather regimes emerge from different statistical classifications applied to long archives (Hannachi et al., 2017). However, it is a source of debate whether these regimes represent metastable states of the atmosphere (Majda et al., 2006), or are merely useful statistical categorizations lacking physical grounding (Fereday, 2017).

A variety of procedures has been used to classify weather regimes (Hannachi et al., 2017). They typically seek to define a low-dimensional phase-space reflecting the key aspects of the atmosphere's variability. A common choice is to compute the Empirical Orthogonal Functions (EOF) of the data. Clustering algorithms

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define weather regimes as distinct states of the atmosphere that have a high probability of occurrence and are separated by transitional lower probability states. Several clustering techniques exist—the most common being the k-means approach (Michelangeli et al., 1995)—aiming to provide partitions of the phase-space into regions, to which datapoints are assigned. A difficulty with cluster analyses is determining the a priori ideal number of clusters (Falkena et al., 2020).

Different numbers of regimes based on geopotential height were proposed to characterize Atlantic-European weather variability. For example, the North Atlantic Oscillation (NAO) provides a two-state classification (Wallace & Gutzler, 1981). Other classifications use 4 (Vautard, 1990) or 6 classes (Falkena et al., 2020). Classifications based on the zonal wind, yield 3–5 jet regimes (Dorrington & Strommen, 2020; Woollings et al., 2010), with four jet regimes corresponding to the four classical weather regimes (Madonna et al., 2017). However, neither are these definitions applicable year-round nor may the number of regimes sufficiently describe the intraseasonal weather variability in the region (Grams et al., 2017). Here, we use the year-round weather regime classification of Grams et al. (2017). This is based on combining EOF analysis and k-means clustering and identifies seven regimes.

We approach the discussion of the weather regimes' physical grounding by leveraging recent advances in dynamical systems theory. These allow to characterize instantaneous atmospheric states in terms of the local dimension (d)—which informs on how the atmosphere evolves to and from a given state—and persistence in phase space (θ^{-1}; Faranda et al., 2017). These metrics are related to the *intrinsic predictability* of the atmosphere and therefore to the *stability* (here in the context of atmospheric variability) of the flow: a highly persistent (low θ), low-dimensional (low d) state will be more stable than a low-persistence (high θ), high-dimensional (high d) one (Messori et al., 2017). This approach has been applied to various atmospheric fields (e.g., Faranda et al., 2019a; Messori et al., 2021). Indeed, it has been shown that d and θ can offer a dynamical characterization of synoptic systems over several geographical regions (Faranda, Alvarez-Castro, et al., 2017; Hochman et al., 2019; Hochman, Alpert, et al., 2020). These studies have focused on individual time-slices of the atmosphere. Yet, recent studies have demonstrated the potential of using the temporal evolution of the metrics to study the predictability of extreme weather events (Hochman, Scher, et al., 2020; Hochman et al., 2021).

We leverage the dynamical systems approach to answer the question: Do weather regimes have a strong physical grounding in the dynamics of the atmospheric circulation, or are they simply convenient statistical categorizations? The governing hypothesis is that if weather regimes are dynamically meaningful states, they should demonstrate unstable flow characteristics (high d and θ) before their onset and after their decay, and relatively stable flow (low d and θ) during their mature stage.

2. Materials and Methods

2.1. Data

The Atlantic-European weather regime life cycle classification and the dynamical systems analysis are based on 6-hourly, 0.7° horizontal resolution European Centre for Medium-Range Weather Forecast (ECMWF) ERA-Interim reanalysis data for 1979–2019 (Dee et al., 2011). The analysis is performed on 500-hPa geopotential height (Z500) for the Atlantic-European region (80°W–40°E, 30–90°N; Figure 1). This variable is routinely used to diagnose the large-scale atmospheric flow characteristics (Ghil & Robertson, 2002).

2.2. Weather Regime Life Cycle

We use the year-round Atlantic-European weather regime definition of Grams et al. (2017). First, we perform a k-means clustering in the phase space spanned by the leading seven EOFs (~76% explained variance) of 6-hourly (1979–2015) 10-day low-pass filtered, normalized Z500 anomalies (Z500′) over the Atlantic-European region. Data is interpolated to a 1.0° grid spacing. Next, we compute the normalized projection of each 6-hourly Z500′ onto the cluster mean, which we term the Weather Regimes Index (IWR; Michel & Rivière, 2011). The IWR time series is extended until February 2019. We then define weather regime life cycles. The key characteristic of an active life cycle for a regime w is that at the time of onset, the respective IWR_w exceeds the value of 1.0 for the first time. Subsequently, IWR_w must remain above 1.0 for ≥5 days. At

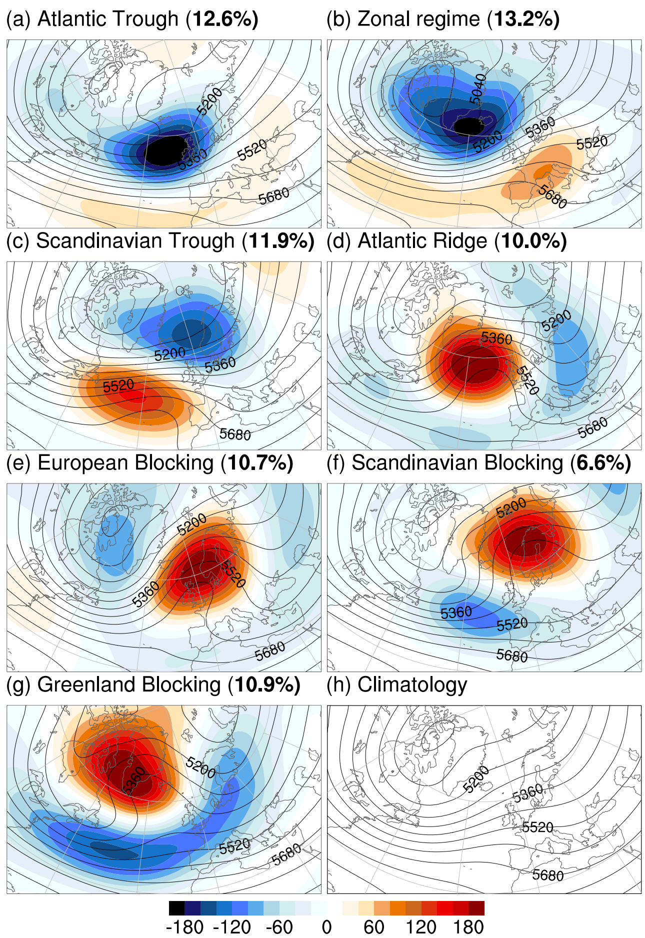

Figure 1. Atlantic-European weather regimes in winter. (a–g) 500-hPa geopotential height mean composites (contours, every 80 gpm) and their anomalies (shading, every 20 gpm) with respect to the seasonal climatology (h) during active regime life cycles (the onset to decay period) in December, January, February of 1979–2019. The weather regimes considered are: (a) Atlantic Trough (AT), (b) Zonal Regime (ZO), (c) Scandinavian Trough (ScTr), (d) Atlantic Ridge (AR), (e) European Blocking (EuBL), (f) Scandinavian Blocking (ScBL), (g) Greenland Blocking (GL). Numbers in the subfigure titles indicate the frequencies of winter days attributed to the respective regime (a–g). The frequency of "no regime" days is 24.1%.

the maximum stage, IWR_w reaches its highest value and it then falls below 1.0 in the decay stage. Still, the projection IWR_i for any other regime i can be computed at each time and reflects the concurrent contribution of different regimes to the circulation pattern.

Dates with all IWR values below 1.0 or none of the IWR_w fulfilling the life cycle criteria have "no regime" (24.1% of winter days). Negative Z500′ dominates in three out of the seven weather regimes ("Atlantic Trough"—AT; "Zonal Regime"—ZO; "Scandinavian Trough"—ScTr), which are termed "cyclonic" regimes (Figures 1a–1c). The remaining regimes are dominated by positive Z500′ and are termed "blocked regimes" ("Atlantic Ridge"—AR; "European Blocking"—EuBL; "Scandinavian Blocking"—ScBL; "Greenland Blocking"—GL; Figures 1d–1g). For more details on the regime characteristics, the reader is referred to Grams et al. (2017). This study focuses on weather regime life cycles being active in the winter months (DJF); summer months (JJA) are briefly discussed. The Kolmogorov-Smirnov test is used for assessing the differences between regime distributions at the 5% significance level.

2.3. Dynamical Systems Analysis

To depict the dynamical evolution of Atlantic-European weather regimes, we rely on an approach combining extreme value theory with Poincaré recurrences (Lucarini et al., 2012, 2016). This approach allows the computation of instantaneous properties of chaotic dynamical systems, and hence it is ideally suited to study the dynamics of the atmosphere. We interpret a temporal succession of two-dimensional Z500 maps as discrete samples from a long trajectory in a reduced atmospheric phase space. For each map, we compute two instantaneous dynamical properties, which are termed local dimension (d) and persistence (θ^{-1}).

The local dimension (d) is a proxy for the active number of degrees of freedom that a system can explore locally. It therefore reflects the way the system approaches and departs from a given atmospheric state. The computation of d stems from the fact that the cumulative probability distribution of suitably defined recurrences of the system converges to the exponential member of the Generalized Pareto Distribution (Freitas et al., 2010).

The persistence (θ^{-1}) of a state intuitively relates to the persistence time of the system near said state. θ^{-1} tends to be more sensitive to small changes in the state of the system than other persistence metrics, such as the conventional definition of weather regime persistence. In the latter case, we are partitioning the atmospheric variability into a small number of states, while in the former we define "similar" states as a small number of close recurrences. Notwithstanding these differences, the two definitions show a close relationship (Hochman et al., 2019). To compute θ^{-1}, we estimate the extremal index using the Süveges (2007) estimator. For details of the computation of the metrics, the reader is referred to Faranda, Messori and Vannistem (2019) and Messori et al. (2017).

Studies have shown that the dynamical systems metrics have a strong seasonal cycle (Faranda et al., 2017; Hochman, Scher, et al., 2020). Since we are comparing weather regime life cycles during different parts of the winter season, we deseasonalize the metrics prior to our analysis. The seasonal cycle is computed by averaging the metrics for a given time step over all years, repeating this for all time steps within the year and finally smoothing the series with a 30-day moving average. A bootstrap test is used to estimate the 95% confidence intervals for the mean temporal evolutions of the metrics. The same test as in Section 2.2 is used for comparing the metrics distributions.

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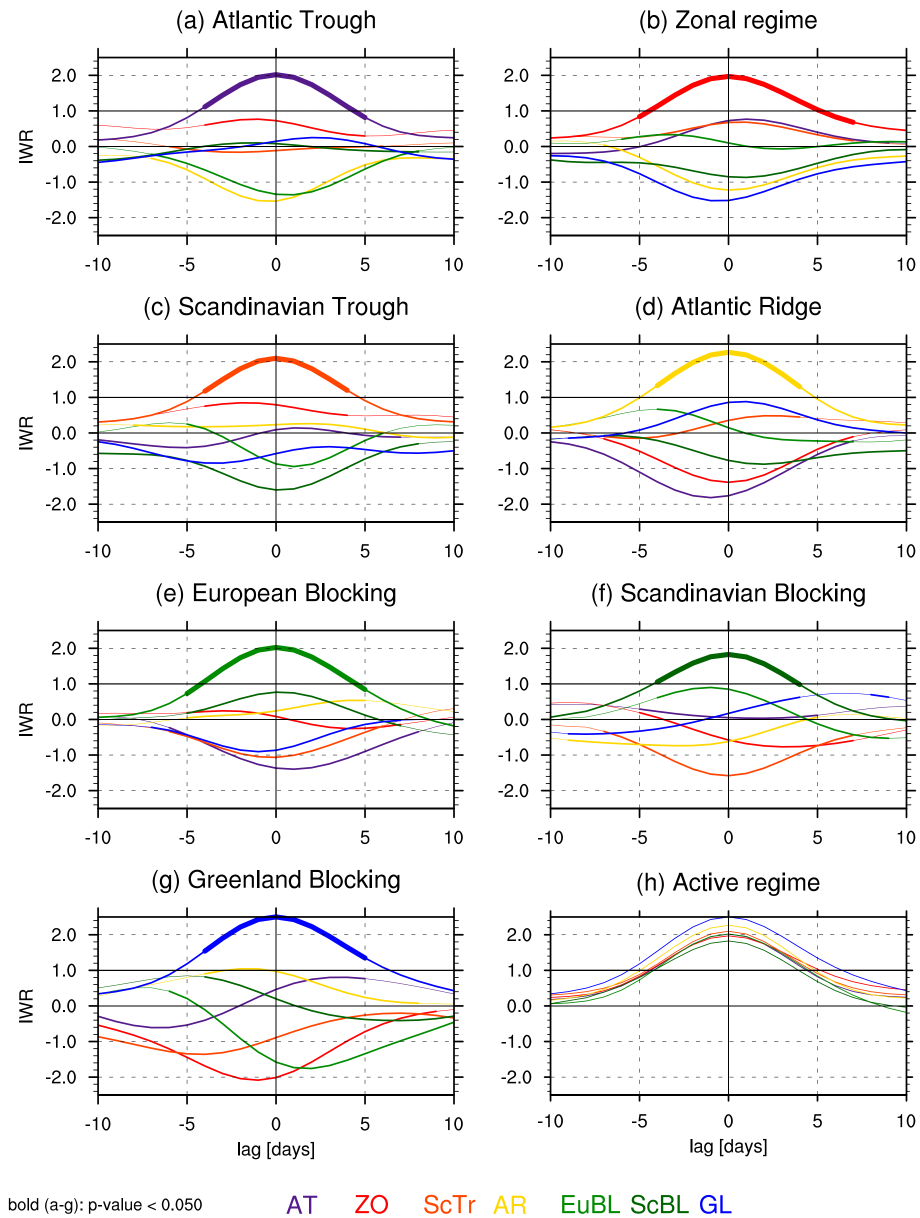

Figure 2. Average temporal evolution of the objective Weather Regimes Index (*IWR*) centered on the weather regime maximum stage (lag on x-axis = 0 days) during the respective active life cycle. Panels (a)–(g) display the mean *IWR* of all regimes during active regime life cycles (IWR_w, see subtitles) of the (a) Atlantic Trough (AT), (b) Zonal Regime (ZO), (c) Scandinavian Trough (ScTr), (d) Atlantic Ridge (AR), (e) European Blocking (EuBL), (f) Scandinavian Blocking (ScBL), (g) Greenland Blocking (GL) regimes. (h) The mean temporal evolution of the respective IWR_w if the weather regimes are active. Very bold sections in the curves for IWR_w of the active regime indicate significant difference of the Cumulative Distribution Functions (CDF) of IWR_w at the 5% level from the CDFs of all other regimes (IWR_i; see text). Bold sections in the curves for IWR_i indicate significant differences of the CDF of IWR_i to the CDF of the active regime's IWR_w.

3. Results

3.1. Atlantic-European Weather Regimes Life Cycles

First, we analyze the temporal evolution of the mean IWR_w during the active life cycle of regime *w*, and IWR_i, for all other regimes *i*. The composites are centered on the maximum stage of regime *w* (Figures 2a–2g). At the time of the maximum (0 days) the mean IWR_w (very bold curves; Figures 2a–2g) is distinct from all other mean IWR_i (bold curves). The distributions of IWR_w over a time window of about ±5 days around the maximum stage are significantly different from the distributions of IWR_i over the same period (very bold sections of IWR_w; Figures 2a–2g). Thus, the atmospheric state in a time window around the maximum stage of a regime is distinct from all other regime states, which suggests a coherent life-cycle evolution, and a low local dimension in terms of dynamical systems theory.

The period of mean $IWR_w > 1.0$ is related to the duration of a regime life cycle, and fulfilled on average for ≥9 days for all regimes (Figure 2h), while the persistence criterion in the life cycle definition is ≥5 days. The mean regime duration in winter, i.e., the mean period between the identified regime onset and decay for each regime life cycle ranges from 10.8 days for EuBL to 16.9 days for GL (not shown). Contrary to what might be expected, the blocked EuBL (10.8 days) and ScBL (11.0 days) regimes display lower mean duration than the cyclonic regimes (13.3–14.6 days).

To further determine whether the IWR_w values are different from IWR_i at the maximum stage, we evaluate their Cumulative Distribution Functions (CDFs; Figures 3a–3g). The CDFs for some regimes tend to be closer to the CDF of the active regime (rightmost CDF; Figures 3a–3g) than others (left CDFs; Figures 3a–3g). During an active ZO regime, the CDFs of the AT and ScTr are closer to the CDF of ZO than the blocked regimes (Figure 3b). This similarity between ZO, AT, and ScTr is also reflected in the mean Z500 patterns, which are characterized by negative anomalies over the Eastern North Atlantic (Figures 1a–1c). During a ScTr regime, the CDFs of the cyclonic regimes, but also of the AR regime are closest to the ScTr (Figure 3c). Vice-versa during an active AR regime, the closest CDFs are those of ScTr, GL, and EuBL (Figure 3d). As a final example, the CDFs of the EuBL and ScBL regimes are closest to each other no matter which regime is active (Figures 3e and 3f). The CDF for GL shows higher IWR_w values than all other regimes, and GL has a longer life cycle. On the other hand, the CDF for ScBL exhibits the overall lowest IWR_w values during its active life cycle (cf. Figures 2h and 3h). It is nonetheless important to emphasize that the active regime CDF is always significantly different from all the others (the CDFs to the left) and this difference persists for about ±5 days around the maximum stage (Figure 2). Thus, the atmospheric state at maximum stage of a regime is distinct from all other regime states, again suggesting a low local dimension in terms of dynamical systems theory.

3.2. Atlantic-European Weather Regimes From a Dynamical Systems Perspective

Next, we characterize the weather regime life cycles directly in terms of the two dynamical systems metrics: local dimension (d) and inverse persistence (θ; Figures 4 and 5). Both metrics are presented as deviations from climatology, thus values below zero indicate a more stable and persistent state compared to climatology. We first discuss the temporal evolution of d and θ centered on the maximum stage (0 day; Figure 4). The metrics are in phase with one another for most regimes. The cyclonic weather regimes and GL display values of d and θ that are significantly below climatology at maximum stage, thus, indicating a low local dimension and enhanced persistence during an active weather regime. The other blocked regimes, except for θ in EuBL and d in ScBL, also display values below climatology, though not significantly so at maximum stage. In addition, d and θ are typically below climatology for several days around the maximum stage. This implies that most weather regimes can be regarded as stable and persistent states from a dynamical systems perspective. In particular, in the cyclonic (Figures 4a–4c) and the blocked AR and GL regimes (Figures 4d and 4g), d and θ start to steadily decrease about 5 days prior to the maximum stage and steadily increase in the 5 days thereafter. This pattern is also found for d in the EuBL regime (Figure 4e). Beyond ±5 days, d and θ exhibit a larger spread around their climatological values. This behavior of d and θ mirrors the onset and decay stages of the active regime life cycle (Figure 2), and is also evident when centering the plots on the onset or decay of the regimes (Figures S1 and S2 in Supporting Information S1). The evolution of d and θ is remarkably consistent with the earlier finding that IWR_w is above 1.0 and significantly different from the other IWR_i in a time window of about ±5 days around the maximum stage (Figure 2).

Some differences between the regimes deserve further attention. GL is the regime with the most pronounced change in amplitude of both d and θ (Figure 4g), indicating the transition from an atmospheric state of low persistence and predictability to a persistent and predictable state. Further, θ is below climatology from 5 days prior to maximum stage until beyond 10 days thereafter, consistent with GL being the regime with the longest mean duration. The cyclonic regimes show a more symmetric evolution of d and θ compared to the others, and d and θ remain below climatology for around ±3 days (Figures 4a–4c). AR exhibits a roughly

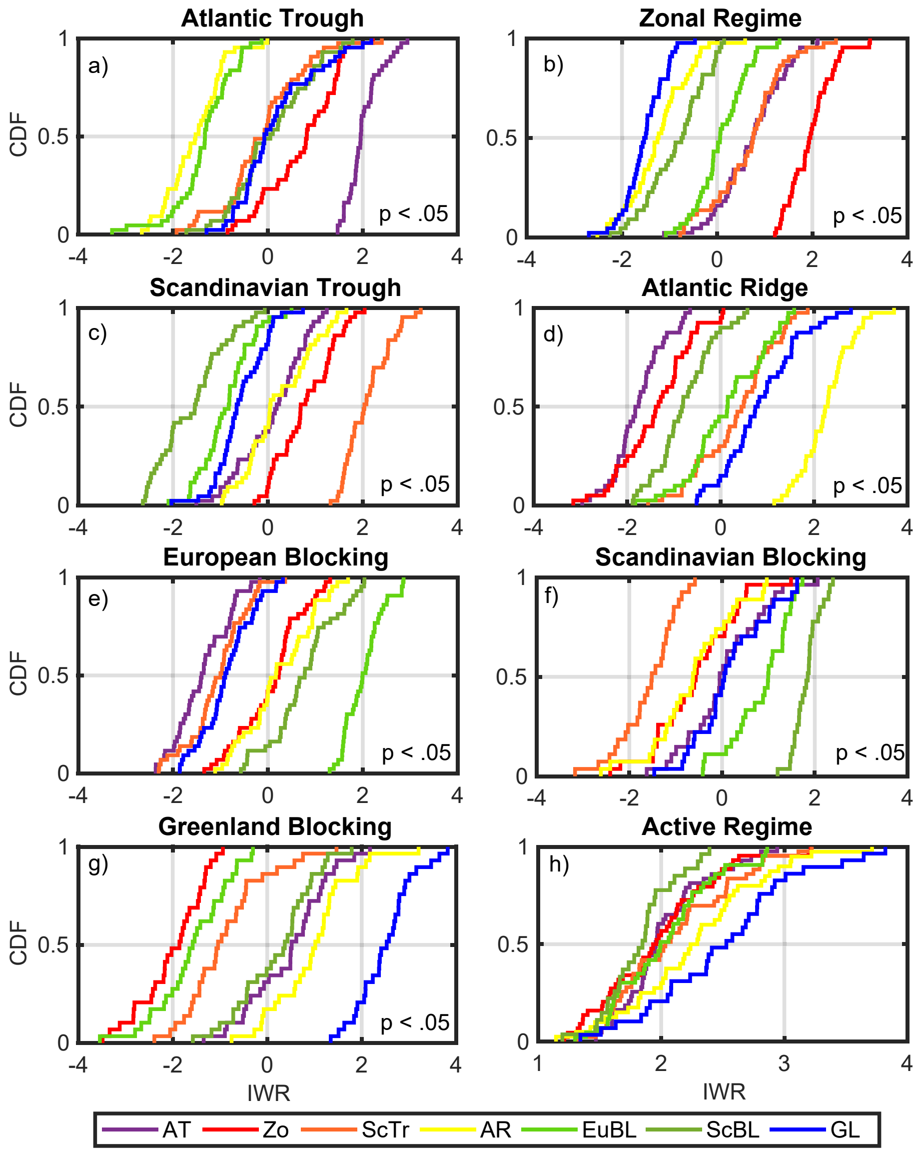

Figure 3. Cumulative Distribution Functions (CDFs) of the objective Weather Regimes Index (*IWR*) at the maximum stage (lag = 0 days in Figure 2) of the Atlantic-European weather regimes. The active weather regimes considered are: (a) Atlantic Trough (AT), (b) Zonal Regime (ZO), (c) Scandinavian Trough (ScTr), (d) Atlantic Ridge (AR), (e) European Blocking (EuBL), (f) Scandinavian Blocking (ScBL), (g) Greenland Blocking (GL). (h) CDFs for all weather regimes at the times when they are active. Significant CDF differences between the active regime and all other regimes are marked with $p < 0.05$ (a–g). The differences between the weather regimes in (h) significant at the 5% level are shown in Table S1 in Supporting Information S1.

symmetric decrease in d and θ toward the maximum stage and a subsequent increase, but the values fall below climatology only for a short period (Figure 4d). EuBL shows similar behavior for d (Figure 4e). Of all regimes, θ values remain highest during EuBL, which is consistent with the overall shortest mean duration. ScBL displays the least systematic changes and largest spread in d and θ; though a decrease toward maximum stage is still evident (Figure 4f). This may partly be due to the rarity of ScBL during winter (Figure 1f), giving a small sample size. The fact that d falls below climatology only for a short period around maximum stage for EuBL, AR, and remains above climatology for ScBL, hints that the statistical characterization of these regimes has a weaker link to the underlying dynamics of the atmospheric flow.

Finally, we analyze the CDFs of d and θ at maximum stage of the regimes (Figure 5). For AT, ZO, ScTr, GL, and to some degree AR, the CDFs for both d and θ shift toward values well below climatology, reflecting

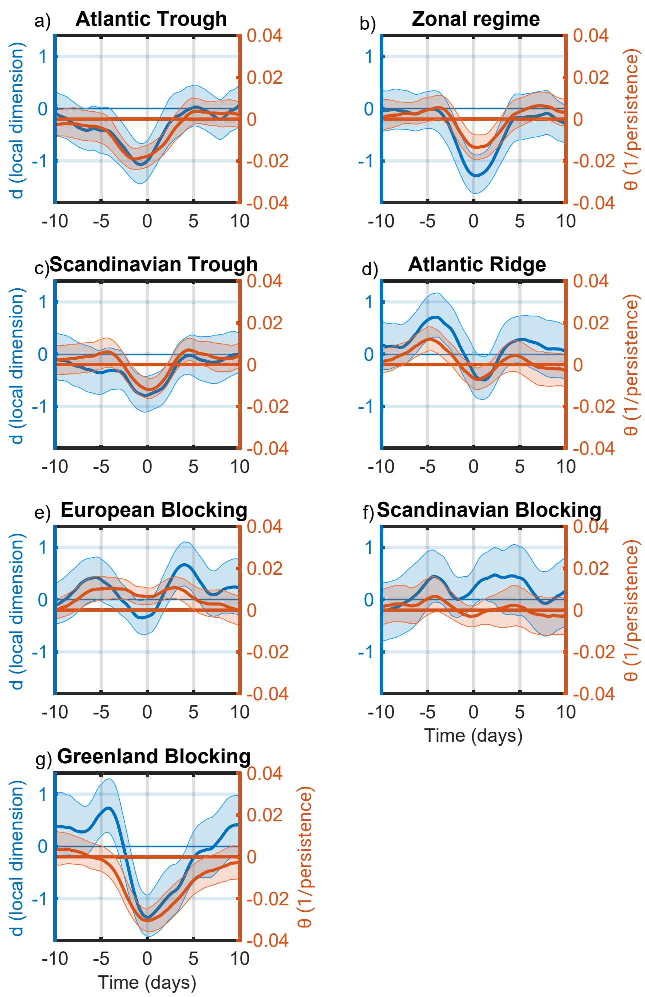

Figure 4. Average temporal evolution of the deseasonalized dynamical systems metrics (d and θ) centered on the weather regime *maximum* stage (time = 0 days). The dynamical systems metrics are computed on 500-hPa geopotential height (Z500). A 95% bootstrap confidence interval is shown in shading. The weather regimes considered are: (a) Atlantic Trough (AT), (b) Zonal Regime (ZO), (c) Scandinavian Trough (ScTr), (d) Atlantic Ridge (AR), (e) European Blocking (EuBL), (f) Scandinavian Blocking (ScBL), and (g) Greenland Blocking (GL).

the low local dimension and enhanced persistence at maximum stage. In contrast, the local dimension of ScBL and persistence of EuBL at maximum stage are close to climatology. The CDFs of d and θ display a relatively large spread around climatology at onset and decay stages (not shown).

Though not being the focus of this study, our findings remain qualitatively valid also in summer (Figures S3–S5 in Supporting Information S1). The metrics are in phase with one another for most regimes. The AT, ScBL, and GL display values of d and θ that are significantly below climatology at maximum stage (Figures S4a, S4f, S4g, and S5 in Supporting Information S1). The other regimes, display a minimum value at the maximum stage of a regime, though not significantly different from climatology. The most pronounced difference from the winter season is found for ScBL (cf. Figures S4f in Supporting Information S1 with Figure 4f). ScBL is more frequent in summer (16.0% of all days) compared to winter (6.5% of all days), and in the former season displays d and θ values that are significantly below climatology at maximum stage (Figures S4f and S5 in Supporting Information S1). This strengthens our interpretation of the winter composite as being affected by small sample size.

In summary, our analysis provides strong evidence that most Atlantic-European weather regimes have a dynamical grounding (Figures 4 and 5), which is largely consistent with the statistical-based weather regime life cycle definition (Figures 2 and 3). In winter, this is most pronounced for the cyclonic regimes, as well as for the GL blocked regime.

4. Discussion

We combine a refined weather regime classification with recent advances in dynamical systems theory to investigate the life cycle and physical grounding of Atlantic-European weather regimes. The agreement between the statistical classification and the dynamical systems analysis provides strong evidence for most Atlantic-European weather regimes being physically meaningful. Interestingly, cyclonic regimes and GL, which corresponds to the negative phase of the NAO, show enhanced flow stability and persistence whereas for the blocked regimes of EuBL, ScBL, and AR local dimension reduces toward maximum stage but remains around climatology. Indeed, GL is the single regime with the lowest local dimension and highest persistence, while the EuBL and ScBL regimes emerge as being amongst the lowest-stability regimes. This may be related to the difficulty in predicting these regimes in extended-range forecasts (Rodwell et al., 2013). The counter-intuitive finding of unstable blocking regimes agrees with Faranda et al. (2016), who linked blocking events to unstable fixed points of the atmospheric dynamics, and Lucarini and Gritsun (2020), who showed in an idealized context that blocking displays anomalously high instability relative to zonal flow.

More generally, we conclude that most Atlantic-European weather regimes display relatively stable flow characteristics (low d and θ) at their maximum stage, yet relatively unstable flow (high d and θ) at onset and decay. Large decreases in d and θ systematically occur toward the maximum stage of each weather regime, even for those that display above average d and θ, whereas large increases in these metrics arise toward their decay stage. We interpret these differences as pointing to most weather regimes being states which have a physical footprint, reflected in the dynamical properties of the atmospheric flow.

Cluster analysis is obviously a valuable tool for simplifying the investigation of large amounts of data, with applications that include revealing atmospheric teleconnections (Kucharski et al., 2010), model

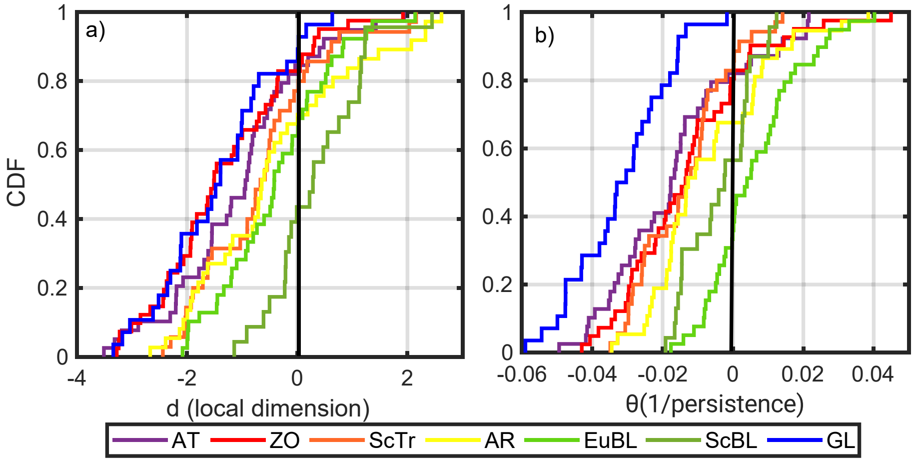

Figure 5. Cumulative Distribution Functions (CDFs) of the deseasonalized dynamical systems metrics (d and θ) at the *maximum* stage of the Atlantic-European weather regimes. The weather regimes considered are: Atlantic Trough (AT), Zonal Regime (ZO), Scandinavian Trough (ScTr), Atlantic Ridge (AR), European Blocking (EuBL), Scandinavian Blocking (ScBL), and Greenland Blocking (GL). The differences significant at the 5% level are shown in Table S2 in Supporting Information S1.

evaluation (Maloney et al., 2019), quantifying the impact of external forcing on climate variability (Peterson et al., 2012), and many more. The results presented here validate the relevance of weather regime clusters for such applications. For example, the dynamical systems metrics combined with cluster analysis may provide a quantitative framework for evaluating the dynamics of Atlantic-European weather regimes in climate models, thus providing the basis for studying the changes in the dynamics of weather regimes under future scenarios. Furthermore, as the dynamical systems metrics provide quantitative information on the intrinsic predictability of weather regimes, they may be used to identify windows of opportunity for subseasonal weather forecasting (Mariotti et al., 2020).

In summary, our findings support the potential of using a dynamical system view of weather regimes for improving our understanding of both weather predictions and climate projections. In particular, we argue that great potential for improvement in subseasonal weather forecasting lies in further understanding of weather regimes and their physical grounding.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The analysis in this study is based on the European Centre for Medium-Range Weather Forecast (ECMWF) ERA-Interim reanalysis (https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era-interim; Dee et al., 2011). The code we have used for our dynamical systems analysis is freely available at this location: https://ch.mathworks.com/matlabcentral/fileexchange/95768-attractor-local-dimension-and-local-persistence-computation. The weather regime life cycle classification is available through Grams et al. (2017).

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