2

Recent Global Warming Induced Climate Changes

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1. Introduction

Climate should be regarded as a complex system, thus requiring an investigation of its complex changes. For this purpose, it is obvious to define climate types that are determined by a number of factors to be able to afterwards investigate the way they are changing. The most popular procedure so far consists in defining threshold values – as a rule for temperature and precipitation for the seasons – to determine those areas as a climate type that are within these threshold values. A popular example of this procedure is the frequently used Köppen climate classification (Köppen, 1931; Fraedrich et al., 2001). The drawback of this methodology consists in the fact that the threshold values can be absolutely plausible but need to be given subjectively in any case. The first question is: Can be a methodology developed here for the identification of climate changes in an objective way? First, all regions with a structural behavior as similar as possible are combined in one climate type and the pertaining threshold values of the meteorological parameters used are determined afterwards. Regions or areas with the same structure can be determined by means of a pattern recognition method. An extended non-hierarchic cluster analysis will be used for this purpose in the investigation. This cluster analysis provides a number of statistically separated patterns (climate types) for the climate classification on earth. So the characteristics of each climate type can be described. The second question that needs to be answered now can be formulated as follows: Are there any changes in the location and dimension of individual climate types due to the global climate changes presently observed? In order to answer this question, the shifting of the climate types during the observed period must be calculated. After calculation, an analysis of the results follows, first for the global scale as a whole and second more detailed for each continent and selected regions. So the chapter gives an overview on the actual climate changes for different scales.
Section 2 describes the basis of the data and its validation. The methodology can be found in section 3 followed by the analysis of the actual climate changes for the whole earth and each continent in section 4. Finally some conclusions are made in section 5.

2. Data

2.1 Introduction

The first step to prove climate change is to provide a data base, i.e., to choose adequate parameters for describing climate types. These parameters must be capable to indicate annual and seasonal differences. As regarding temperature, the following parameters were chosen:

- annual mean value
- 3 months mean, calculated from the 3 highest monthly values
- 3 months mean, calculated from the 3 lowest monthly values
- spread between highest and lowest monthly value

For precipitation, the parameters are defined as follows:

- annual sum
- 3 months sum, calculated from the 3 highest monthly sums
- 3 months sum, calculated from the 3 lowest monthly sums

On the basis of the so chosen parameters, one can produce an equivalent climate classification. At the same time, the demand for a cluster analysis developed under conditions of parameters highly independent from each other is fulfilled.

To provide these parameters, an appropriate data set for temperature and precipitation based on monthly values had to be produced. On the one hand, we used a temperature data set (TS3.0, 1901–2005) compiled by the Climate Research Unit (CRU) of the University of East Anglia (Mitchell & Jones, 2005), and, on the other hand, we employed a data set of the Global Precipitation Climatology Centre (GPCC, 1901–2009) for precipitation (Rudolf et al., 2010). In both cases, the values of the data sets were available at a grid of 0.5° x 0.5°.

Investigations of the CRU temperature data set and the GPCC precipitation data set revealed that, with regard to the temporal structure, there were a number of grid points with inhomogeneities (leaps) that could not be neglected. Hence, both data sets were statistically homogenized and regularly actualized at PIK until 2009.

2.2 Methods to identify inhomogeneities

We will just briefly go into the method how to check inhomogeneity in data sets. There are lots of publications on this. An elaborate survey can be found, e.g., in Peterson et al. (1998). For the investigation presented, the t-test or Student's t-test (Taubenheim, 1969; Österle et al., 2003) was applied. For this test, both data sets were "seasonally cleaned" in a first step, i.e., the long-time mean value (here: 1961–1990) was derived from the particular value of the single month.

By the t-test one checks if the mean value from two random samples come from one and the same basic entity, i.e., they derive from each other only within a defined probability value. The floating t-test was applied here: two random samples of the length 5 years lying side by side in the particular time series were defined, e.g., 1/1901–12/1905 and 1/1906–12/1910, and the t-value was identified. After this, the random samples were shifted by a month (2/1901–1/1906 and 2/1906–1/1911), and the t-value was identified once more, and so on. In the end, one receives a time series of t-values. If the local maxima resp. minima of these t-values exceed the defined significance level of 0.1 %, this points to one or more leaps within the time series. These leaps separate quasi-homogenous periods from each other. Starting with the last homogenous period within the time series, the homogenous partial periods which lie before were adapted by a bias correction.

2.3 Temperature

As remarked above, CRU contains temperature data for the period 1901–2009. The particular outliers were identified by simple $\pm 5 \cdot$ Sigma test and the monthly values in which the deviations from the long-time monthly values exceeded 10K were equalized to the mean value.

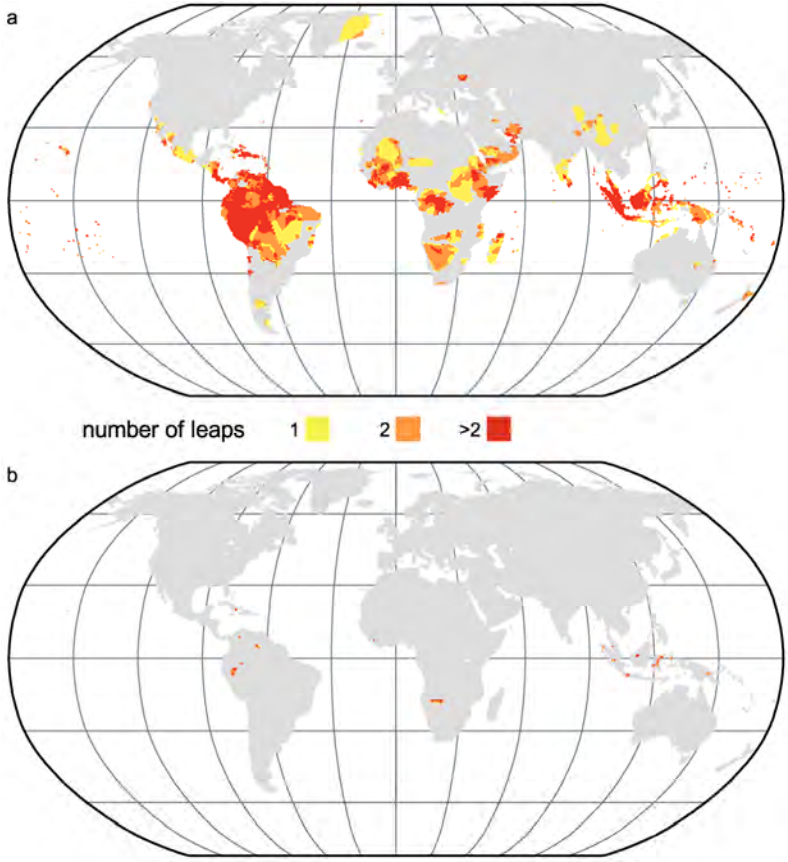

Fig. 1. (a) Regions with inhomogeneities in CRU temperature time-series 1901–2009, localized by the t-test, (b) homogenized data set of temperatures

An investigation of data concerning its temporal behavior revealed that there are a number of grid points with inhomogeneities (leaps) that cannot be neglected. In the TS3.0 version, approximately 19 % of the grid rows were found with inhomogeneities (t-test with a critical t-value = 6.0). The affected area is indicated in Figure 1a. The areas with a relatively bad observation grid also show the most inhomogeneities, such as parts of South America, Southeast Asia, and Africa. This means that, in most cases, inhomogenous grid points do not occur insulated.

The data set was homogenized with the method as explained before.

The homogenization resulted in a significant improvement of the spatial structure as a whole (Figure 1b).

4.500 stations, 3.200 out of which on a daily-value basis, delivered the initial dates for the temperature updates from 2006 on. The rest was derived from the journal Monthly Climate Reports. The data from these 4.500 stations were interpolated to the grid and adapted to the TS3.0 data set.

2.4 Precipitation

The precipitation data used for this investigation come from the data set "Full Data Reanalyse (V.5)" with a grid of 0.5° x 0.5° developed at GPCC in Offenbach. The data set contains data for all months within the period 1901 to 2009 basing on quality-controlled data of the available number of stations with an irregular temporal coverage during the analysis period (max. number of approx. 45.000 stations in 1986/87). This product is optimized for best spatial coverage and usage in water balance assessments but it contains gridded data sets (Rudolf et al., 2010; Rudolf & Schneider, 2005).

Akin to temperature, the analysis of the precipitation data sets showed some inhomogeneities (Figure 2a). As already described, these were homogenized as well so that a significant reduction of inhomogeneities was achieved (Figure 2b).

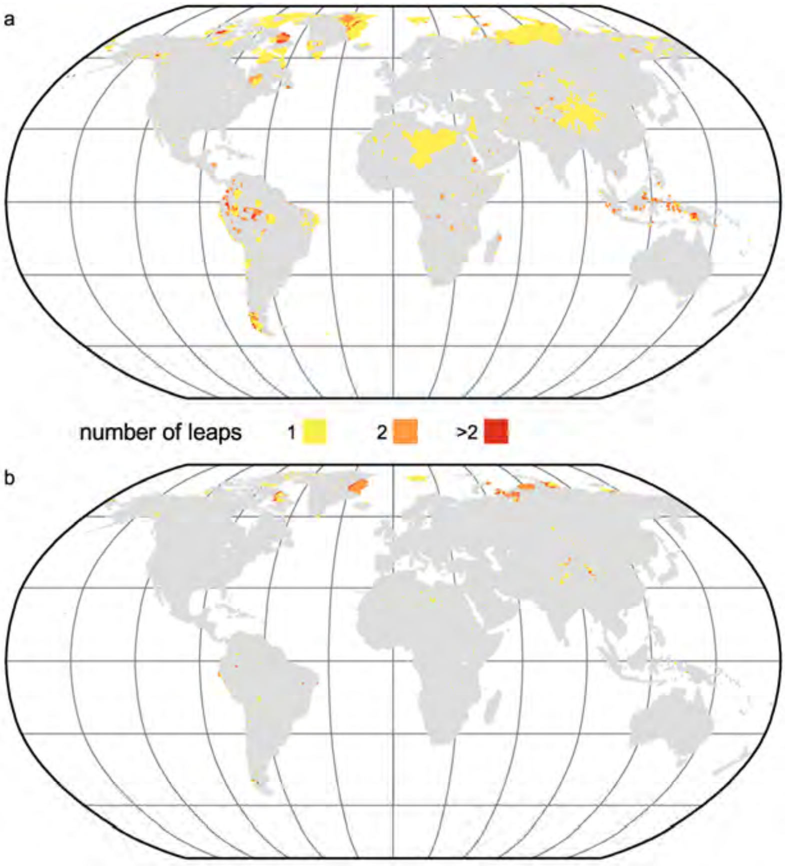

Fig. 2. (a) Data set GPCC V 5.0; grid points with inhomogenous time series found by floating t-test, (b) homogenized data set GPCC V 5.0

3. Methodology
3.1 Introduction

The main idea of the cluster analysis is to relate to each other an existing number M of elements e_i which are each described by N parameters p, i.e.:

$$\mathrm{e_i} = f(p_{i1}, \ldots, p_{iN}) \tag{1}$$

Two main techniques are possible:
Using hierarchical methods, different sequences of groups on different levels are constructed. The result is a hierarchy of clusters in a "tree structure". The disadvantage of this technique lies in the fact that an exchange of elements is impossible if the "tree structure" is built up. This disadvantage restricts the application.
With the non-hierarchical methods, the elements e_i are simultaneously partitioned into a given number of clusters K: by displacing the elements between the clusters in case of a given quality criterion, a given initial partition is built up step by step, and developed into steadily improving groupings until reaching the optimum. For more details, see Steinhausen & Langer (1977). The starting point for concerning the description of the following method is the non-hierarchical minimum-distance method according to Forgy (1965). The starting condition when applying the above method is to have the elements e_i equally distributed over a number K of given clusters (initial partition). In the case of M given elements and K clusters each cluster receives $L = M/K$ elements as follows:

$$\begin{array}{lll} e_1, \ldots, & e_L & \ni \; c_1 \\ e_{L+1}, \ldots, & e_{2L} & \ni \; c_2 \\ \vdots & & \;\;\; \vdots \\ e_{(k-1)L+1}, \ldots, & e_{kL} & \ni \; c_k \end{array} \tag{2}$$

(The number of clusters K must be defined empirically; the number of elements depends on the data series and the problem which has to be investigated.)
A so-called group centroid $\overline{e}_k$ is then calculated for each k of the K clusters (cluster mean value under consideration of those existing parameters that have to be normalized accordingly in the case of different scalings):

$$\overline{e}_k = \frac{1}{L} \sum_{i=(k-1)L+1}^{kL} e_i . \tag{3}$$

By applying the Euclidean distance, the following objective function $a(g)$ for each grouping step g can be defined:

$$a(g) = \sum_{k=1}^{K} \sum_{i \in k} \left| e_i - \overline{e}_k \right|^2 . \tag{4}$$

By considering the Euclidean distance, each grouping step can be seen as a displacement of the element e_i into that cluster which contains the respective nearest centroid. The objective function can thus be minimized:

$$a(g) \; \forall g \rightarrow \min . \tag{5}$$

This procedure is repeated until a local minimum of the objective function is reached. The objective function reaches a local minimum if two successive grouping steps show the same result; the iteration is in this case discontinued, i.e., the optimum classification with respect to the given number of clusters has been reached.
An important disadvantage of this method is that one does not know whether an absolute or just a secondary minimum of the objective function has been obtained (Fovell & Fovell, 1993). That is why the quality of separation is unknown, as is the objective number of clusters. The following procedure shows a solution of this problem.

3.2 Definition of quality criterion to separate clusters

The quality criterion represents the statistical security of the cluster separation. The basic idea to define this criterion can be described as follows (Gerstengarbe & Werner, 1997):
After having reached the local minimum, each cluster is equipped with a generally varying number of elements. Each element is defined by N parameters, i.e., it is located in a N-dimensional parameter space. As each cluster consists of a certain number of elements, they each represent a scatterplot of elements in the above space. If the clustering leads to a local secondary minimum, overlaps occur between the scatterplots of single clusters. The principle of this method is presented in Figure 3, which depicts the projection of two parameters within the N-dimensional space.

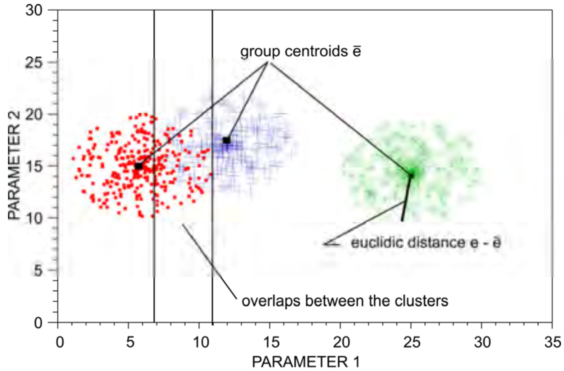

Fig. 3. Principle scheme of the description of the clustering quality (red/blue – overlapped clusters, green – full separated cluster)

The number of overlaps O of the two clusters a and b of N parameters can accordingly be defined as follows:

$$O_{a,b} = \sum_{i_a=1}^{L_a} \sum_{i_b=1}^{L_b} \sum_{j=1}^{N} O_{i_a,i_b,j} \qquad \begin{array}{l} a = 1, \ldots, k \\ b = 2, \ldots, k \end{array} \tag{6}$$

with

$$o_{i_a\ ,\ i_j\ \ ,j} = \begin{cases} 1 & p_{i_b,j} \geq p_{i_a,j} \\ 0 & p_{i_b,j} < p_{i_a,j} \end{cases} \tag{7}$$

under the additional condition

$$\overline{e}_1 > \overline{e}_2 > \ldots > \overline{e}_k \tag{8}$$

If $O_{a,b} = 0$, than the clusters a and b are completely separated from each other. The maximum possible number of overlaps is

$$O_{a,b}^{\max} = NL_a L_b \tag{9}$$

This number is reached if both clusters cover the same region within the N-dimensional space.

Thus by applying the equations (6) to (9) the quality of the separation of clusters can be determined statistically by the following steps:

- Calculation of the mean number of the maximum possible overlaps $\overline{O}^{\max}$ as well as the mean actual number of overlaps $\overline{O}$ over all combinations of cluster pairs.
- Subsequently, a test is carried out to see whether $\overline{O}$ and $\overline{O}^{\max}$ originate from the same basic population. Assuming that there is a normal distribution, Student's t-test can be used. (Because of the necessary normalization of the parameters, a normal distribution is generally realized.) The null hypothesis implies that both mean values originate from the same population. The clusters can be separated only when the null hypothesis is rejected. Otherwise, the procedure is as follows:
- The ratio $\nu_{a,b}$ of the actual to the maximum possible number of overlaps is determined for each cluster pair:

$$\nu_{a,b} = \frac{O_{a,b}}{O_{a,b}^{\max}} \tag{10}$$

- The mean value $\overline{\nu}$ over all $\nu_{a,b}$ is calculated. It is the empirical estimate of the actual occurrence probability of overlaps.
- In the case that not all mean values $\overline{\nu}$ are identical, the second bullet point implies that there is – according to the chosen level of significance – a statistically significant separation of those clusters for which $\nu_{a,b} < \overline{\nu}$.
- The quality of separation in the case $\nu_{a,b} > \overline{\nu}$ still needs to be determined. The point is hence to clarify whether a certain value of the number of the actual overlaps $O_{a,b}$ is compatible with the mean value of all numbers of the actual overlaps $\overline{O}$ or not. If one interprets the overlaps as empirical occurrence frequencies, a statistical comparison between both is possible. This can be done for instance by the χ^2-test (e.g. Taubenheim, 1969) which can be written as follows:

$$\chi^2 = \frac{(O_{a,b} - \overline{O})^2 \cdot (2\, O_{a,b}^{\max} - 1)}{(O_{a,b} + \overline{O}) \cdot (2\, O_{a,b}^{\max} - O_{a,b} - \overline{O})} \tag{11}$$

with the degree of freedom $d_f = 1$.

The result of the test can be interpreted in the following way: If the calculated χ^2-value is greater than a given threshold of significance, the frequency of overlaps exceeding the mean value $\overline{O}$ differs significantly from the χ^2-value. The separation between the clusters is hence statistically not significant, in contrast to the other case where a statistically reliable separation exists.

3.3 Determination of an optimum number of clusters

The optimum number of clusters is defined as that number which realizes the best separation between all clusters. The method presented above allows the optimum number of clusters for the non-hierarchical clustering to be determined in the best possible way. The following procedure is required to this end:

- If a clustering with a given initial number of clusters does not lead to a separation, then the initial number of clusters is varied until at least a single statistically reliable separation between one cluster and the rest exists.
- If the first bullet point. is fulfilled, the elements of the separated clusters are noted as being a final partial result.
- The initial series is reduced by the separated cluster elements.
- This algorithm is repeated using the method presented above until all clusters are statistically reliably separated.
- The optimum number of clusters results from the amount of clusters separated per algorithm step.

Nevertheless, some problems applying this method remain:

- a correct prevision of the initial partition (Is valid also for all other cluster analysis methods).
- an estimation of the optimal initial number of clusters
- a reduction of the error appearing in connection with the delimitation of the level of significance for cluster separation.

In the following, solutions to these problems are proposed and discussed. Chapter 3.4 contains the theoretical basis of the improvements. In Chapter 3.5 the theoretical mechanisms are discussed by a one parameter oscillation.

3.4 Theoretical basis of improvements

3.4.1 The initial partition

For each statistical investigation, the elements of the sample must be independently and identically distributed. This principle is also valid for cluster analysis. If neglected the following course of events may appear (s. also Gerstengarbe et al., 1999):

In the first step of the clustering, the elements of the sample are regularly distributed in the initial number of clusters. In this case, the sequence of the distribution depends on the position of each sample element. That is, in each cluster of the initial partition there is a number of elements which are sorted one following the other in the sample. Thus these elements are not necessarily independent which means that the structure of the sample may create “pre-grouping”. As a consequence, a greater number of dependent elements must exist within a sample. Then, a secondary minimum of the target function can be reached already after only a few iterations devoid of an optimal grouping. This defect can be avoided in a simple way by a random ranking of the elements of the sample so that the persistence of the series tends to 0.

3.4.2 The initial number of clusters

Given is a sample with a limited number n of elements and their regular distribution in the initial number of clusters. This means that a too large or too small initial number of clusters leads to a situation in which some clusters can be separated significantly before the optimum distribution of the elements was been reached. If, for example, the initial number

of clusters is too small, the number of elements within a single cluster is relatively large. As a result possible internal structures of a separated cluster cannot be considered. In the other case, artificial structures can be occurred. To estimate the optimum initial number of clusters the following procedure can be carried out:
The starting point for the calculation of the initial cluster number is the target function (eq. 4). The target function is constructed in such a way that the partition for which the function reaches a minimum defines the most favorable grouping of the clusters. If, for a varying number of clusters (from 2 to m), the value of the target function is calculated, a series is obtained whose values can be included for the estimation of the optimum initial number of clusters. As each value of the target function is equivalent to a specific number of clusters, the initial number of clusters can be defined as that inflection point within the series (of target function values) where a trend disappears. From this point on significant changes within the series do not exist. This idea can be solved practically with the following steps:

- Calculation of the differences between neighboring values of the target function series and creation of a differential series with $m1 = m - 1$ values,
- Using the Pettitt-test (Pettitt, 1979) to estimate the beginning of a trend (inflection point) within the differential series.

The Pettitt-test can be derived from the U-test (Mann & Whitney, 1947), based on the ranks of the series. The inflection point is defined as that point for which the absolute value of X_k reaches a maximum with

$$X_k = 2 \cdot R_k - k \cdot (m1 + 1) \tag{12}$$

where

$$R_k = \sum_{i=1}^{k} r_i \tag{13}$$

k is the position within the series, $m1$ is the number of values of the differential series, and r_i is the rank of the ith target function value. Continuously increasing the initial number of clusters, the Pettitt-test finally defines that position within the series of the target function values where the series is divided into a part with significant changes of the target function values and another one without changes.

3.4.3 The error margin

In general, the χ^2-test is connected with an error probability of 1 % or 5 %. That is, in spite of a statistically significant separation of two clusters, a small number of overlaps can occur so that some clusters may contain "strange" elements. In a statistical sense, this case is without any consequence. In some cases, however, such outliers can have a negative influence on the clustering.
This problem can be circumvented as follows using the definition of an outlier as a value deviating significantly from the basic sample: After a significant separation of all clusters has been achieved, the distance between each element within the cluster and the group centroid is calculated. These distances within each cluster are defined as a basic sample and utilized for identifying outliers. Here we suggest the square of the Euclidean distance as the

measure for the estimation of the outliers. For each element of a cluster, we calculate the sum of Euclidean distances between the single parameters and the group centroid. This leads to a sample of these sums for each cluster. Using the Thompson-rule (Müller et al., 1973) we can estimate the outliers of the clusters. The test value is defined as:

$$t_i = \frac{x_i - \overline{x}}{s^*} \quad (i = 1, ..., n) \tag{14}$$

where $\overline{x}$ is the arithmetical mean of the sample and s^* the standard deviation of the sample. Outliers are all values $x_i (i = 1, ..., n)$ for which $|t_i| > z_{m,\alpha}$ is valid, with $m = n - 2$ ($z_{m,\alpha}$ = critical value). In this sense the Thompson rule is a two-sided test to examine the hypothesis H_0: "The sample has no outliers for a chosen level of significance α". If outliers exist, the Euclidean distance makes it possible to test a better assignment of the outlier to another cluster.

3.5 Validation of the method

As an example for a one parameter oscillation, a simple sine-oscillation is selected and described by 200 values. Its regular course is replaced by 10-value steps in form of stairs. In case of clustering of the new curve the boundaries between the clusters have to be identical with those between the steps of the curve. The partition of the clusters must be symmetric in two respects: First, the positive part of the oscillation must be symmetric as well as the negative. Second, the positive region must mirror the negative region symmetrically. Three variants of clustering are investigated on the basis of the discussed procedures:

1. the defined initial number of clusters is set to $k_0 = 8$; the initial partition consists of random ranked values
2. the optimal initial number of clusters is counted; the values of the initial partition are ordered from 1–200 in the same course like the sine oscillation
3. the optimal initial number of clusters is calculated; the initial partition consists of random ranked values.

Figure 4a shows the result of variant 1. One can see that the boundaries of the clusters are coincided with the spots. Additionally, the symmetry is fulfilled within the positive part as well as within the negative part. The positive and negative parts are asymmetric with respect to each other. If we define cluster 4 as "neutral", 3 clusters remain in the positive part, 4 in the negative one, while cluster 1 contains 5 steps and cluster 8 as the pendant only 3.

The results of version 2. are presented in Figures 4b and 5. Figure 5 gives an overview of the course of the target function values with respect to the number of clusters. Also included is the result of the Pettitt-test with an optimal initial cluster number of 5. This number agrees coincidentally with the optimal separated number of clusters (Figure 4b). The symmetry in the positive and negative parts is fulfilled, but a "neutral" cluster does not exist. Thus an asymmetry exists between both parts: the positive one includes 3 clusters (1–3), while the negative one only 2 (4–5). This is why the ranges of the clusters are different.

For variant 3. we start with the same initial number of clusters as calculated for 2. The number of statistically separated clusters is also 5. In this case all conditions of symmetry are fulfilled (Figure 4c).

This example shows that a correct solution exists for the clustering, if data of the initial partition are ranked randomly and the optimal initial number of clusters is used.

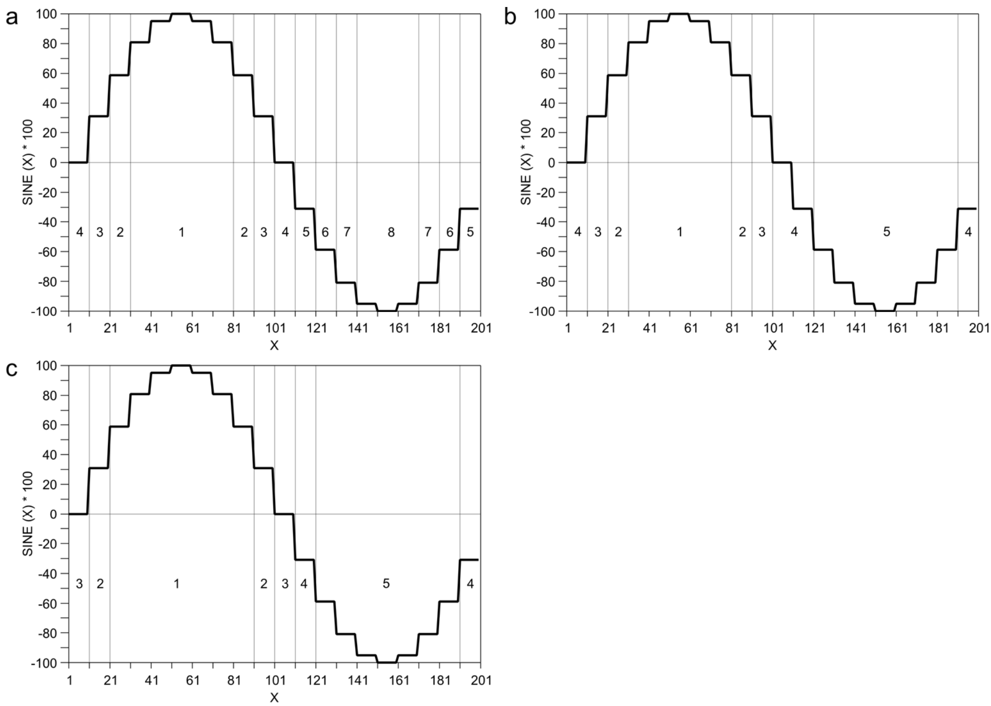

Fig. 4. Theoretical test calculation; random ranked values of the initial partition (a): a defined initial number of clusters $k_0 = 8$; (b): optimal initial number of clusters; the values of the initial partition are ordered from 1–200 in the same course like the sine oscillation, (c): optimal initial number of clusters

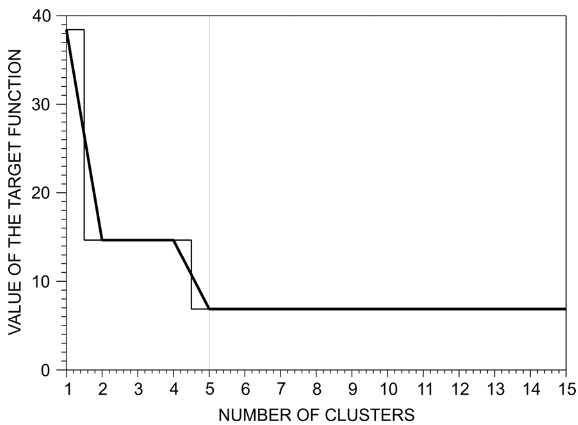

Fig. 5. Result of the Pettitt-test for the estimation of the initial number of clusters (sine oscillation)

The presented results show that the suggested procedure is the first which allows the quality of the separation of clusters to be calculated in a statistically well-founded way; it replaces the often adverse effects of a given number of clusters when employing the non-hierarchical cluster analysis by the application of the optimum number of clusters guaranteeing a statistically reliable separation of all clusters from each other. Additionally for all cluster analysis methods the following conclusions can also be drawn:

- Each method has to guarantee the statistically significant separation of the clusters.
- The ranking of the data within the initial partition must be random.
- A computer program for a cluster analysis has to be built up in such a way that the access to the elements is random.
- For the optimum cluster separation the initial number of clusters is of great importance. It can be calculated using the target function values.
- It is recommendable that existing outliers sort into the cluster with the smallest distance between the outlier parameters and the respective group centroid.

Considering these aspects yields a cluster analysis method which fulfills all the demands of an optimum multivariate climate classification.

4. Analysis

4.1 Climate type characterization

4.1.1 Global

If one calculates a global climate classification for the reference period 1901–1994 with the method as described in 3., and the parameters as provided in 2., this operation produces 30 climate types altogether. These climate types have to be classified in the following (Gerstengarbe & Werner, 2008). For this, the marginal thresholds for every climate type and every parameter will be derived from the data of the respective area. Since it is common in climatology to determine a verbal characterization for the regions in addition to the exact indication of threshold values, the particular parameters are separated into categories – from very cold to very hot for temperature, from very dry to very humid for precipitation, and from very low to very high for the temperature amplitude. For better illustration, the climate types will afterwards be numbered according to the ascending-ordered values of the parameter annual mean temperature.

The thresholds and the verbal characteristics of the single climate types as well as the synopsis of climate types are captured in a table.

In a second step, the climate types for partial periods of 15 years are calculated. This length of partial periods was chosen in order to guarantee for a stable estimation of the employed parameters. To capture the spatial alteration of climate types for the time elapsed, the 15-year window was shifted floating over the whole period 1901–2009 at shifting-time steps of one year. Finally, the current climate changes were determined by calculating the differences between the last shifting period (1995–2009) and the reference period (1901–1994).

If one would cluster each of the partial periods according to the method described, this would result in different group centroids, in addition to different cluster numbers. This will make it nearly impossible to compare a partial period to the whole period. One can elude this by scaling the values of the whole period and allocating the elements of the particular partial period to the group centroids of the reference period, instead of clustering the partial periods. For this, the minimum of the Euclidean distance (equation 4) has to be determined. The results are presented in Chapter 4.2.1.

4.1.2 Continental

In referring to the continents, the global results were augmented, and, thus, the following regions were evaluated: Europe, Asia, Africa, North America, South America, Australia/Oceania. For each of these regions, the areas of the several climate types were determined in a first step, based on the global results. Analogically to the global analysis, the change in area over the last 15-year period was determined and evaluated per climate type in relation to the reference period. So a detailed survey of climate changes per continent could be established. The results are discussed in Chapter 4.2.2. (Preliminary investigations were carried out by Werner et al., 2002; Gerstengarbe & Werner, 2003, 2004.)

4.2 Results

4.2.1 Global

Table 1 contains the thresholds and their verbal characterization for the single climate types. Table 2 comprises the synopsis of climate types. Figure 6a depicts the global distribution of climate types in the reference period. Figure 6b displays the areas where climate types have changed between the last 15-year period and the reference period. Table 3 lists the areas covered by the climate types during the reference period. The dimensions of these areas differ largely, they vary from 556,000 km² (type 23 – monsoon-influenced luffs) to 15,082,000 km² (type 27 – deserts). Moreover, this table contains the changes in area which emerged between the reference period and the last period 1995–2009. Type 24 with 900,400 km², type 27 with 829,500 km², and type 30 with 659,300 km² encountered the biggest gains. These are tropical and subtropical steppe and desert areas.

parameter	very cold VC	cold C	cool c	moderate M	warm W	hot H
annual mean temperature T	< − 10.0	< − 5.0	< 5.0	< 12.0	<20.0	≥ 20.0
Tmax	< 0.0	< 8.0	< 12.0	< 21.0	< 28.0	≥ 28.0
Tmin	< − 25.0	< − 10.0	< 0.0	< 12.0	< 20.0	≥ 20.0
	very small vs	small s	mean m	large l	very large vl	extra large el
amplitude T	< 5.0	< 10.0	< 21.0	< 30.0	< 40.0	≥ 40.0
	very dry VD	dry D	moderately dry MD	moderately humid MH	humid H	very humid VH
annual precipi-tation sum N	< 200.0	< 400.0	<600.0	< 1000.0	< 2000.0	≥ 2000.0
Nmax	< 30.0	< 60.0	< 100.0	<300.0	<500.0	≥ 500.0
Nmin	< 6.0	< 16.0	< 25.0	< 40.0	< 100.0	≥ 100.0
characteristics	1	2	3	4	5	6

Table 1. Thresholds for the climate type characterization

type	Parameter						
	Tmean	Tmax	Tmin	Ampl	Nyear	Nmax	Nmin
1	VC	VC	VC	l	D	VD	D
2	VC	C	VC	vl	VD	VD	VD
3	VC	c	VC	vl	D	D	D
4	VC	C	VC	vl	D	D	D
5	C	C	C	l	D	D	D
6	C	M	VC	el	D	MD	D
7	c	M	C	vl	MD	MD	MD
8	c	C	C	l	MD	MD	MD
9	c	M	C	vl	MH	MD	MD
10	c	M	C	vl	D	D	D
11	c	M	c	m	H	MH	H
12	M	M	c	m	VH	MH	VH
13	M	M	c	l	MH	MD	MH
14	M	M	M	s	D	D	D
15	M	M	c	l	D	D	D
16	M	M	M	m	MH	MD	H
17	M	W	c	vl	VD	VD	VD
18	W	M	M	s	MH	MH	D
19	W	W	M	l	MH	MH	MD
20	W	W	M	m	H	MH	H
21	W	W	M	m	D	D	D
22	H	W	H	vs	H	MH	H
23	H	H	W	m	VD	VD	VD
24	H	W	H	s	VH	VH	MD
25	H	W	H	s	H	MH	D
26	H	W	H	vs	VH	H	VH
27	H	W	H	s	MH	MH	D
28	H	W	H	vs	VH	H	MH
29	H	W	H	vs	VH	MH	VH
30	H	H	H	s	MD	MD	VD

Table 2. Characterization of the climate types

With 569,000 km², type 13 from the temperate zone gains remarkably, too. According to area, type 22 (subtropics) suffers the biggest loss with 978,200 km². According to percentage, the cold types 2 and 3 with minuses of 27.7 % resp. 15.8 % encountered the biggest losses. This is a significant indicator for global warming. Another sign of the impact of warming appears when one considers the shift directions of climate types between the reference period and the last period, with the annual mean temperature as the point of reference. Only 5,479,360 km² (3.81 % of the whole land area) have changed to colder types but 14,815,086 km² (10.31 %) have changed to warmer ones. So, during a relatively short time, climate types have changed in 14.12 % of the area. Only the continents of Africa and South America (with no or a just little share in cold climate types) have a lesser tendency towards a change to warmer types (see Chapter 4.2.2). This points out to the fact that the rise in temperature is stronger in higher latitudes than in the lower ones.

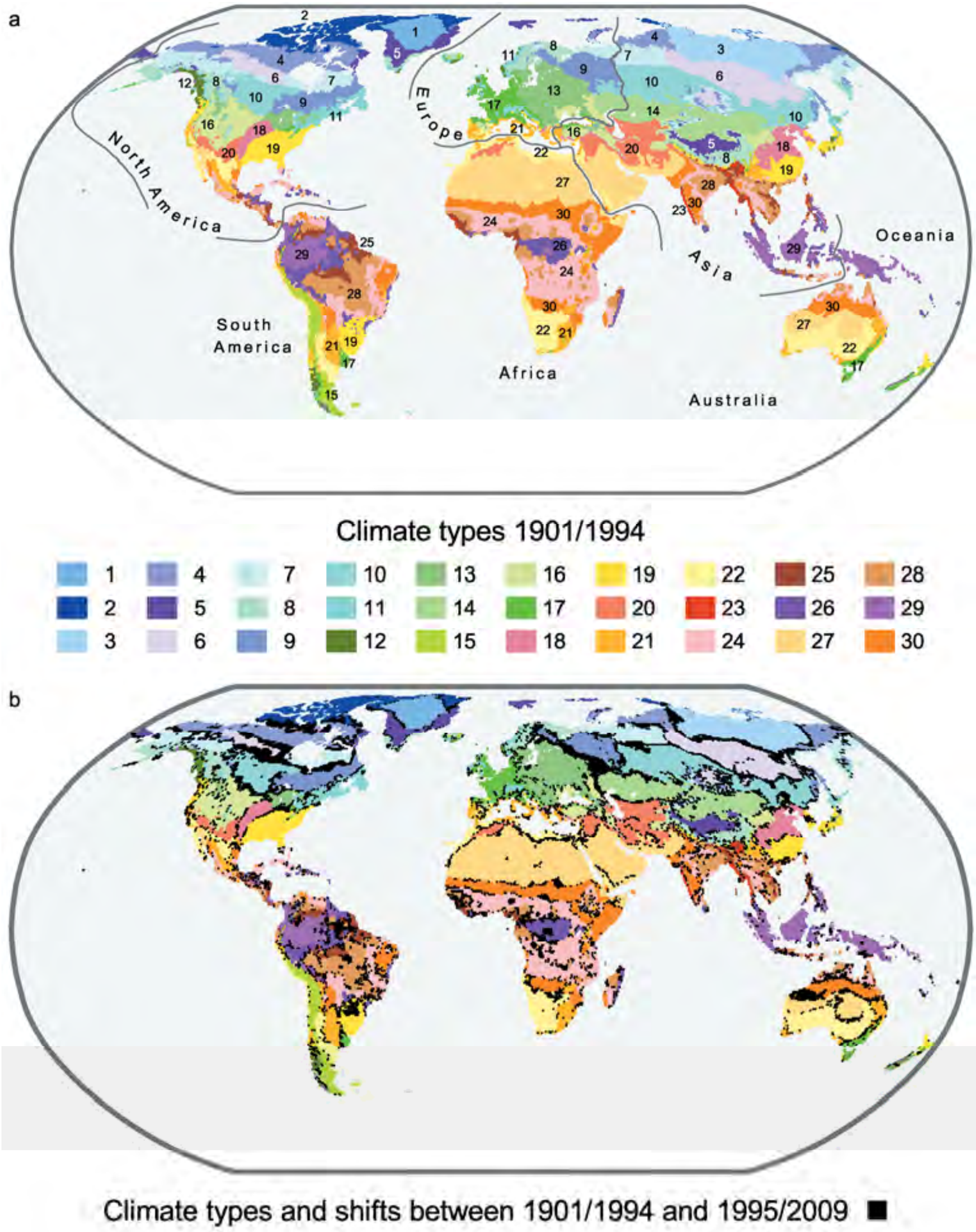

Fig. 6. (a) Global climate type distribution, (b) climate type shifts 1995/2009 vs. 1901/1994

climate type	area * 1901/1994 [10^3 km²]	difference *1995/2009−1901/1994 [10^3 km²]	change * [%]
1	1090	−34.9	−3.2
2	2028	−561.8	−27.7
3	3503	−553.5	−15.8
4	4141	−335.4	−8.1
5	2473	−9.9	−0.4
6	4706	−296.6	−6.3
7	4643	−120.7	−2.6
8	3540	−155.8	−4.4
9	3886	124.4	3.2
10	7161	43.0	0.6
11	2503	−12.5	−0.5
12	799	10.4	1.3
13	4516	569.0	12.6
14	4694	93.9	2.0
15	1867	67.2	3.6
16	4435	323.8	7.3
17	2856	−194.2	−6.8
18	2691	−88.8	−3.3
19	5594	−139.8	−2.5
20	3780	192.8	5.1
21	4908	−88.3	−1.8
22	8084	−978.2	−12.1
23	556	−30.0	−5.4
24	13049	900.4	6.9
25	3461	83.1	2.4
26	5137	−354.4	−6.9
27	15082	829.5	5.5
28	8303	107.9	1.3
29	5568	−44.5	−0.8
30	8675	659.3	7.6

* rounded values

Table 3. Changes of climate type areas 1995/2009 – 1901/1994

The correlation between the time series of global warming and the area of the cold type 3 for 15-year estimation intervals (Figure 7a) is −0.83 and statistically firm with a probability value of 1 %. The hot type 27 (Figure 7b) develops with a correlation of 0.72 that is nearly so high. Further close interrelations emerged for the types 2, 4, 5, 6, 14, 16, 17 23, 27, and 28. All firm correlations are collected in Table 4.

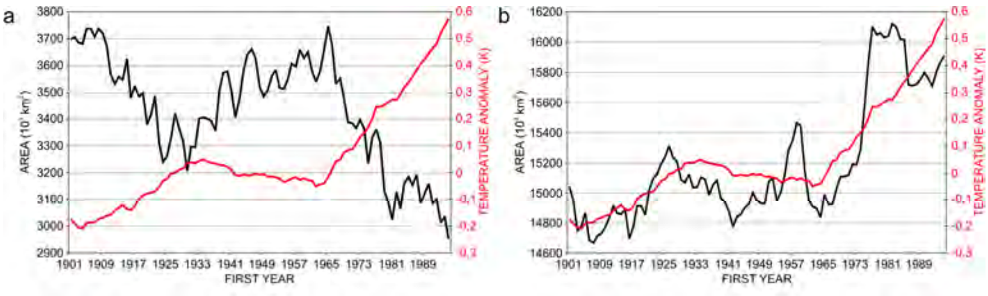

Fig. 7. Area of climate types (black) and anomaly of the global mean temperature 1901–2009 (shifting window 15 years), (a) type 3, (b) type 27

Tendencies did not come out so clear when examining the change to dryer or more humid types. With reference to the annual sum of precipitation, 6.11 % of the area changed to dryer types, and 8.01 % to more humid ones. The gain in area among more humid types, though rather little, is, however, an indicator that, together with warming, precipitation increases globally – with an aggravation in extremes, though, since deserts have grown simultaneously.

(Remark to the shifts cold-warm, dry-humid: The conclusions drawn are only tendencies since one cannot reconstruct in every particular case which of the seven parameters is crucial for the change.)

type	2	3	4	5	6	8	10	13
correlation	−0.43	−0.83	−0.65	0.52	−0.65	−0.37	0.34	0.34
probability value (%)	1	1	1	1	1	5	5	5
type	14	16	17	19	21	23	27	28
correlation	0.46	0.52	−0.49	0.52	−0.37	−0.49	0.72	−0.49
probability value (%)	1	1	1	1	5	1	1	1

Table 4. Significant correlations between the global mean temperature and the area extension of the climate (estimation interval 15 years)

4.2.2 Continental

In the following, the impacts of global warming on the climate types of the several continents will be examined. Therefore, the continents were separated against each other as shown in Figure 8. The analyses were done as described above.

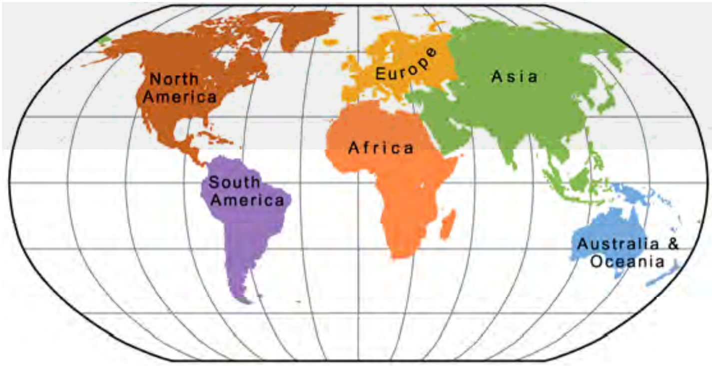

Fig. 8. Continent areas

4.2.2.1 Europe

The distribution of climate types and their shifts in the period 1995/2009 – 1901/1994 is depicted in Figure 9 and all numerical values are noted in Table 5.

type	area (10^3 km^2) 1901–1994	area (%) 1901–1994	area (10^3 km^2) 1995–2009	change (10^3 km^2)	change (%) *	change (%) **
2	22.7	0.20	16.1	−6.6	−0.06	−29.07
4	67.4	0.59	73.8	6.4	+0.06	+9.50
5	140.1	1.23	135.4	−4.7	−0.04	−3.35
7	392.8	3.46	279.9	−112.9	−0.99	−28.74
8	808.6	7.12	670.1	−138.5	−1.22	−17.13
9	1629.4	14.35	1411.7	−217.7	−1.92	−13.36
10	337.2	2.97	61.2	−276.0	−2.43	−81.85
11	655.1	5.77	614.7	−40.4	−0.36	−6.17
12	99.1	0.87	120.9	21.8	+0.19	+22.00
13	3325.0	29.28	3901.3	576.3	+5.08	+17.33
14	618.7	5.45	531.5	−87.2	−0.77	−14.09
15	15.3	0.13	16.6	1.3	+0.01	+8.50
16	650.3	5.73	625.0	−25.3	−0.22	−3.89
17	1623.0	14.29	1696.2	73.2	+0.64	+4.51
18	56.3	0.50	117.8	61.5	+0.54	+109.24
19	105.9	0.93	156.0	50.1	+0.44	+47.31
20	69.8	0.06	47.5	−22.3	−0.20	−31.95
21	597.5	5.26	599.9	2.4	+0.02	+0.40
22	204.3	1.80	279.7	75.4	+0.66	+36.91

*change 1995/2009 − 1901/1994 in relation to the whole area of the continent
**change 1995/2009 − 1901/1994 in relation to the area of the type 1901/1994

Table 5. Climate type extension and change, Europe

The extension of the continental-moderate climate type 13 towards the east can clearly be seen. This type enlarges its whole area about 576,300 km² which makes a gain of 17.33 % resp. an area which is 25,000 km² larger than France. On the other hand, the climate types 7 to 10 ranging from cold to moderately cold suffer from area losses which sum up to approximately 745,000 km². The largest alteration in percentage with 109.24 % can be found in the warm-moderate climate type 18. However, this is "only" an extension of 61,500 km² since the area of this climate type was "only" 56,300 km² during the reference period.

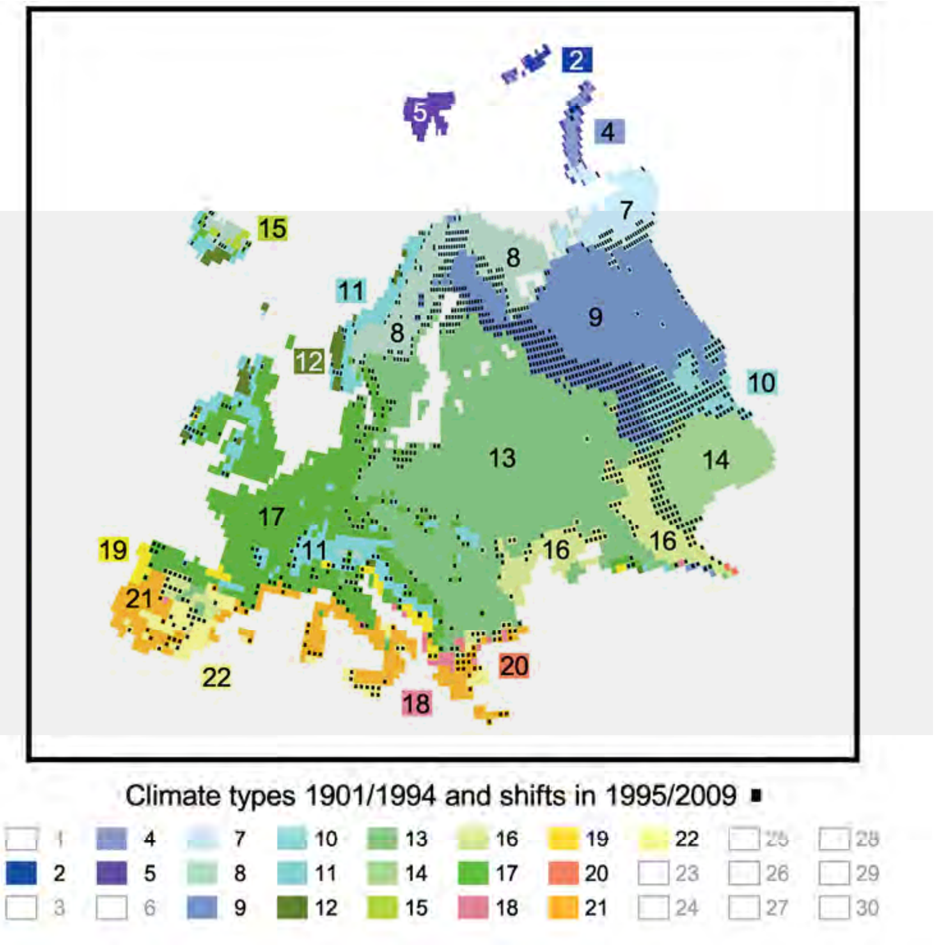

Fig. 9. Climate type distribution and shifts (black squares), Europe, 1995/2009 – 1901/1994

4.2.2.2 Asia

On the Asian continent, all climate types apart from type 1 are affected by area shifts. The widest changes can again be found in the more northern climate types: type 3 with a loss of 551,700 km², and type 4 with a loss of 274,900 km². But also climate type 18 (warm-moderate) with a minus of 187.100 km², the warm-dry type 22 with a minus of 153,900 km², and type 26 (hot-humid) with a minus of 160,700 km² are affected by considerable area losses. Type 27 (hot-very dry; desert) shows the biggest gain with 395,500 km², followed by type 9 (moderate-cold, moderately humid) with 290,700 km² and type 14 (from moderately warm to cool and very dry) with 271,100 km². The relatively greatest changes can be found in type 15 (moderate-cool, dry) with 109.32 %. Nevertheless, the default value of the area is very low in this case. All data and changes can be found in Table 6 and Figure 10.

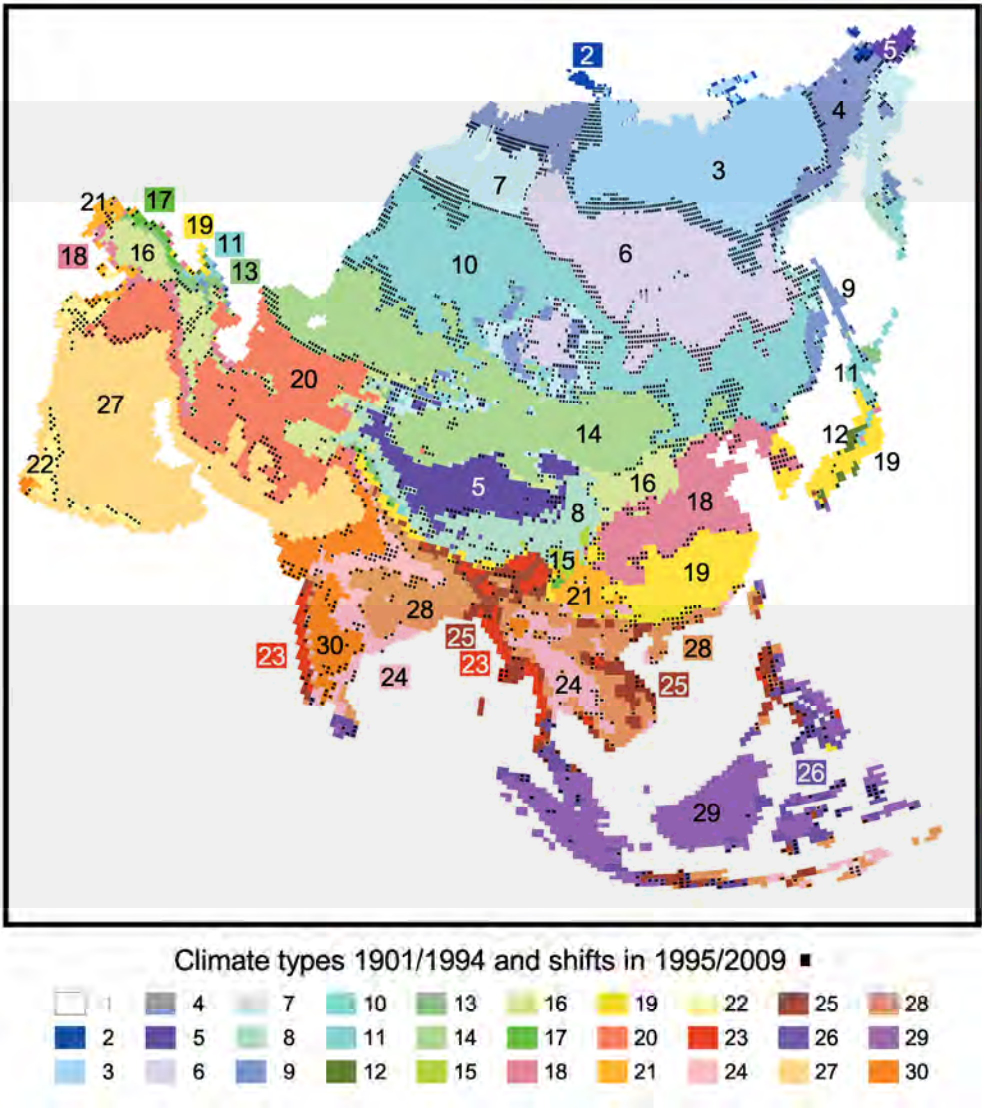

Fig. 10. Climate type distribution and shifts (black squares), Asia, 1995/2009 – 1901/1994

type	area (10^3 km²) 1901–1994	area (%) 1901–1994	area (10^3 km²) 1995–2009	change (10^3 km²)	change (%) *	change (%) **
2	135.0	0.29	115.2	−19.8	−0.04	−14.67
3	3503.0	7.56	2951.3	−551.7	−1.19	−15.75
4	1685.6	3.64	1410.7	−274.9	−0.59	−16.31
5	1382.9	2.98	1311.7	−71.2	−0.15	−5.15
6	3775.3	8.15	3817.0	41.7	+0.09	+1.10
7	2200.1	4.75	2082.0	−118.1	−0.25	−5.37
8	1409.9	3.04	1395.3	−14.6	−0.03	−1.04
9	489.0	1.06	779.7	290.7	+0.62	+59.45
10	5078.7	10.96	5051.8	−26.9	−0.06	−0.53
11	313.3	0.68	278.3	−35.0	−0.08	−11.17
12	77.6	0.17	77.1	−0.5	negligible	−0.64
13	231.0	0.50	254.1	23.1	+0.05	+10.00
14	3967.6	8.56	4238.7	271.1	+0.58	+6.83
15	59.0	0.13	123.5	64.5	+0.14	+109.32
16	1617.7	3.49	1753.2	135.5	+0.29	+8.38
17	97.0	0.21	72.7	−24.3	−0.05	−25.05
18	1857.5	4.01	1670.4	−187.1	−0.40	−10.07
19	1755.0	3.79	1757.0	2.0	negligible	+0.11
20	2722.6	5.88	2863.1	140.5	+0.30	+5.16
21	466.8	1.01	458.5	−8.3	−0.02	−1.78
22	434.1	0.94	280.2	−153.9	−0.33	−35.45
23	500.8	1.08	494.9	−5.9	−0.01	−1.18
24	1567.9	3.38	1698.6	130.7	+0.28	+8.34
25	1105.0	2.38	1127.4	22.4	+0.05	+2.03
26	776.2	1.68	615.5	−160.7	−0.35	−20.70
27	4025.6	8.69	4421.1	395.5	+0.85	+9.82
28	2138.2	4.61	2193.0	54.8	+0.12	+2.56
29	1975.1	4.26	2110.0	134.9	+0.29	+6.83
30	986.6	2.13	932.3	−63.3	−0.12	−5.50

*change 1995/2009 − 1901/1994 in relation to the whole area of the continent
**change 1995/2009 − 1901/1994 in relation to the area of the type 1901/1994

Table 6. Climate type extension and change, Asia

4.2.2.3 Africa

The climate types in Africa are characterized by two significant features. On the one hand, an extreme reduction of the Savanna has to be observed (climate type 22 with a minus of 662,800 km² = 21.21 % of the whole area). On the other hand, the desert enlarges to the same extent (climate type 27 with a plus of 689,500 km²). This trend towards a shift from “humid” to “dry” can be noticed with the other climate types which are characteristic of Africa. So the predominantly humid climate types 21, 25, 26, 28, and 29 loose an area of 671,400 km² altogether. It is remarkable here that the loss in area in climate type 29 is 77.66 %. In contrast to this development, the more dry types 24 and 30 show an increase in area of 698,400 km².

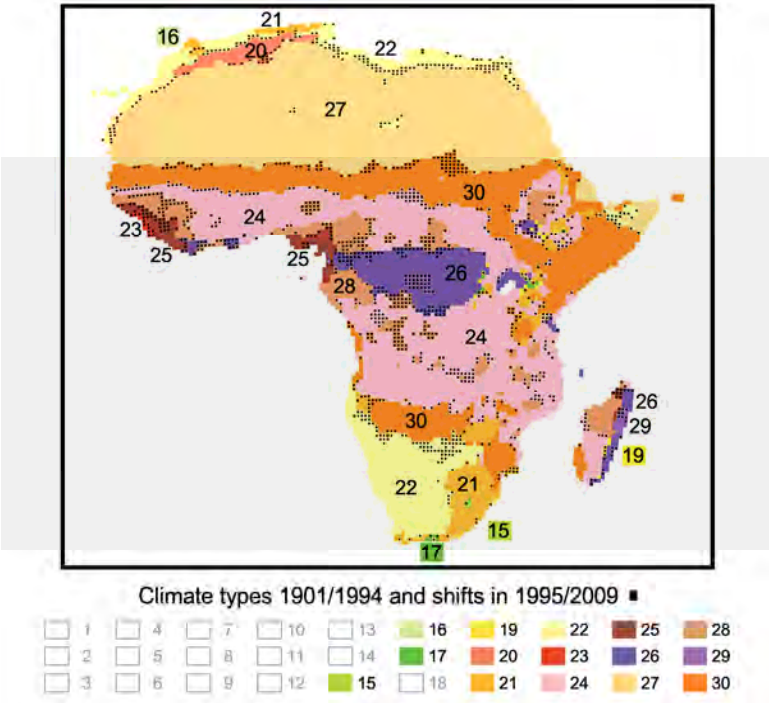

Fig. 11. Climate type distribution and shifts (black squares), Africa, 1995/2009 − 1901/1994

type	area (10^3 km^2) 1901–1994	area (%) 1901–1994	area (10^3 km^2) 1995–2009	change (10^3 km^2)	change (%) *	change (%) **
15	11.0	0.04	8.0	−3.0	−0.01	−27.27
16	15.5	0.05	7.9	−7.6	−0.02	−40.03
17	45.4	0.15	40.2	−5.2	−0.02	−11.45
19	86.6	0.28	75.0	−11.6	−0.04	−13.39
20	372.7	1.20	389.2	16.5	+0.05	+4.43
21	1388.7	4.49	1245.0	−143.7	−0.46	−10.35
22	3124.4	10.11	2461.6	−662.8	−2.14	−21.21
23	48.8	0.16	6.1	−42.7	−0.14	−87.50
24	7661.3	24.78	8001.0	339.7	+1.10	+4.43
25	483.2	1.56	363.9	−119.3	−0.38	−24.69
26	1651.5	5.34	1483.0	−168.5	−0.54	−10.20
27	8751.4	28.31	9440.9	689.5	+2.23	+7.88
28	2001.1	6.47	1895.0	−106.1	−0.34	−5.30
29	172.3	0.56	38.5	−133.8	−0.43	−77.66
30	5098.3	16.49	5457.0	358.7	+1.16	+7.04

*change 1995/2009 − 1901/1994 in relation to the whole area of the continent
**change 1995/2009 − 1901/1994 in relation to the area of the type 1901/1994

Table 7. Climate type extension and change, Africa

Since these two climate types already covered large areas in Africa between 1901 and 1994, the relative increase is “only” 4.43 % resp. 7.04 %. Figure 11 and Table 7 give an overview of the shifts. In summary, one can state that the climatic situation in Africa has remarkably changed for the worse during the period 1995/2009.

4.2.2.4 Australia and Oceania

If one considers the climate development in Australia and Oceania, the changes are little in Papua New Guinea and New Zealand. Nevertheless, the situation in Australia is different. Here we find distinct losses of area within the types 17 (−109,400 km²), 22 (−151,500 km²), and 27 (−310,500 km²). There are gains for the types 24 (+165,200 km²) and 30 (+272,300 km²). Type 27 (desert) looses area to the types 22 and 30, and type 30, in turn, to type 24. The great relative changes in the climate types 15 (+206.15 %), 23 (320.69 %), and 25 (242.86 %) are of only little influence since their particular shares in the whole area are only very little during the period 1901/1994. Overall one can say that there is a tendency towards a change from the very hot and dry climate types in Australia to the less dry types. All changes are summarized in Figure 12 and Table 8.

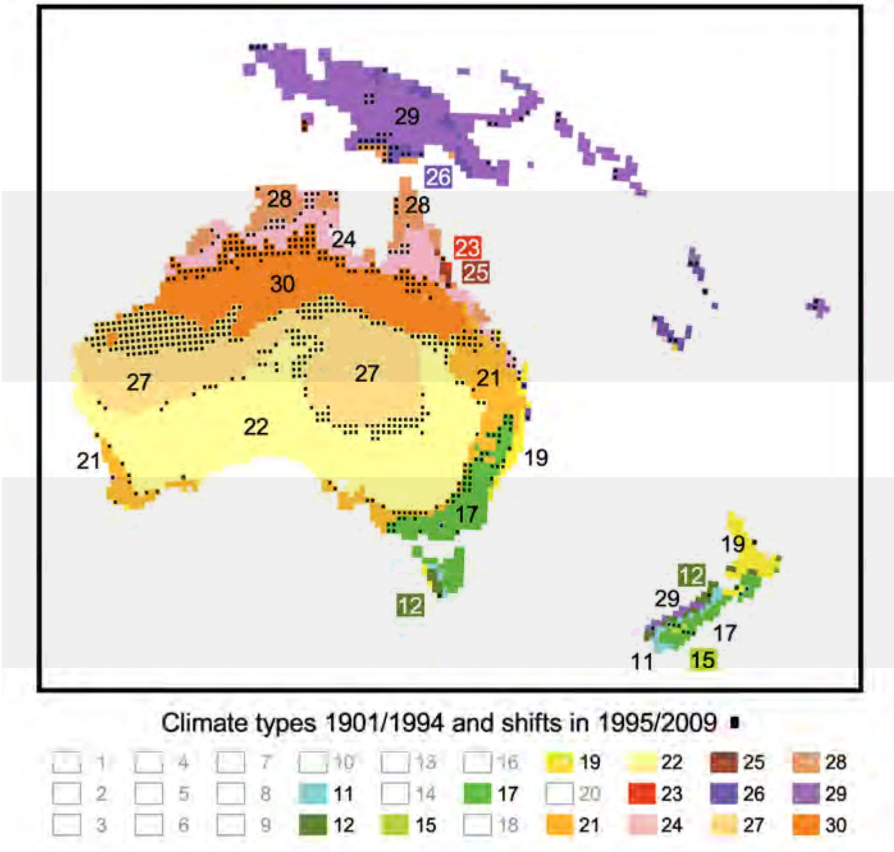

Fig. 12. Climate type distribution and shifts (black squares), Australia and Oceania, 1995/2009 – 1901/1994

type	area (10^3 km^2) 1901–1994	area (%) 1901–1994	area (10^3 km^2) 1995–2009	change (10^3 km^2)	change (%) *	change (%) **
11	66.9	0.66	59.9	−7.0	−0.07	−10.46
12	73.2	0.72	68.3	−4.9	−0.05	−6.69
15	6.5	0.06	19.9	13.4	+0.13	+206.15
17	564.0	5.59	454.6	−109.4	−1.08	−19.40
19	216.5	2.15	225.8	9.3	+0.09	+4.30
21	665.4	6.60	702.8	37.4	+0.37	+5.62
22	2676.5	26.54	2525.0	−151.5	−1.50	−5.66
23	2.9	0.03	12.2	9.3	+0.09	+320.69
24	571.2	5.66	736.4	165.2	+1.64	+28.92
25	23.8	0.24	81.6	57.8	+0.57	+242.86
26	216.1	2.14	180.9	−35.2	−0.35	−16.29
27	2078.1	20.61	1767.6	−310.5	−3.08	−14.94
28	387.0	3.84	464.6	77.6	+0.77	+20.05
29	1161.9	11.52	1138.1	−23.8	−0.24	−2.05
30	1374.7	13.63	1647.0	272.3	+2.70	+19.81

*change 1995/2009 − 1901/1994 in relation to the whole area of the continent
**change 1995/2009 − 1901/1994 in relation to the area of the type 1901/1994

Table 8. Climate type extension and change, Australia and Oceania

4.2.2.5 North America, Central America and Greenland

Except for climate type 3, all other types can be found in this region. The two cold or very cold and, in addition, dry climate types 2 (−535,700 km²) and 6 (−340,000 km²) show significant losses in area, with climate type 2 loosing substantial shares to type 4. The latter, nevertheless, increases only about 69,400 km² which is due to the fact that, in turn, type 6 shifts to the north. Concurrently, the neighboring climate type 10 spreads to the same direction (+345,800 km²) so that type 6 shrinks at the already mentioned value, which brings about a loss of area of 36.51 %. This development continues into the Midwest of the USA which is basically represented by climate type 16 (moderately warm, dry) and expands to the north for 222,600 km². Climate type 19 (warm, humid) behaves in a similar way, and it also spreads to the north for 157,200 km². Concerning the changes in Central America, only type 28 is of importance with a plus of 117,600 km². This equates to an increase in area of 30.88 %. Figure 13 and Table 9 summarize all changes.

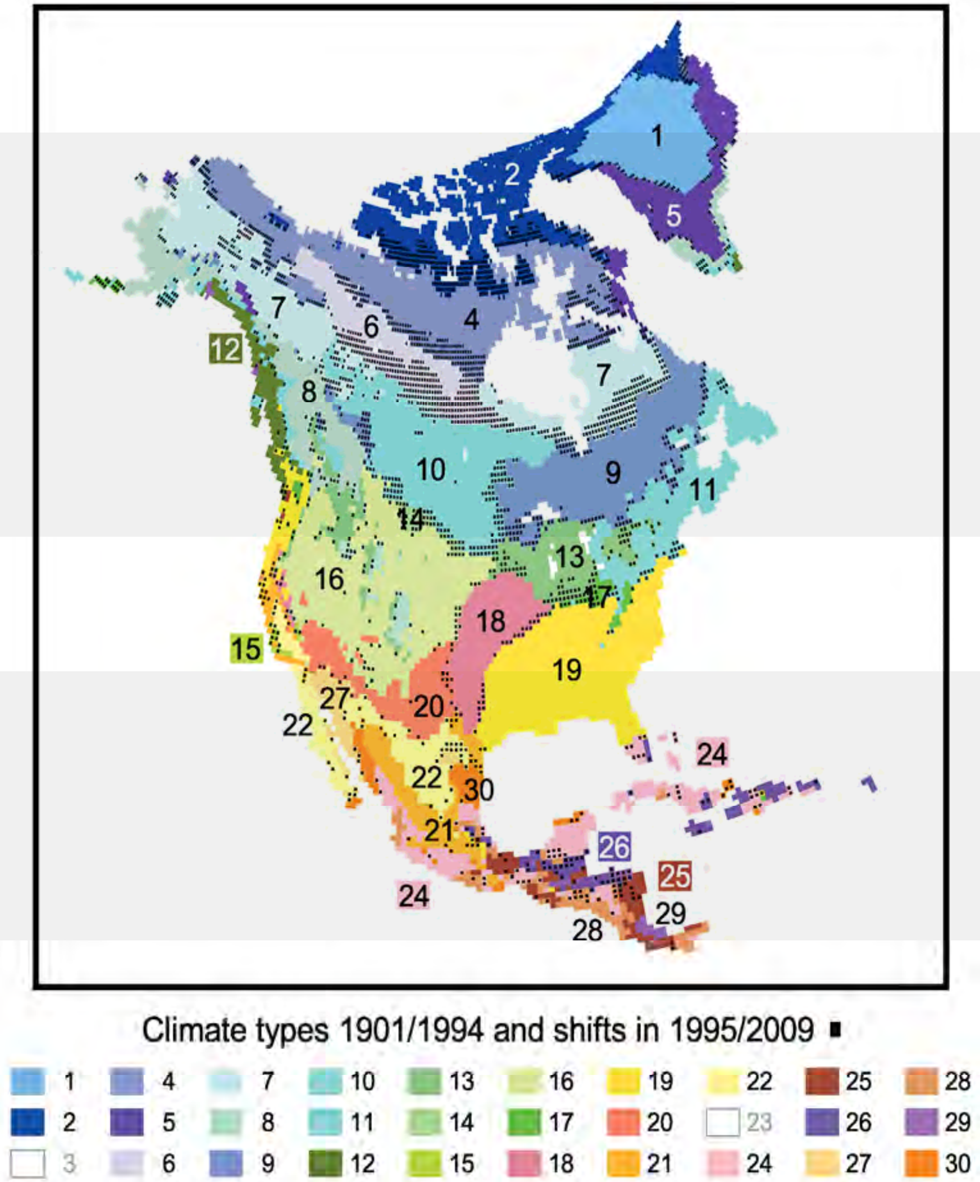

Fig. 13. Climate type distribution and shifts (black squares), North America, 1995/2009 – 1901/1994

type	area (10^3 km^2) 1901–1994	area (%) 1901–1994	area (10^3 km^2) 1995–2009	change (10^3 km^2)	change (%) *	change (%) **
1	1089.9	4.11	1055.4	−34.5	−0.13	−3.16
2	1870.3	7.05	1334.6	−535.7	−2.02	−28.64
4	2388.2	9.01	2321.5	−66.7	−0.25	−2.79
5	947.2	3.57	1016.4	69.2	+0.26	+7.30
6	931.3	3.51	591.3	−340.0	−1.28	−36.51
7	2050.0	7.73	2158.6	108.6	+0.41	+5.30
8	1311.7	4.95	1306.7	−4.1	−0.02	−0.38
9	1768.1	6.67	1818.7	50.6	+0.19	+2.86
10	1744.9	6.58	2090.7	345.8	+1.30	+19.82
11	1398.3	5.27	1471.0	72.7	+0.27	+5.20
12	321.3	1.21	352.6	31.3	+0.12	+9.74
13	960.6	3.62	930.9	−29.7	−0.11	−3.09
14	107.9	0.41	16.8	−91.1	−0.34	−84.43
15	37.6	0.14	20.9	−16.7	−0.06	−44.41
16	2147.1	8.10	2369.7	222.6	+0.84	+10.37
17	153.1	0.58	125.6	−27.5	−0.10	−17.96
18	777.0	2.93	814.8	37.8	+0.14	+4.86
19	2091.8	7.89	2249.0	157.2	+0.59	+7.52
20	677.4	2.56	674.1	−3.3	−0.01	−0.49
21	628.9	2.37	596.4	−32.5	−0.12	−5.17
22	777.2	2.93	719.1	−58.1	−0.22	−7.48
23	0.0	0.00	2.9	2.9	+0.01	new
24	853.5	3.22	818.3	−35.2	−0.13	−4.12
25	305.2	1.15	318.0	12.8	+0.05	+4.19
26	313.5	1.18	269.6	−43.9	−0.16	−14.00
27	226.6	0.85	279.9	53.3	+0.20	+23.52
28	308.8	1.16	426.4	117.6	+0.44	+30.88
29	95.3	0.36	77.7	−17.6	−0.07	−18.47
30	230.3	0.87	285.4	55.1	+0.21	+23.92

*change 1995/2009 − 1901/1994 in relation to the whole area of the continent
**change 1995/2009 − 1901/1994 in relation to the area of the type 1901/1994

Table 9. Climate type extension and change, North America

type	area (10^3 km²) 1901–1994	area (%) 1901–1994	area (10^3 km²) 1995–2009	change (10^3 km²)	change (%) *	change (%) **
5	2.6	0.01	0.0	−2.6	−0.01	not to apply
8	9.8	0.05	10.2	0.4	negligible	+4.08
11	69.8	0.38	67.4	−2.4	−0.01	−3.44
12	228.2	1.23	191.0	−37.2	−0.20	−16.30
15	1737.2	9.38	1745.6	8.4	+0.04	+0.48
16	4.8	0.03	5.0	0.2	negligible	+4.17
17	373.8	2.02	271.4	−102.4	−0.55	−27.39
19	1338.1	7.22	990.1	−348.0	−1.88	−26.01
21	1160.7	6.26	1216.4	55.7	+0.30	+4.80
22	867.2	4.68	842.1	−25.1	−0.14	−2.89
23	3.1	0.02	9.2	6.1	+0.03	+196.77
24	2395.4	12.93	2692.5	297.1	+1.60	+12.40
25	1543.8	8.33	1653.7	109.9	+0.59	+7.12
26	2179.8	11.76	2233.3	53.5	+0.29	+2.45
28	3467.8	18.71	3429.3	−38.5	−0.21	−1.11
29	2162.9	11.67	2159.4	−3.5	−0.02	−0.16
30	985.1	5.32	1013.3	28.2	+0.15	+2.86

*change 1995/2009 − 1901/1994 in relation to the whole area of the continent
**change 1995/2009 − 1901/1994 in relation to the area of the type 1901/1994

Table 10. Climate type extension and change, South America

4.2.2.6 South America

In South America, there are two climate types with relatively big area losses; on the one hand, climate type 17 (moderately warm, moderately humid with a minus of 102,400 km²), on the other hand, climate type 19 (warm, humid, with a minus of 348,000 km²).
In essence, type 17 looses area to the types 19 and 21. The losses of climate type 19 are caused by an extension of the neighboring types 24 and 26 into this region. Climate types 24 and 25 are the types with the biggest gain in area (type 24 with a plus of 297,100 km², and type 25 with a plus of 109,900 km²). Overall, the observed shifts on the South American continent are moderate, in comparison to the changes on other continents. Figure 14 and Table 10 give a detailed survey of the changes.

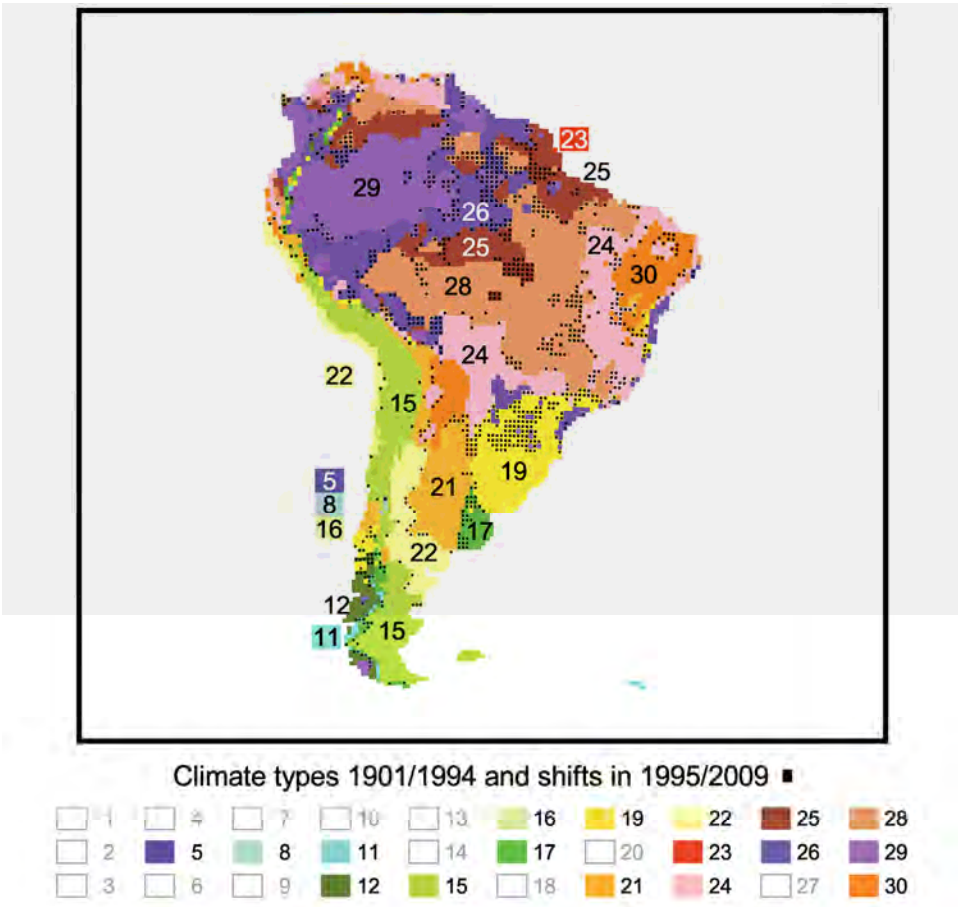

Fig. 14. Climate type distribution and shifts (black squares), South America, 1995/2009 – 1901/1994

5. Conclusions

It could be shown that the new developed cluster analysis algorithm leads to objective classifications. On this basis it was possible to define a new climate type classification of the earth. Since the beginning of the last century and lasting until today, an increase of the global annual mean temperature of approximately 0.8 K has been observed. This change can be classified as moderate in comparison to the temperature deviations which occurred in the history of the earth. However, this moderate rise in temperature has already remarkable impacts on climate as a complex factor. Because of this fact and the use of the new developed methodology an investigation was carried out to estimate the shifts of single climate types during the observation period.

In principle, one could expect that the “cooler” climate types would give off area to the “warmer” types, in case of an increase in temperature. This could be proved. It is remarkable that the ice and tundra climates have disproportionately lost area when compared to other climate types (Europe – type 7; Asia – types 3, 4, 7; North America – types 2, 6). At the same time, the dry climates in Asia and Africa have significantly expanded (Asia – types 14, 16, 20, 27; Africa – type 27). However, there are considerable gains in the more humid climate types (Europe – type 13; Asia – types 9, 24, 29; Africa – type 24; Australia/Oceania – type 24; North and Central America – types 19, 28; South America – types 24, 25). So, by trend, the development expected by climatologists (e.g., Flohn, 1988) that humid regions will get still more humid and dry ones will still get dryer proves true. It is also remarkable that the percentaged change in area of a climate type is greatest in Europe, in relation to the whole area of the particular continent (type 13 +5.08 %, type 10 −2.43 %). For Asia, all values of change lie below one percent due to the dimension of the continent. In Africa, the maximum gains and losses keep the balance with +2.23 (type 27) und −2.14 % (type 22). For Australia/Oceania, the decrease in type 27 of 3.08 % and the increase in type 30 of 2.70 % are of especial importance. There are only 4 climate types on the whole American continent with changes of above one percent (type 6 = −1.28 %, type 10 = +1.30 %, type 19 = −1.88 %, type 24 = +1.60 %). If one considers the percentaged changes in relation to the whole area of the climate type, the margins of deviation are particularly wide. Their values lie between 0.11 % (Asia, type 19) and 320.69 % (Australia/Oceania, type 23). Altogether, one can state that the shifts in climate regions which have taken place in the investigation period during the last 15 years are a factor that can no longer be neglected for both humankind and environment. This holds true in particular because of the high velocity of the changes observed, and also because of the dimension of these changes in relation to the comparatively short period.

6. References

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