Cost733cat – A database of weather and circulation type classifications

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1. Introduction

Classification of weather and atmospheric circulation states into distinct types is a widely used tool for describing and analyzing weather and climate conditions. The general idea is to transfer multivariate information given on the metrical scale in an input dataset, e.g. time series of daily pressure fields, to a univariate time series of type membership on the nominal scale, i.e. a so called classification catalog. The advantage of such a substantial information compression is the straightforward use of the catalogs. On the other hand the loss of information caused by the classification process makes it sometimes difficult to clearly relate the remaining information to other weather elements like temperature or precipitation, which in many cases is the main objective for the applications of classifications. The reason may be due to the lack of compact cohesive clusters in the input data (see e.g., Christiansen, 2009) but also an unintended mixing of circulation states with different physical meaning for the target variable (see e.g. Yarnal et al., 2001). For other applications which are just interested in a compact description of atmospheric dynamics the challenge is the same, since as much information as possible should be recorded by a single nominal variable. It may be a consequence of this contrariness between the demand for simplification and the demand for thoroughness, that the number of different classification methods is huge and still increasing, in the hope to find a method producing a simple catalog but still reflecting the most relevant parts of the climate variability. However, the multitude of classification methods and their results is a drawback as it is hard to decide which one to use for a certain application. In order to provide a systematic evaluation of classifications, a consistent database of classification catalogs was created within the COST (European Cooperation in Science and Technology) Action 733 entitled "Harmonisation and Applications of Weather Type Classifications for European regions", henceforth referred to as cost733-cat. Since there is a European focus and there was the need to select a manageable number of methods the collection is not intended to be exhaustive. Thus, approaches like those presented by Barry (1960) using trajectories for eastern Canada, Dzerdzeevskii (1962) classifying northern hemispheric circulation, Thompson (1973) classifying airflow for Australia, Muller (1977) typing weather maps for New Orleans, Davis and Kalkstein (1990) creating spatial distribution maps for US-stations which were then used for temporal classification, Kalkstein et al. (1996) using 12 variables to discriminate air masses or Sheridan (2002) implementing a further developed Spatial Synoptic Classification for the US, just to mention a few, were not included (see El-Kadi and Smithson (1992) and Huth et al. (2008) for further reviewing).

In order to describe the included methods a new categorization has been developed within the COST Action. For a long while classification methods have been divided into two main groups, namely *manual* and *automated* classifications (e.g. Yarnal, 1993). An alternative discrimination refers to *subjective* versus *objective* methods, which is not quite the same since automated methods, which are often regarded as objective always include subjective decisions. A third group of *hybrid* methods has been established (e.g., Frakes and Yarnal, 1997; Sheridan, 2002) accounting for methods that define types subjectively but assign all observation patterns automatically. Another distinction could be made between circulation type classifications (CTCs) utilizing solely atmospheric circulation data like air pressure, and the so called weather type classifications (WTCs) using additional information on other weather elements like temperature or precipitation. WTCs also include classifications developed for very specific applications e.g. for downscaling where the target element is integrated into the classification process (e.g. Bárdossy et al., 2002; Zorita and von Storch, 1999). Since those specialized classifications are not transferable to different regions or purposes they are not included in the presented study. New developments of generalized WTCs and subjective classifications, including information about the synoptic weather situation of a circulation type, are rare and actually only one automated method (called WLK) using other parameters than pressure fields is included in cost733cat. The reasons are probably the high efforts to create classifications manually as well as the higher demand for CTCs in so called circulation-to-environment applications (Yarnal, 1993) relating circulation to other weather elements after the classification process. With the growing availability of computing capacities during the last decades, the number of automated CTC methods increased considerably, since it is easy now to modify existing algorithms and produce new classifications (see Huth et al. (2008) and Jolliffe and Philipp (2010) for further developments) and it is getting more and more difficult to maintain an overview of the various classification methods. Yarnal et al. (2001) therefore introduced three categories of techniques: (i) *manual typing*, (ii) *correlation based analyses* and (iii) *eigen-vector-based analyses*, the latter subdivided into *PCA*, *EOFs* and *other multivariate classifications*. Since PCA (Principal Component Analysis) and EOFs (Empirical Orthogonal Functions) are strongly related on the one hand and *other multivariate classifications* on the other hand is rather unspecific it seemed necessary to find a new categorization of methods especially accounting for the increased diversity of automated methods and the algorithms they use. Therefore an attempt is made in the paper to distinguish between five basic classification strategies in order to survey the characteristics of related classification methods.

This paper is organized as follows: a review of the classification methods included into the cost733cat catalog database is given in Section 2 structured according to a methodological categorization which is explained for each method group respectively. Section 3 describes the dataset compilation concerning the input dataset and the standardized method configurations. In Section 4, five indices describing classification characteristics based on class frequencies are presented for a comparable subset of the catalogs. Finally in Section 5 shared features and differences between methods and method groups are discussed leading to first conclusions about the presented dataset.

2. Classification methods and their categorization

In order to get an overview of commonly used methods an initial inventory of European classification schemes was produced by a questionnaire sent to European authors in the year 2006 (Huth et al., 2008). By removing redundant methods and adding some classical ones (e.g. Lund, 1963) a broad spectrum of different strategies for classification became apparent. A summary of the 23 selected classification methods is given in Table 1 including five subjective and 18 automated methods and their variants resulting in a total of 72 classification schemes. In order to categorize these different approaches concerning methodological commonalities, the kind of type definition can be utilized. Two main strategies can be discerned concerning the relation between type definition and assignment of objects. The first strategy is to establish a set of types in prior to the process of assignment (called *predefined types* hereafter, see Section 2.1 below), while the second way is to arrange the entities to be classified (daily patterns in this case) following a certain algorithm such that the types are, together with the assignment, the result of the process (called *derived types*, see section 2.2 below). The use of predefined types corresponds to a deductive top down approach where it is already known how the relevant types look like, while the generation of derived types corresponds to the inductive bottom up approach where more or less

Table 1
Methods and variants overview. Individual variants of classification configurations sorted by method groups are listed by : abbreviation used (column 2); number of types (column 3); parameters used for classification (column 4) (MSLP: mean sea level pressure, *Z*: geopotential height, U/V: zonal and meridional wind components, PW: precipitable water, SFC: surface, numbers: the referring pressure level in hPa); availability for the 12 spatial domains (see text of Section 3) denoted by Y (yes) or N (no) (column 5); key reference (column 6).

#	Abbreviation	Types	Parameters	Standard domains	Key references
SUB (subjective methods)					
1	HBGWL	29	not specified	N	Hess and Brezowsky (1952)
2	HBGWT	10	not specified	N	
3	OGWL	29	MSLP, Z500	N	James (2007)
4	OGWLSLP	29	MSLP	N	
5	PECZELY	13	not specified	N	Péczely (1957)
6	PERRET	40	not specified	N	Perret (1987)
7	ZAMG	43	not specified	N	Lauscher (1985)
THR (threshold based methods)					
8	GWT	18	MSLP	Y	Beck (2000)
9	GWTC10	10	MSLP	Y	
10	GWTC18	18	MSLP	Y	
11	GWTC26	26	MSLP	Y	
12	LITADVE	9	MSLP	Y	Litynski (1969)
13	LITTC	27	MSLP	Y	
14	LITTC18	18	MSLP	Y	
15	LWT2	26	MSLP	Y	James (2006)
16	LWT2C10	10	MSLP	Y	
17	LWT2C18	18	MSLP	Y	
18	WLKC09	9	U/V700	Y	Dittmann et al. (1995)
19	WLKC18	18	U/V700, Z925	Y	
20	WLKC28	28	U/V700, Z925/500	Y	
21	WLKC733	40	U/V700, Z925/500, PW	Y	
22	SCHUEPP	40	MSLP, Z500, U/VSFC/500	N	Schüepp (1979)
PCA (PCA based methods)					
23	TPCA07	7	MSLP	Y	Huth (1993)
24	TPCAC09	9	MSLP	Y	
25	TPCAC18	18	MSLP	Y	
26	TPCAC27	27	MSLP	Y	
27	TPCAV	6–12	MSLP	Y	
28	P27	27	Z500	Y	Kruizinga (1979)
29	P27C08	8	MSLP	Y	
30	P27C18	18	MSLP	Y	
31	P27C27	27	MSLP	Y	
32	PCAXTR	11–17	MSLP	Y	Esteban et al. (2005, 2006)
33	PCAXTRC09	9–10	MSLP	Y	
34	PCAXTRC18	15–18	MSLP	Y	
LDR (methods based on leader algorithm)					
35	LUND	10	MSLP	Y	Lund (1963)
36	LUNDC09	9	MSLP	Y	
37	LUNDC18	18	MSLP	Y	
38	LUNDC27	27	MSLP	Y	
39	ESLPC09	9	MSLP	Y	Erpicum et al. (2008)
40	ESLPC18	18	MSLP	Y	
41	ESLPC27	27	MSLP	Y	
42	EZ850C10	10	Z850	Y	
43	EZ850C20	20	Z850	Y	
44	EZ850C30	30	Z850	Y	
45	KHC09	9	MSLP	Y	Blair (1998)
46	KHC18	18	MSLP	Y	
47	KHC27	27	MSLP	Y	
OPT (optimization methods)					
48	CKMEANSC09	9	MSLP	Y	Enke and Spekat (1997)
49	CKMEANSC18	18	MSLP	Y	
50	CKMEANSC27	27	MSLP	Y	
51	PCACA	4–5	MSLP	Y	Yarnal (1993)
52	PCACAC09	9	MSLP	Y	
53	PCACAC18	18	MSLP	Y	
54	PCACAC27	27	MSLP	Y	
55	PETISCO	25–38	MSLP, Z500	Y	Petisco et al. (2005)
56	PETISCOC09	9	MSLP	Y	
57	PETISCOC18	18	MSLP	Y	
58	PETISCOC27	27	MSLP	Y	
59	PCAXTRKM	11–17	MSLP	Y	Esteban et al. (2005, 2006)
60	PCAXTRKMC09	9–10	MSLP	Y	
61	PCAXTRKMC18	15–18	MSLP	Y	
62	SANDRA	18–23	MSLP	Y	Philipp et al. (2007)
63	SANDRAC09	9	MSLP	Y	
64	SANDRAC18	18	MSLP	Y	
65	SANDRAC27	27	MSLP	Y	
66	SANDRAS	30	Z925, Z500	Y	

Table 1 (*continued*)

#	Abbreviation	Types	Parameters	Standard domains	Key references
67	SANDRASC09	9	MSLP	Y	
68	SANDRASC18	18	MSLP	Y	
69	SANDRASC27	27	MSLP	Y	
70	NNW	9–30	Z500	Y	Michaelides et al. (2001)
71	NNWC09	9	MSLP	Y	
72	NNWC18	18	MSLP	Y	
73	NNWC27	27	MSLP	Y	

no knowledge about the structure of the dataset or effects of certain types is assumed but should be derived by data mining. This fundamental difference will be specified in the following.

2.1. Methods using predefined types

Methods using predefined types include those with subjectively chosen weather situations (Section 2.1.1) and those where the allocation of days to one type depends on thresholds or rules (2.1.2). They have in common a presumed concept of the relation between circulation and surface weather variables like temperature and precipitation even though it is rarely formulated explicitly. Especially for European surface weather it is, for example, important whether the large scale flow is organized zonally or meridionally. Therefore predefined types are preferentially defined to clearly discern between these two configurations, while this is not necessarily the case for derived types. The difference between subjectively defined types and their definition by thresholds is just the formulation of explicit rules for the latter.

2.1.1. SUB – subjective definition of types

Subjective classifications are based on the expert knowledge about the effect of certain circulation patterns on various surface climate parameters, i.e. they try to discern between typical synoptic situations. A main problem for this approach (as well as for the subject of weather and circulation type classification as a whole) is the diffuse meaning of *typical*. To define *typical* in the meaning of *more often than other situations* does not solve the problem, because there is no obvious way how to separate different situations from each other, since there are smooth gradual transitions from one situation to another. However, typical situations may be further obtained by including (not always in an explicit way) the effects of circulation on associated surface climate variables. Thus a typical westerly pattern for central Europe might be defined for prevailing westerly winds combined with a high probability for stratiform precipitation and warm temperatures in winter. It might be this integration of effects increasing the spread of possibilities for different situations which results in the characteristic high number of types of subjective classifications, ranging between 29 for Hess and Brezowsky (1952) and 43 for the ZAMG-classification (Lauscher, 1985) including originally over 80 classes (see below). The only subjective classification with a small number of classes is the classification by Péczely (1957) with 13 types. There are several drawbacks of subjective classifications. One is that they are not transferable and scalable to other regions. Another one is the high likelihood for artifacts caused e.g. by changing classifiers which at least in the case of the Hess–Brezowsky-classification has to be considered (Cahynová and Huth, 2009). However in order to compare non-subjective classifications concerning their information content with the existing subjective expert classifications some of them are included in the dataset.

2.1.1.1. HBGW(HBGWL/HBGWT) – Hess and Brezowsky European Grosswetterlagen/-typen. One of the most famous catalogs focusing on central Europe is the one founded by Baur (1948) and revised and further developed by Hess and Brezowsky (1952) and more recently by Gerstengarbe and Werner (1999). The concept of type definition strongly follows the flow direction of air masses onto central Europe discerning zonal, mixed and meridional types which are further discriminated into 10 *Großwettertypen* (HBGWT) and on the last hierarchical level into 29 *Großwetterlagen* (HBGWL) and one undefined or transitional type. The subjective definition of types and assignment of daily patterns includes the knowledge of the authors about the importance of the specific circulation patterns for temperature and precipitation conditions in central Europe.

2.1.1.2. OGWL – objective Grosswetterlagen. An objectivized version of the Hess and Brezowsky (1952) *Großwetterlagen* was produced by James (2007) using only circulation composites using mean sea level pressure (MSLP) and geopotential height at 500 hPa (Z500) of the 29 original types and subsequently assigning the daily circulation patterns to them. This was done for winter and summer separately and by applying temporal filters in order to achieve a minimum persistence of 3 days. However in the cost733cat dataset an unfiltered version is included and a second one based solely on MSLP.

2.1.1.3. PECZELY – Carpathian basin weather types. György Péczely, a Hungarian climatologist and professor of the Szeged University, Hungary (1924–1984), originally published his macrocirculation classification system in 1957. The system was defined on the basis of the geographical location of cyclones and anticyclones over the Carpathian basin, however the positions of cold and warm fronts were also considered. All together 13 types were composed which were pooled into five main groups of meridional-northern, meridional-southern, zonal-western, zonal-eastern and central types (Péczely 1957, 1961, 1983). After the passing of Péczely, one of his followers, Csaba Karossy has continued the coding process till present (Károssy, 1994, 1997).

2.1.1.4. PERRET – Alpine Weather Statistics. The Swiss weather type classification after Perret (1987) is part of the Alpine Weather Statistics, a comprehensive characterization of the regional synoptic situation in a circle with radius of 2° latitude (ca. 222 km) centered at Switzerland. The concept of the Perret classification shows some concordance to the Hess and Brezowsky (1952) classification. However, the main idea behind it differs in so far that not the main flow direction determines the main groups but the intensity and cyclonicity of the circulation within the target area. Thus, the main distinction is made between types dominated by: (i) upper level flow, (ii) upper level highs and (iii) upper level lows. On a second hierarchy level five flow directions are distinguished for the first main group which are further characterized by being cyclonic or anticyclonic leading to a total of 12 types. On the other hand the upper level high and low groups are further divided according to the position of the pressure centers on a second and third detail level, leading to 9 and 10 types respectively and a total of 31 types.

2.1.1.5. ZAMG – Central Institute for Meteorology and Geodynamics Eastern Alpine weather types. Since the 1950s weather types have been identified on a daily basis at the Central Institute of Meteorology in Vienna (Austria). Weather types according to Baur (1948) and Lauscher (1985) as well as air masses and passages of surface fronts over the Eastern Alpine edge have been logged. Individual knowledge and education of the forecasters lead to a mixture of applications of methods during the following years, the classification types from Lauscher and Hess and Brezowsky (1952) being mostly reported in the catalog. Also, eight circulation types (cyclonic or anticyclonic), and weak gradient situations result in 17 additional classes. Altogether more than 80 different classes had been found on handwritten sheets during the process of digitalization and had been reduced to 43 classes. However, types leading to resembling flow regimes and to similar weather over the reference point Vienna are still present, e.g. a low over the western parts of Europe and a southwesterly anticyclonic flow at the Eastern Alpine edge, are registered as separate types despite being causally related. Consequently, additional work is needed for further homogenization of the catalog. Besides this weather type classification, the ZAMG catalog also includes the detection of six cold and six warm air masses at an upper level (<850 hPa) and a surface level (>850 hPa). Their possible changes during the day indicate advection without fronts. Further, fronts and frontal passages over the town of Vienna are logged (11 different surface and upper fronts). This manual classification is still performed regularly by the night shift forecaster in Vienna around 2200 UTC.

2.1.2. THR – threshold based methods

Compared to subjective classifications, threshold based methods define their types indirectly by declaration of a borderline between different types in the form of thresholds. Alternatively the distinction between types can be realized by predefined rules for assignment, which is essentially the same. For example a distinction can be made between days with a westerly main flow direction over the domain and days with northerly, easterly or southerly direction, where the angles used to delimit the sectors represent the thresholds or borderlines between the types. In contrast to the subjective methods the use of thresholds or explicit rules allows for automated classification. However, the term *objective* which is sometimes used to point out the difference to subjective classifications is debatable, since the predetermination of thresholds and rules also involves subjective decisions. However their advantage is the reproducibility and of course their computer based fast processing.

2.1.2.1. GWT – Grosswetter-types or prototype classification. Ten main circulation types are determined according to the so called *Großwetter*-types of HBGWT (see above). The basic idea is to characterize the circulation patterns in terms of varying degrees of zonality, meridionality and vorticity of the large scale MSLP field (Beck 2000; Beck et al. 2007). Coefficients of zonality (Z), meridionality (M), and vorticity (V) for each case (day) are determined as spatial correlation coefficients between the respective MSLP field and three prototypical patterns representing idealized W–E, S–N, and central low-pressure isobars over the region of interest. The 10 main circulation types are then defined by means of particular combinations of these three coefficients. Assignment to central high and central low-pressure types results from a maximum V coefficient (negative and positive respectively). The eight directional types are defined in terms of the Z and M coefficients (e.g., $Z = 1$ and $M = 0$ for the W–E pattern, $Z = 0.7$ and $M = 0.7$ for the SW–NE pattern, and so on), and remaining cases are assigned to one of these types according to the minimum Euclidean distance of their respective Z and M coefficients from those of the predefined types. A subdivision of the directional circulation types into cyclonic and anticyclonic subtypes according to the sign of the V coefficient leads to 18 types, and an even finer partitioning into subtypes of negative, indifferent and positive V coefficient results in 27 circulation types.

2.1.2.2. LIT (LITADVE/LITTC) – Litynski advection and circulation types. This classification scheme is based on three indices, calculated from gridded MSLP data, for estimating the advection of air masses as well as a cyclonicity characteristic (Pianko-Kluczynska, 2007). Meridional (Wp) and zonal (Ws) indices are calculated as spatially averaged components of the geostrophical wind vector while cyclonicity (Cp) is estimated as the MSLP value over the central grid point of the domain (Litynski, 1969). Threshold values for these three indices are defined for each day of the year utilizing the respective long-term means $\bar{I}$ and standard deviations $sdev_I$ resulting in three categories for each index (negative, indifferent, positive), where the indifferent category includes all I for

$$\bar{I} - 0.433 sdev_I \leqslant I \leqslant \bar{I} + 0.433 sdev_I \tag{2.1}$$

approximating one third of the sample if normal distribution is assumed. Circulation types are defined as distinct combinations of index categories for Wp and Ws, leading to nine advection types for the LITADVE classification, characterized by the direction of advection (e.g., Wp = negative and Ws = positive for type NW). Including Cp, results in a further subdivision of directional types into 27 LITTC circulation types according to their cyclonicity characteristics (e.g. Wp = positive, Ws = indifferent and Cp = negative for a southerly cyclonic type). Finally each case (day) is assigned to a circulation type according to its categorized index values.

2.1.2.3. LWT 2 – Lamb-weather types version 2. LWT 2 (James, 2006) is a modified version of the Jenkinson and Collison (1977) system for classifying daily MSLP fields according to the subjectively derived Lamb-weather types (Lamb, 1950). Daily MSLP fields are classified into 26 circulation types, indicating flow direction and vorticity. Based on a selection of grid points, direction and intensity of flow as well as vorticity are computed for each daily MSLP field. The appropriate circulation type is determined according to vorticity-flow ratio thresholds resulting in eight pure directional types (e.g. W = West), two pure anticyclonic/cyclonic types (A,C) and 16 hybrid types (e.g. ANE = North–East, partly anticyclonic). In contrast to Jenkinson and Collison (1977) no unclassified days are allowed in LWT 2 (James, 2006) and the vorticity and flow strength thresholds are adjusted so that exactly 33% of the days fall into each of the three vorticity classes anticyclonic, indeterminate and cyclonic.

2.1.2.4. WLK – Objektive Wetterlagenklassifikation. This method is based on the OWLK weather type classification by Dittmann et al. (1995) and Bissolli and Dittmann (2003), originally including 40 different types. The alphanumeric output consists of five letters: the first two letters denote the dominant wind sector counting clockwise 01 = NE, 02 = SE, 03 = SW, 04 = NW and 00 = undefined (varying directions). For determination of the dominant wind sector the true wind direction obtained from U and V-components at 700 hPa is used. In a first step the central direction of the 90°-sector including the maximum of the wind directions is determined among all 90°-sectors shifted by an interval of 10°. For counting the respective wind directions a weighting mask, putting higher weights on grid points in the center of the domain, is applied. If there is no 90°-sector including 2/3 of the weighted directions, the main direction for this day is undefined. Otherwise the final dominant sector is defined to be the quadrant of the central direction of the maximum 90°-sector (i.e. SW = [190°, 280°]). The third and fourth letter denote *A*nticyclonicity or *C*yclonicity at 925 hPa and 500 hPa, respectively, based on the weighted mean value of the quasi-geostrophic vorticity, again putting higher weights on central grid points. The fifth letter denotes *D*ry or *W*et conditions, according to an weighted area mean value of precipitable water (whole atmospheric column) which is compared to the long-term daily mean. For calculating the precipitable water the GPH, temperature and relative humidity at 955, 850, 700, 500 and 300 hPa are used. The classification WLKC733 included in cost733cat provides a few simplifications: circulation patterns are derived from a simple majority (threshold) of the weighted wind field vectors at 700 hPa while the integrated precipitable water content is replaced by the towering water content. In order to achieve a classification system for 28 types (WLKC28) six main wind sector types are used (**01** = 330–30° and so on in 60° steps) plus one undefined type, which are further discriminated by cyclonicity as described above. 18 types (WLKC18) are produced by using nine wind sector types (sector **01** = 345–15°, **02** = 15–75°, **03** = 75–105°, **04** = 105–165°, **05** = 165–195°, **06** = 195–255°, **07** = 255–285°, **08** = 285–345°, **00** = undefined) and cyclonicity at 925 hPa, while the latter is omitted for producing nine types (WLKC09).

2.1.2.5. SCHÜEPP – Alpine Weather Statistics. Although initially developed as a manual classification scheme (Schüepp 1957, 1968, 1979) – explicitly focusing on the western Alpine region and Switzerland – this classification may be assigned to the threshold based methods, as it utilizes distinct numerically derived thresholds. The classification of days into 40 classes is based on surface and 500 hPa data for a spatial domain of 2° radius centered at 46.5°N, 9°E. Circulation types are defined by thresholds with regard to the following variables: surface pressure gradient and wind direction, 500 hPa wind direction and intensity, 500 hPa GPH, vertical wind shear and baroclinicity. The resulting 40 classes are grouped into three generic main groups. Advective/convective types, characterized by pressure gradients above/below a certain threshold and mixed types showing intermediate characteristics concerning horizontal and vertical dynamics. Although the Schüepp classification scheme could be programmed and applied to other regions it is the only threshold based classification within the dataset, that is available for the original spatial domain only.

2.2. Methods producing derived types

In contrast to methods utilizing predefined types all of the following methods are based on the idea to identify types which are indicated by any structure existing in the dataset itself. In particular three main strategies may be discerned. The first group, presented in Section 2.2.1 utilizes principal component analysis (PCA) to determine principal components (PCs) explaining major fractions of the variance of the input data while the patterns to be classified are assigned to classes according to some measure of relation to the PCs. The second strategy in Section 2.2.2 is to find leading patterns according to the number of patterns similar to them within a certain distance, called leader algorithm (Hartigan, 1975), while the third strategy is the combinatorial approach to optimize a partition according to a function, commonly the minimization of within-type variability (Section 2.2.3).

2.2.1. PCA based methods

The potential of PCA to be used as a classification tool was suggested by Richman (1981) and more deeply discussed and elaborated by Gong and Richman (1995). The basic idea of using PCA as a classification tool consists in assigning each case to a PC according to some rule. However there are several different modes for PCA differing fundamentally from each other. In the most often used s-mode the results are score time series representing the most important types of data variability in time, while the loadings indicate the location and extend to which these time series are realized. Things are reversed in t-mode, where the scores describe important spatial patterns and the loadings reflect the amount of their time variant realization. Thus the t-mode seems more appropriate for pattern classification, however also the s-mode might be utilized.

2.2.1.1. TPCA – principal component analysis in t-mode. To classify circulation patterns by PC loadings, PCA is used in a t-mode with oblique rotation (e.g. Richman, 1986; Huth, 1993; Compagnucci and Richman, 2008). Here we apply TPCA in a setting similar to Huth (2000): PCA is first conducted on ten subsets of data, the first subset being defined by selecting the 1st, 11th, 21st, etc. day; the second subset by selecting the 2nd, 12th, 22nd, etc. day, and so on. The solutions are projected onto the entire data set by solving the matrix equation

$$\Phi A^T = F^T Z, \tag{2.2}$$

where F and Φ are matrices of PC scores and PC correlations, respectively, Z is the full data matrix, and A are pseudo-loadings to be determined. Each day is classified with that PC (type) for which it has the highest loading. Contingency tables are finally used to compare the 10 classifications and, based on the tables, the classification most consistent with the other nine classifications is selected as the resultant one.

2.2.1.2. P27 – Kruizinga empirical orthogonal function types. The P27 classification scheme developed at the Royal Netherlands Meteorological Institute (Kruizinga, 1979; Buishand and Brandsma, 1997) utilizes the s-mode variant of PCA. Originally, daily 500 hPa GPH were transformed to patterns p_{tq} of reduced seasonal variability by subtracting the daily average GPH calculated over the grid from each grid point's actual GPH.

The pattern of each day t is approximated as:

$$p_t \approx s_{1t}a_1 + s_{2t}a_2 + s_{3t}a_3, \quad t = 1, \ldots, N. \tag{2.3}$$

Here, a_1, a_2, and a_3 are the first three principal component vectors and s_{1t} to s_{3t} are the respective scores. Instead of using the correlation or covariance matrix, the eigenvectors are calculated from the unadjusted (neither with regard to mean nor variance) product matrix. The amplitudes of the scores of the first three components, representing zonality, meridionality and cyclonicity respectively, are subdivided into n_1, n_2 and n_3 equiprobable intervals. Finally each object (day) is assigned to one of the $n_1 \times n_2 \times n_3$ possible interval combinations. The original classification has three equiprobable intervals for all components, resulting in 27 classes. However, varying numbers of classes can be achieved by defining different numbers of amplitude intervals (e.g. $3 \times 3 \times 2$ = 18 classes). The original interpretation of the three first PCs being connected to the zonal and meridional components of the flow and to cyclonicity is not always applicable, depending on the location and the scale of the grid used.

2.2.1.3. PCAXTR – principal component analysis extreme scores. This method is based on the establishment of initial centroids by using orthogonally rotated (method Varimax) scores time series of PCA in s-mode. In contrast to t-mode, which is much more demanding in compute time, s-mode PC scores represent the degree of representativeness of the PC loadings' patterns with respect to the original data. Thus, they can be utilized to establish the number of circulation types of the classification as well as its centroids. By using orthogonal VARIMAX rotation loadings patterns are independently closer to real anomaly patterns than unrotated loadings and therefore include a physical meaning. In order to define the types, the *extreme scores* criterion is used (Esteban et al., 2005, 2006, 2009). For each PC and phase (positive or negative) a type is created by selecting only those cases presenting high absolute scores for that PC and phase (values above 2 or below −2) while at the same time having low values (between +1 and −1) for the rest of the PCs. This allows us to assume that the selected sub sample of observed cases (usually 2.5–5% of the sample size) is very well represented by one of the PCs and that this PC is exclusively representative for these cases due to the orthogonal rotation. In other words, the mode of spatial variation represented by the components reflects at least one case in reality and is not an artefact due to statistical forcing of the PCA. This further implies that the potential number of classes will be twice the number of PCs retained (counting the positive and negative phases). This total can be reduced if any of these possible types does not have any observed cases assigned to it, according to the *extreme scores* criterion, therefore being discarded as an artefact of the PCA procedure. Once the final number of types is established, their centroids are calculated by averaging the score values of the cases assigned to them, being the reference in the multivariate space for the rest of the sample which is finally classified using the shortest Euclidean distance (without any further optimization).

2.2.2. LDR – leader algorithms

Methods based on the so called leader algorithm (Hartigan, 1975) have been established at a time when computing capacities have been available but were still limited. These methods seek for key (or leader) patterns in the sample of maps, which are located in the center of high density clouds of entities (days) within the multidimensional phase space spawned by the variables, i.e. grid-point values.

2.2.2.1. LUND – classical leader algorithm. Lund (1963) used a simple linear correlation method to identify frequently appearing, well separated SLP patterns over the northeastern USA. To do so, Pearson correlation coefficients between all days are calculated and for each day all coefficients of $r > 0.7$ to any other pattern are counted. The first key pattern (leader) is defined as the day with the largest number of correlation coefficients $r > 0.7$. This day and all days with correlation coefficient $r > 0.7$ to that key day are then removed from the dataset. On the remainder data the search for the second and following leaders is performed in the same manner, until all types (of the predefined number of types) have a key day. Finally all days are just assigned to a key day according to the highest correlation coefficient, regardless of which key day they had been assigned initially.

2.2.2.2. ERPICUM (ESLP/EZ850) – Erpicum and Fettweis. This classification algorithm is similar to LUND, however, differing by the calculation and use of the similarity measure (Fettweis et al., 2010). Another difference is the omission of the final step. Thus the final classification of the days is based on their initial assignment to a key day. However, to avoid large dissimilar class sizes a novel scheme varying the threshold is introduced as explained below. Before the similarity index computation, the data are preprocessed by normalization over the temporal dimension. This allots the same weight for all grid points of the input maps. Then, for each pair of days the similarity index, I:

$$I(day_1, day_2) = 1 - \frac{1}{2} \cdot \sum |Z(day_1) - Z(day_2)| \tag{2.4}$$

is calculated, where $Z(day)$ is the vector of normalized pressure values for one day. This index equals to a maximum of 1 if a Z surface is compared to itself, and it is negative if the two Z surfaces are very different. Departing from Lund (1963) the distance threshold for the determination of key patterns, ic, is progressively decremented, starting from 1 and being reduced by a factor epsilon, ε, for each type, i.e.

$$ic(k) = 1 - \varepsilon \cdot k, \quad k = 1, \ldots n, \tag{2.5}$$

where k is the number of the class and n is the maximum number of types. The whole classification scheme (see above) is iteratively applied for different values of *epsilon* in order to optimize the skill score (percentage of explained variance) defined by Buishand and Brandsma (1997). For each run *epsilon* is increased by

$$\varepsilon = 0.05 \cdot (j - 1), \quad j = 1, \ldots, m, \tag{2.6}$$

where j is the number of the iterative run and m is the maximum number of runs. Thus, compared to the Lund (1963) classification this procedure is considerably more time demanding, but on the other hand includes a mechanism for reducing within-type variability.

2.2.2.3. KH – Kirchhofer types. The method initially introduced by Kirchhofer (1974) was intended to classify 500 hPa GPH patterns over Europe, using as criterion the squared distances between normalized grid-point values. Two patterns were allowed to be classified as similar only if this so called Kirchhofer score was high enough, and if the Kirchhofer scores for a set of user-defined sub-sections of the two patterns were also acceptable. The method implemented here is a variation of the original based on Yarnal (1984), who suggested that the columns and rows of the grid could serve as sub-domains, and Blair (1998), who replaced the squared distances with, equivalent, linear correlation coefficients between map patterns. Since this distance measure is considerably lower than the usual pattern correlation coefficient, the threshold for finding key patterns is set to 0.4. Apart from that the procedure follows exactly the Lund (1963) classification scheme (see above).

2.2.3. OPT – optimization algorithms

Optimization methods are combinatorial approaches to arrange a set of objects (days) within groups (or clusters) in such a way that a certain function is optimized. This function is the minimization of the within-type variability measured as the overall sum of the Euclidean distances between the member objects of a type and the average of that type (centroid). Most of the optimization methods included in cost733cat are based on the k-means clustering algorithm (e.g., Hartigan, 1975). In order to avoid repetition its principal is described here. k-means starts with an initial partition of the objects (daily pressure maps) and, for each object evaluates whether it is in the most similar cluster, and if not re-assigns it to another more similar cluster in terms of the Euclidean distance between the object and the centroid of the cluster. By doing so, the affected centroids in turn have to be recalculated which in turn changes the situation for the subsequent checks. Apparently it is necessary to repeatedly iterate through the list of objects and check them again at each re-assignment. At some point in this process all objects are assigned to their nearest cluster and no re-assignment is necessary and possible anymore, i.e. convergence to an optimum is reached. Most of the following optimization methods only differ concerning the starting partition or data pre-processing for k-means. Only SANDRA and NNW method use alternative ways for optimization. The PETISCO classification does not really terminate with the partition of the entire data set being optimized but iteratively tries to find optimal leading centroids. Thus this method represents a hybrid between the leader algorithm and a kind of cluster analysis and might be also assigned to the method group of leader algorithms. However due to its iterative optimization step it is listed here along with the actual optimization methods. Likewise NNW does not converge to an optimum since its iterations were limited to 2000 here.

2.2.3.1. CKMEANS – k-means by dissimilar seeds. For this classification method the k-means algorithm is initiated using a starting partition based on dissimilar pressure fields of the dataset to be classified following Enke and Spekat (1997). The initialization takes place by randomly selecting one object (pressure map). The seed for the second cluster is then determined as the object most different to the first, while the seed for the third cluster is the object with the highest sum of the distances to the first two seed-patterns, and so on, until every cluster has one seed-pattern. In a stepwise procedure the starting partition, initially consisting of the k seed-patterns is gradually identified: all remaining days are assigned to their most similar class. With each day entering a class, the centroid positions are re-computed. As a consequence the multi dimensional distance between class centroids continually decreases while the variability within the individual classes of the starting partition increases. After the initial assignment of all days has been performed the iterative k-means clustering process is launched (see above). The centroids converge towards a final configuration which has no similarity with the starting partition. In order to retain representativity, classes are kept in the process only if they do not fall short of a certain number, e.g., 5% of all days. Otherwise the class is removed and its contents distributed among the remaining classes.

2.2.3.2. PCACA – k-means by seeds from hierarchical cluster analysis of principal components. This method follows some recommendations proposed by Yarnal (1993). In a preprocessing step, a high-pass filter using the 13-day running mean is applied on the input data in order to remove the seasonal cycle. Afterwards a s-mode PCA (Varimax rotated using the correlation matrix) is applied on the filtered data (Hewitson and Crane, 1992) to reduce the co-linearity, simplifying the numerical calculations and improving the performance of the subsequent clustering procedure. The daily PC-score time series of the retained PCs (nine PCs for domain 00 and three PCs for the other domains) are the input of the clustering procedure. In order to obtain the starting partition for the k-means procedure (see above) the hierarchical cluster algorithm by Ward (1963) is applied.

2.2.3.3. PETISCO – leader algorithm with optimized key patterns. This method resembles some aspects of the leader algorithm, however includes an optimization procedure for the classification seeds (Petisco et al., 2005). As for LUND (see above) key patterns are determined among all days but here with a threshold of 0.9 for the pattern correlation r. In case of using more than one atmospheric level (originally both the MSLP and 500 hPa GPH fields were used) r is the minimum of the correlation coefficients calculated separately for each level. In contrast to the leader algorithm the key pattern is calculated as the centroid of the so called key group that consists of the key day and all days strongly correlated to it ($r > 0.9$). Iteratively the calculation for the key group centroid and the search for new members of the key group is repeated, until optimized key patterns exist, i.e. they do not change anymore. Thus the key group is optimized in terms of maximum member quantity. From these key groups the largest are selected as final types and all remaining days are assigned to these according to their maximum correlation coefficient.

2.2.3.4. PCAXTRKMN – k-means using PCA derived seeds. For this k-means variant the starting partition is determined by the PCAXTR method described above. Consequently this is the only optimization method with some restrictions on the number of types.

2.2.3.5. SANDRA – simulated annealing and diversified randomization clustering. As discussed in literature the k-means clustering algorithm is, by design, a potentially unstable method (see e.g. Michelangeli et al., 1995; Philipp et al., 2007; Fereday et al., 2008), since it has no strategy to avoid convergence in the various local optima of the optimization function. In contrast, the heuristic simulated annealing algorithm used in SANDRA is able to approximate the single global optimum. The only difference to k-means are so called *wrong* re-assignments, i.e. objects may be removed from their nearest cluster, depending on a probability, P, which is high at the beginning but slowly decreases during the optimization process. Thus, if the process is trapped in a local optimum of poor quality some objects can be re-assigned which might lead to an overall improvement in the following steps. In order to slowly reduce P a control parameter T (for *temperature*) which is a huge number at the beginning, is stepwise reduced by a cooling factor C (e.g., $C = 0.999$) in each iteration:

$$T = T \cdot C. \tag{2.7}$$

P is then calculated as

$$P = \exp[(D_{current} - D_{new})/T], \tag{2.8}$$

where $D_{current}$ is the Euclidean distance of the object to its current cluster and D_{new} the distance to a potentially new cluster. If a random number r ($0 < r < 1$) is less than P, the wrong re-assignment takes effect. At the end when T is a tiny number and hopefully all poor quality local optima have been bypassed, only improving re-assignments are in effect (like in k-means) and convergence is reached. In order to speed up the run time SANDRA uses a relatively low cooling factor ($C = 0.999$) leading to a quick convergence but repeats the whole process 1000 times with randomly diversified starting partitions and a randomized scheme for object and cluster ordering leading to a diversified chronology for the tests and thus different ways to approach to the global optimum. From these 1000 results the best, according to within-type variance, is finally selected.

2.2.3.6. SANDRAS – classification of sequences of days with SANDRA. This method differs from SANDRA only by data preprocessing. Instead of single daily patterns, three-day-sequences are used, thus the history of the development of the final day in this sequence is included on the type definition, resulting in types of successions of maps (Philipp, 2008). In principle this approach might be applied to all classification methods, but was included in the dataset only for the SANDRA scheme in order to have a preview of the associated effects.

2.2.3.7. NNW – neural network self-organizing feature maps. The Neural Network architecture proposed for the classification of weather patterns (see e.g., Michaelides et al., 2001; Michaelides et al., 2007; Tymvios et al., 2007, 2008, submitted for publication) is the Kohonen's (1990) SOFM (Self-Organizing Features Map). The SOFM network has the ability to learn without being shown correct outputs in the sample patterns (unsupervized) and is able to separate data into a specified number of categories with only two neuron layers: an input layer and an output layer, the latter consisting of one neuron for each possible output category. The objective is to discover significant features or regularities in the input data $X^{(k,j)}$; $k = 1, 2, \ldots, p$; $j = 1, 2, \ldots, M$; where k is a day and p is the total number of days and j is a grid point and M the total number of grid points. The input vector $X(p)$, representing a pressure pattern, is connected with each output neuron through weights $w(j)$, $j = 1,2, \ldots, M$ which are randomly chosen at the beginning. The output neuron whose weight vector is most similar to the input vector X is the so called winner neuron. The weight vector of the winner neuron, as well as those of its neighborhood neurons, are updated to become more similar to the input pattern following the learning rule:

$$w_i^{(new)} = \begin{cases} w_i^{(old)} + a(X - w_i^{(old)}), & i \in N(I,R) \\ w_i^{(old)}, & i \in N(I,R), \end{cases} \tag{2.9}$$

where the neighborhood set $N(I,R)$ of neuron I, within radius R consists of the neurons I, $I \pm 1, \ldots, I \pm R$, assuming these neurons exist, with the maximum adjustment being around the winner I and decreasing for more distant neurons in terms of the distance within the (hexagonal) network topology. The coefficient α in the above relationship is called the learning factor and decreases to zero as the learning progresses. Also the radius R of the neighborhood around the winner unit is relatively large to start with, so as to include all neurons and is consecutively shrunk down to the point where only the winner unit is updated (Kohonen, 2001). When all vectors in the training set were presented once at the input (one epoch), the whole procedure was repeated for 2000 iterations. In the end, this algorithm organizes the weights of the two-dimensional map, so that topologically close nodes become sensitive to input that is physically similar. These networks are extremely demanding as far as computing power and memory is concerned.

3. Method configuration and dataset compilation

The different methods reviewed above represent a large variety of strategies to distinguish synoptic situations into classes. Except for the subjective classifications which are included to provide a historical context, all methods are automated and allow for recalculation which is a basic requirement for further usage since the methods should be applicable to different regions, datasets, periods etc. However, in order to examine the effects caused by different classification methods, comparable catalogs are needed. Therefore it is necessary to apply the methods in a standardized way on a standardized input dataset. This should suppress differences in the resulting classification catalogs caused by other conditions than by the classification method alone. Therefore standard guidelines have been defined and all automated methods were recalculated accordingly. The homogenization was applied in two steps, the first concerning the input data source and the temporal and spatial domain, and the second step additionally specifying the number of types produced and MSLP as the only variable.

The predefined input dataset is the ERA40 reanalysis dataset provided by the European Centre for Medium-Range Weather Forecasts (Uppala et al. 2005), which is available for the period 09/1957–08/2002 in $1° \times 1°$ grid resolution and in 6-h time steps. It was decided to use only 12:00 UTC data and to apply all methods for the full year period. Another important feature is the definition of standard regions within the ERA40 $1° \times 1°$ grid. Different spatial scales and regions are covered by a set of 12 common domains throughout Europe presented in Fig. 1 and Table 2. The largest is covering the entire Europe domain (domain 0) using 32×24 grid points at a reduced resolution of 3° longitude by 2° latitude, while the smallest is confined to the greater Alpine area (domain 6) comprising 12×18 grid points at 1° resolution. All methods were applied to all 12 domains.

Several of the catalogs listed above use other or more variables than MSLP in their original variants. To exclude the use of different variables as a potential factor influencing the results of a method, in a second step towards homogenization all methods (except WLK) were recalculated using only MSLP, again for all domains, and the resulting catalogs have been added to the dataset. Another possible source of considerable differences is the number of types. There are different opinions whether it is possible to objectively determine an appropriate number of types and how (Milligan and Cooper, 1985; Chen and Harr, 1993; Michelangeli et al.,

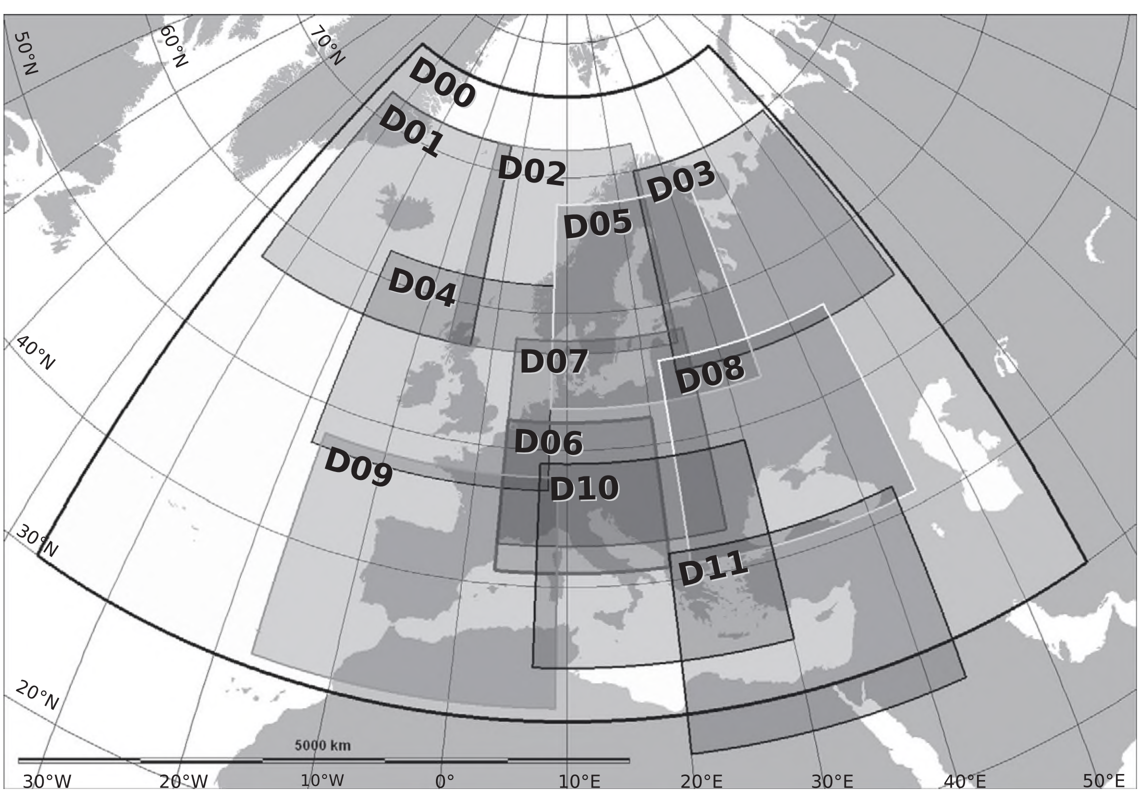

Fig. 1. Spatial domains of input data for standardized classification catalogs. Each of the 12 domain frames is denoted by the specified domain number. The map projection is Lambert Azimuthal Equal Area.

Table 2
Spatial domains: identification numbers, names and coordinates of spatial domains defined for the classification input data.

#	Region	Longitudes	Latitudes	Number of grid points
00	Europe	37°W to 56°E by 3°	30°N to 76°N by 2°	32 × 24
01	Iceland	34°W to 3°W by 1°	57°N to 72°N by 1°	32 × 16
02	West Scandinavia	06°W to 25°E by 1°	57°N to 72°N by 1°	32 × 16
03	Northeastern Europe	24°E to 55°E by 1°	55°N to 70°N by 1°	32 × 16
04	British Isles	18°W to 08°E by 1°	47°N to 62°N by 1°	27 × 16
05	Baltic Sea	08°E to 34°E by 1°	53°N to 68°N by 1°	27 × 16
06	Alps	03°E to 20°E by 1°	41°N to 52°N by 1°	18 × 12
07	Central Europe	03°E to 26°E by 1°	43°N to 58°N by 1°	24 × 16
08	Eastern Europe	22°E to 45°E by 1°	41°N to 56°N by 1°	24 × 16
09	Western Mediterranean	17°W to 09°E by 1°	31°N to 48°N by 1°	27 × 18
10	Central Mediterranean	07°E to 30°E by 1°	34°N to 49°N by 1°	24 × 16
11	Eastern Mediterranean	20°E to 43°E by 1°	27°N to 42°N by 1°	24 × 16

1995; Gerstengarbe and Werner, 1997; Stephenson et al., 2004; Christiansen, 2007; Philipp et al., 2007; Fereday et al., 2008; Christiansen, 2009). However, further discussion in this issue would be beyond the scope of this paper. While some methods allow to choose an arbitrary number of types (like cluster analysis) others are limited to one or a few numbers, either due to their concept (e.g. by division into a fixed number of wind sectors) or due to technical reasons (e.g. leading to empty classes). The original numbers of types are varying between 4 and 43 types which make it rather difficult to compare the classifications directly. Preliminary analyses suggested that the quality of classifications, e.g. regarding their power to discriminate surface temperature and precipitation patterns, is highly sensitive to the number of types (Huth, 2010; Beck and Philipp, 2010; Schiemann and Frei, 2010). In order to eliminate this effect, fixed numbers of types were used for the classifications. To span the range of the numbers of types in circulation classifications, and to allow methods with non-flexible numbers of types (such as LIT) to be included, it was decided to fix the numbers of types at 9, 18, and 27 with deviations by up to two from these numbers being allowed. Therefore, for each spatial domain, each method had been run three times where necessary and possible, one for each of the reference number of types.

All in all 73 method variants, each of them applied to the 12 spatial domains where possible, were included in cost733cat version 1.2. An overview of the variants of classifications is presented in Table 1. It includes variants created for the first standardization phase concerning only the data source and the temporal and spatial domain as well as variants produced for the second standardization step (MSLP and number of types). The abbreviations (column 2) reflect the method (e.g. CKMEANS) or the authors name (e.g. LUND) as well as sometimes the input parameter (e.g. SLP) and the number of types (e.g. C09). The number of types (column 3) may be given as a range, which applies to catalogs with different numbers of types for the 12 spatial domains. A key reference for more detailed descriptions of the method is added in column 6.

4. Characteristics of class frequencies

As the methodological concept of these classification schemes varies considerably it is of particular interest the extend to which the resulting catalogs differ, concerning basic properties for the description of atmospheric variability. In order to characterize the classifications in this respect, five indices were calculated describing aspects of varying type frequencies for each classification. The first one describes variations of class sizes within each classification by:

$$VF = \frac{s_f}{\bar{f}}; \quad \bar{f} = \frac{\sum_{i=1}^{k}(f_i)}{k}; \quad s_f = \sqrt{\frac{\sum_{i=1}^{k}(f_i - \bar{f})^2}{(k-1)}}, \tag{4.1}$$

where s_f is the standard deviation of the class sizes, $\bar{f}$ is the mean of the class sizes, f_i is the frequency of class i, and k is the number of classes. The division of s_f by $\bar{f}$ provides the coefficient of variation which is independent of the mean class size and thus comparable between classifications with different numbers of types.

In order to indicate the day-to-day variability of the classifications, the mean duration of consecutive occurrences of each class is aggregated into a mean persistence value for the entire catalog:

$$MP = \frac{\sum_{i=1}^{k} P_i}{k}, \tag{4.2}$$

where P_i is the mean duration of class i, in days, from the first day of each occurrence until the occurrence of another class.

The mean seasonal variation of frequencies MVM is calculated by:

$$MVM = \frac{\sum_{i=1}^{k}(Ms_i \overline{Mf_i}^{-1})}{k}; \quad Ms_i = \sqrt{\frac{\sum_{m=1}^{12}(f_{m,i} - \overline{Mf_i})^2}{(12-1)}}; \quad \overline{Mf_i} = \frac{f_i}{12}, \tag{4.3}$$

where Ms_i is the standard deviation of the 12 monthly frequencies $f_{m,i}$ of class i for month m and $\overline{Mf_i}$ is the mean class frequency over the 12 calendar months.

Accordingly the mean inter-annual variation of frequencies MVA is given by:

$$MVA = \frac{\sum_{i=1}^{k}(As_i \overline{Af_i}^{-1})}{k}; \quad As_i = \sqrt{\frac{\sum_{a=1958}^{2001}(f_{a,i} - \overline{Af_i})^2}{(2001-1958)}}; \quad \overline{Af_i} = \frac{f_i}{(2001-1958+1)}, \tag{4.4}$$

where As_i is the inter-annual standard deviation of the 44 annual frequencies $f_{a,i}$ of class i and year a and $\overline{Af_i}$ is the mean annual frequency (omitting years 1957 and 2002 which are not fully covered by the dataset).

Finally the mean trend-noise-ratio MTN is given by:

$$MTN = \frac{\sum_{i=1}^{k}\left(\frac{(T_i)}{As_i}\right)}{k}; \quad T_i = f'_{a=2001,i} - f'_{a=1958,i}; \quad f'_{a,i} = x_{0,i} + ax_{1,i}, \tag{4.5}$$

where T_i is the linear long-term trend of class i expressed by the difference between the frequencies f' of the last year 2001 and the first year 1958, estimated from the linear regression equation of the frequencies $f'_{a,i}$ depending on year a using the regression constant $x_{0,i}$ and the regression coefficient $x_{1,i}$.

All these properties are naturally varying according to the geographic region, due to the spatial variation of circulation dynamics. Moreover the indices are systematically affected by the number of types of the classifications, e.g. the persistence is expected to increase with decreasing numbers of types. Therefore the mean

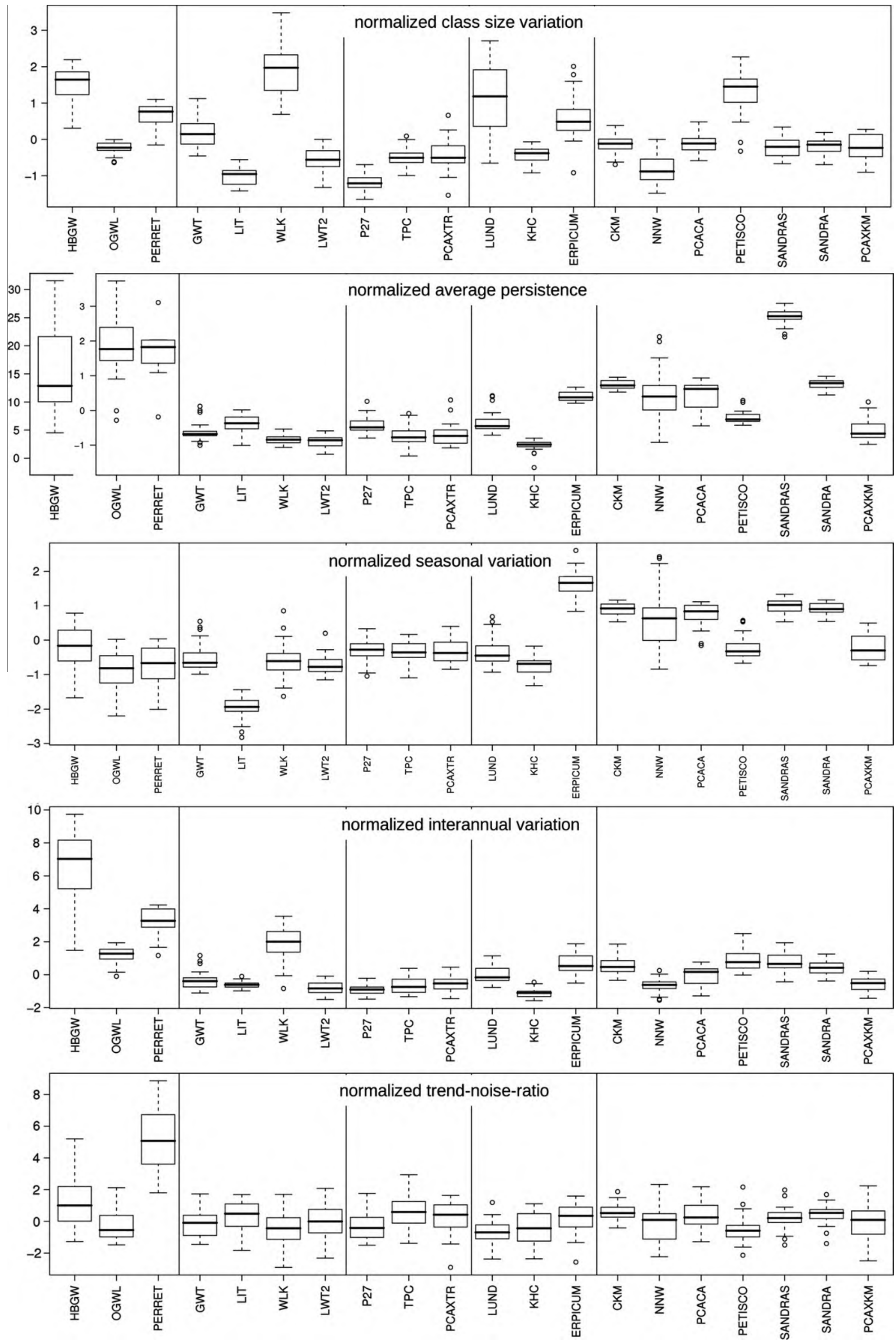

Fig. 2. Normalized class frequency indices characterizing different classification methods and method groups. The indices are normalized separately for each spatial domain and category of type numbers. Groups of methods are distinguished by vertical lines and cover from left to right the following groups: SUB, THR, PCA, LDR, OPT (see text).

and standard deviation of each index is determined separately for each spatial domain and each category of type numbers over all methods available for all domains and all three categories of numbers of types (excluding methods from group SUB as well as the methods PCAXTR and PCAXTRKM which show missing values for some numbers of types and therefore could produce a bias). Using these domain and number of types specific means and standard deviations all values (now including SUB-methods and PCAXTR and PCAXTRKM) are normalized to allow comparisons across the methods. In case of the subjective classifications, which cannot be assigned to one of the standard domains, their only catalogs are used as duplicates within each domain to be able to compare them with automated methods. Classifications with numbers of types differing by more than 2 from the reference values 9, 18 and 27 are omitted. The results are shown in Fig. 2 for comparison across the methods, indicating some distinct characteristics of the methods and method groups mentioned above.

Concerning the variation of class sizes some methods show remarkably high values like the HBGW, WLK, LUND (with a large bandwidth as well) and PETISCO. On the other hand the group of PCA based methods and the OPT group show a tendency to produce equally sized classes. The low values for LIT, P27 and LWT 2 are due to the definition of types using centered indices (for the latter only in parts), while those for NNW are obviously caused by the limitation of training iterations, leading to a relatively weak separation between the types.

Regarding mean persistence the subjective and the optimization methods show a tendency towards higher values, while threshold based, PCA based and leader methods (with the exception of ERPICUM) produce types of relatively short duration. Classifications designed to enhance persistence, like HBGW, OGWL, PERRET and SANDRAS, in fact do show highest values.

Distinctive differences also exist for the seasonal variation of type frequencies. Relatively low variation is shown for all methods except for ERPICUM and the optimization methods. The reason is probably that the latter all use distance measures considering gradients of the pressure fields, while the others use similarity metrics which do not account for the seasonal cycle in this manner. Further differences exist with the threshold methods, especially LIT, tending to show reduced seasonal variability compared to the other automated methods.

The inter-annual variability of type frequencies appears to be positively correlated with the class size variation. Thus classifications with more equally sized classes show a tendency towards reduced inter-annual variability. However, highest values are shown for the manual HBGW and PERRET classifications, which might be attributable to subjectivity of these manual methods or a variant data basis, while the objectivized OGWL shows distinctively lower variability. The same reason seems to be responsible for the trend-noise-ratio being largest for HBGW and PERRET while no further clear differences among the rest of the methods can be observed.

5. Discussion and concluding remarks

Among the included classification methods five method groups (SUB, THR, PCA, LDR and OPT) were identified as described in Section 2. Where possible each single method was applied to standardized datasets using the same numbers of types (9, 18 and 27 respectively) in order to make them comparable concerning the properties of the resulting catalogs. To provide an overview of the basic properties, five simple indices describing variation of class size, mean persistence, seasonal and inter-annual variability and the trend behavior were presented, which can be important for specific applications of the classifications, depending on the temporal properties of variables involved in these applications.

Apparently the subjective classifications (SUB) differ considerably from all other methods due to the subjective definition of types and assignment procedure. This is expressed by a distinctively high inter-annual variability and larger long-term trends of the types' frequencies compared to the automated methods. The reason for those differences might be found in subjectivity. Although no significant inhomogeneities had been found in the HBGWL catalog by Werner et al. (2000), Cahynová and Huth (2009) do report on artifacts. Another reason can be the consideration of other weather elements than SLP, the latter being partly supported by an also high inter-annual variability of the WLK classification which is in parts based on wind components. However, subjective classifications are not transferable to other geographic regions and therefore show considerable limitations for some applications. On the other hand they can include important expert knowledge which is hard to formulate in precise rules for automated classification. Furthermore they feature some properties which might be favorable for many applications like a high persistence of types. The problems of potential artifacts in manual classifications can be overcome by the automatic assignment of days according to their pressure patterns, as it is done by the OGWL method, however the problem of geographical limitations remains, and the integration of expert knowledge in the assignment of days may be lost.

The second group of threshold based methods (THR) has the advantage of automatic processing and a lower degree of subjectivity. However, subjectivity is also present with regards to the definition of the thresholds. Although their common concept is based on air mass flow characteristics, the implementation of thresholds can lead to large differences. Such differences among threshold based methods are indicated by class size variation and seasonal or inter-annual variability of class frequency, where outliers exist with the LIT and the WLK methods. However, the threshold based methods show a tendency to lower seasonal variation of type frequencies compared to the other automated methods.

Even though the conceptional differences among the PCA based methods are rather large they show relatively similar properties concerning the class frequencies with equally sized types, low persistence, intermediate seasonal and long-term variability and low inter-annual variability. Thus it seems that the use of eigenvectors and the associated centered indices (scores or loadings) for type definition leads to more similar properties of the frequency distributions on various time scales, compared to the other groups of methods.

Compared to the PCA methods, those based on the leader algorithm (LDR) are relatively similar concerning the classification concept. Nevertheless they differ largely concerning their frequency properties. The main reason is probably a high sensitivity of these methods concerning different distance metrics used for determining the similarity between spatial patterns and the distance threshold used to define the leader-patterns. In conjunction with the low degree of classifiability of the input data as indicated by Stephenson et al. (2004), Christiansen (2007), Philipp et al. (2007), Fereday et al. (2008) and Christiansen (2009) this leads to largely differing frequency properties of the catalogs.

All of the optimization methods (OPT) use the Euclidean distance for similarity estimation and all of them are designed to minimize within-type variance, except for the PETISCO method that optimizes the member quantity of the classification seeds only and as a possible consequence presents considerably higher class size variation than the other optimization methods. All in all its properties show more similarity to those of the leader methods. Therefore and because of its methodological relation to the leader algorithm the PETISCO method should be placed into the LDR group in the future. Another outlier is the NNW method due to the effect of the uncompleted optimization procedure which was stopped after 2000 iterations, far before reaching convergence for the optimization function. Therefore it should be re-evaluated using converged partitioning in the future. Further differences within this method group are due to different starting partitions and data preprocessing. The extremely high persistence of the SANDRAS method is explained by the concept of classifying pattern sequences instead of single day patterns, as is the case for all other methods. Apart from that, the optimization methods consistently show intermediate variation of class sizes, above average persistence and high seasonal variation.

It is concluded that the categorization of methods as presented in this paper is considerably reflected in the frequency based properties of the catalogs. At least the group of subjective methods and the group of optimization methods can be clearly discerned from the others. On the other hand there are some outliers within most of the method groups. This is interpreted as being due to other factors than the classification concept itself. Even though the application of the algorithms has been standardized to a large degree, obviously there still exist important differences in the classification procedures like different similarity metrics and data preprocessing. Thus it is recommended that future evaluations pay more attention to those classification features. Nevertheless, the presented results might help for the decision on a classification method for specific applications and provide a basis for further, more detailed examination of classification properties.

The cost733cat dataset of classification catalogs is freely available on request.

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