Using maps of city analogues to display and interpret climate change scenarios and their uncertainty

Sebastian Kopf* Minh Ha-Duong† Stéphane Hallegatte‡

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Abstract

We describe a method to represent the results of climate simulation models with analogues. An analogue to a city A is a city B whose climate today represents A's simulated future climate. Climates were characterized and compared non-parametrically, using the 30-years distribution of three indicators: Aridity Index, Heating Degree Days and Cooling Degree Days. Analogy was evaluated statistically with the two-samples Kolmogorov-Smirnov test, generalized to 3 dimensions. We looked at the climate of 12 European cities at the end of the century under an A2 climate change scenario using two high-resolution regional climate simulation models datasets from the Hadley Center and Meteo France. Climate analogues were generally found southward of present locations, a clear warming trend even if much model and scenario uncertainty remains. Climate analogues provide an intuitive way to show the possible effects of climate change on urban areas, offering a holistic approach to think about how cities adapt to different climates. Evidence of its communication value comes from the reuse of our maps in teaching and in several European mass-media.

Keywords: Climate change, Climate analogues, Climate relocation, Urban Areas, Uncertainty

*Jacobs University Bremen, s.kopf@jacobs-university.de, 2006 summer intern at CIRED.
†Corresponding author. Chargé de recherche at CIRED-CNRS. haduong@centre-cired.fr
‡CIRED and CNRM

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1 Introduction

Most Europeans live in urban areas nowadays. In cities, weather patterns interact with the socio-economic structures directly and indirectly in many uncounted and mostly unaccountable ways. Elevated temperatures, particularly during extremes like the 2003 and 2006 summers, have shown the heavy strain on and need for adaptation of sanitary systems, production strategies (above all in construction and agriculture), power supply systems, living comfort and so forth. All these consequences of climate change were not credibly predicted. Their full extent can only be analyzed in retrospect, and because of adaptation and evolution of societies, the next event will be lived differently. An integrated assessment of the impact of future climate change on urban areas would require not only the description of vegetational response to changing conditions, but also an systematic consideration of a large number of heavily interwoven urban attributes which affect the adaptation process, such as architectural styles, transport infrastructure and cultural lifestyles. Defining a convincing reference scenario under these conditions, together with a consistent vision of economic and cultural drivers of the adaptation process, is a daunting task. Predicting the consequences of climate changes on human settlements is impossible.

Hallegatte et al. [2007] suggested an alternative, holistic approach to the assessment of socio-economic consequences of climate change. The authors proposed to search and evaluate current analogues of the future climate of urban areas. In order to think about how city A will be in the future, it suggests to look at how city B is in the present, those current climate is like the simulated future climate of A. This circumvents the obstacle of having to theorize adaptation to the climate change consequences.

The analogue concept is not new, and has indeed been used previously to assess climate change impacts on agriculture [Darwin et al., 1995, Mendelsohn and Dinar, 1999]. This research's contribution is to extend and improve the approach initially proposed by Hallegatte et al. [2007], by presenting a statistical methodology to identify climate analogues. This method is generally applicable to high spatial resolution climate simulation models, computationally light, and does not need heuristics nor hand tuning.

There are two key methodological choices for a climate analogue method. The first is which climate indicators to use. As the next section discusses, climates are characterized here using three indicators: Aridity Index, Heating Degree Days and Cooling Degree Days. The second choice is how to compare climates, statistically. As discussed in Section 3, the proposed method does not rely on averages or on parametric tests, but applies the 3-dimensional two-samples Kolmogorov-Smirnov test directly to the 30-years distribution of the indicators. Section 4 demonstrates applicability by computing analogues for 12 large European cities using data from two high-resolution regional climate simulation models from the Hadley Center and Meteo France. In the concluding section 5, we discuss the method's limits, potential improvements, and communication value in several European mass-media channels.

Three technical appendices describe respectively A/ the parameterization of the K-S test, based on Monte-Carlo simulations in the literature, B/ more detailed results on the comparison between using 3 indicators versus only 2, and C/ the difference between p-value maps versus maps of the KS statistic, that we use preferentially because they offer a better visual contrast.

2 Characterizing climate with indicators

2.1 On indicators

Climate can be defined as the weather conditions in a certain geographical area averaged over a long period of time. A more quantitative definition is needed for a computer-based method. A well accepted approach to characterize climates is to select a few aggregate indicators quantifying the most relevant attributes. Many climate indicators exist [Thornthwaite, 1948], as climates can be defined in different ways for different purposes. For example in agriculture, the total annual evapotranspiration is an important indicator for plant growth whereas in tourism the total number of rainy days might be of primary interest instead. The literature suggests that general-purpose characterizations of climates, such as the Köppen classification, tend to include at least one indicator related to temperature (or energy) and one indicator related to moisture (or water). Holdridge [1947] Life Zone system's popularity shows that three indicators are sufficient to define a useful classification of climates (these zones are usually represented on a two dimensional triangle).

In order to characterize climate from the point of view of its impact on cities and urban life, we considered the combination of the following three climate indicators: annual Aridity Index, annual Heating Degree Days and annual Cooling Degree Days. The annual Aridity Index represents aridity, a key factor defining a climate's vegetation. This index is widely used in the categorization of climate types, and water stress is expected to be a key social impact of climate change too. The Heating and Cooling Degree Days are known to correlate well with the energy demand for heating and air conditioning, respectively. They are actually used in financial markets to settle the price of weather derivatives and futures, or to estimate a building's or a city's energy needs. From an agricultural point of view, they relate directly to the Effective Temperature Sum (ETS) used by Fronzek and Carter [2003] as an energy requirement indicator for crop species sustainability.

Although capturing additional aspects of climate or investigating selected features or particular subsystems of urban areas might require additional indicators, there is a certain trade-off between the exhaustivity of climate description and the applicability of the method of finding climate analogues. We believe that the combination of these three indicators provides a sufficient description of a city's climate to assess the impact of climatic change on urban areas, so we define climate for this study as the 30-years joint distribution of the triple (Aridity Index, Heating Degree Days and Cooling Degree Days). In order to statistically compare climatic (dis-) similarities of different times and places, we assume stationarity, as if the 30 years were drawn from the same unchanging distribution. No assumption is made on the shape of this distribution. The three indicators are defined in principle from daily data, but monthly mean temperature and precipitation data are more readily available. As we show next, they can be computed to a good approximation from monthly data.

2.2 Aridity

Aridity describes the availability of water that plants can use. It is a fundamental indicator for a climate's vegetation, likely to change significantly in a

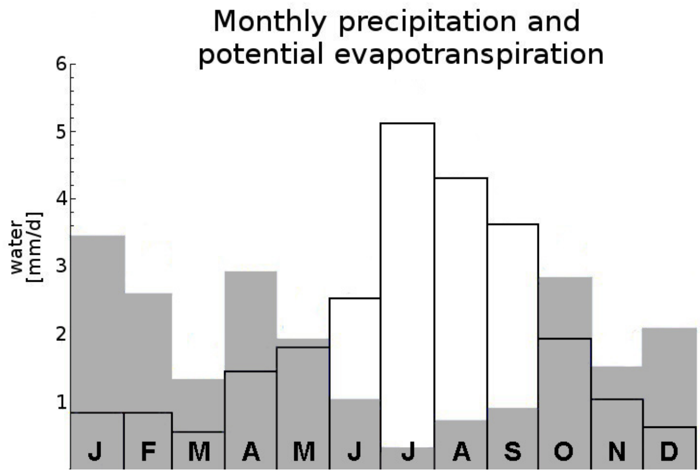


Figure 1: Precipitations and potential evapotranspiration of the simulated climate of Paris in 2071 (HadRM3H model). Absolute aridity is the area above the precipitation and below evapotranspiration bars of the deficient months (hollow rectangles). It is divided by total evapotranspiration of the deficient months to get the aridity index.

changing climate. There are several variants of an aridity index available in literature: absolute or relative, aridity or humidity. For the purpose of describing climates statistically, they are largely equivalent so we settled on the classical Aridity Index AI as defined by Thornthwaite [1948] and reminded below:

In any given month, the water deficit is the difference between the monthly potential evapotranspiration e and the precipitation p which sums up for all water deficient months of a year to the annual water deficit. The annual Aridity Index is defined relative to the total potential evapotranspiration of the deficient months:

$$AI = 100 \, \frac{\sum_{i=1}^{12} \delta_i (e_i - p_i)}{\sum_{i=1}^{12} \delta_i e_i} \begin{cases} \delta_i = 1 \; ; & e_i > p_i \\ \delta_i = 0 \; ; & e_i \leqq p_i \end{cases} \tag{1}$$

Thornthwaite [1948] also provides an empirically derived method for closely estimating the monthly potential evapotranspiration e of a standard month of 30 days in cm from the mean monthly temperature in ℃:

$$e_i = 1.6 \left(\frac{10\, t_i}{I} \right)^a \; ; \; t_i > 0°C \tag{2}$$

with

$$I = \sum_{i=1}^{12} \left(\frac{t_i}{5} \right)^{1.514} \; ; \; t_i > 0°C \tag{3}$$

$$a = 0.000000675 I^3 + 0.0000771 I^2 + 0.01792 I + 0.49239 \tag{4}$$

As the days in a month vary and the number of hours of sunshine per day depend on the seasons and the latitude, Thornthwaite [1948] also introduced an

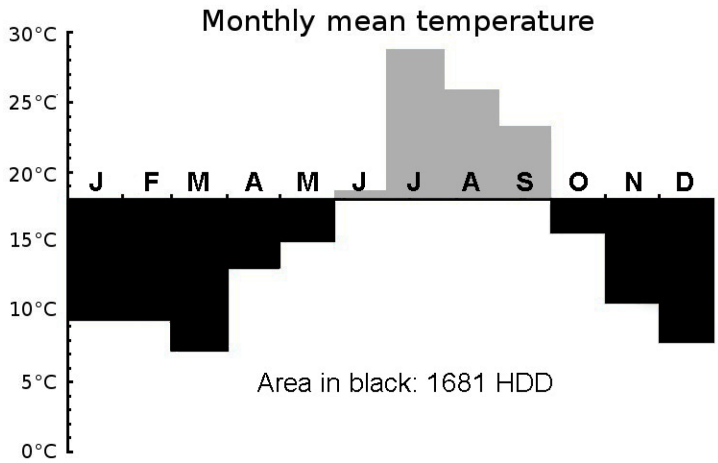


Figure 2: Temperature simulation for Paris in 2071 (HadRM3H model). Cooling Degree Days (CDD) correspond to the area above the 18°C line (grey area). Heating Degree Days (HDD) correspond to the area below the 18°C line (black area).

adjustment factor for the above calculated unadjusted potential evapotranspiration. In the present work, we neglected this adjustment but follow-up studies should investigate this aspect.

2.3 Cooling and heating degree days

Heating and cooling degree days (HDD and CDD) can be seen as measures of heating and air conditioning needs, respectively. They are based on the simple idea that heaters (or air conditioners) are turned on when temperature drops below (or rise above) a reference temperature b, commonly set at 18°C. They are doubly relevant for the climate change issue: changes in their distributions are an expected important impact. And they also matter for mitigation, since empirically degree days characterize households' energy consumption very well. Mathematically, annual heating and cooling degree days are defined as follows:

$$HDD = \sum_{i=1}^{365} \delta_i (b - t_i) \begin{cases} \delta_i = 1 \; ; & b > t_i \\ \delta_i = 0 \; ; & b \leqq t_i \end{cases} \tag{5}$$

$$CDD = \sum_{i=1}^{365} \delta_i (t_i - b) \begin{cases} \delta_i = 1 \; ; & t_i > b \\ \delta_i = 0 \; ; & t_i \leqq b \end{cases} \tag{6}$$

Although by definition based on a daily difference to the base, observing that the daily temperature distribution has a known shape, it is possible to estimate monthly degree days statistically from monthly temperature means, neglecting Schaer et al. [2004]'s suggestion that climate change will alter this known shape. Thom [1954, 1966] proposed a method to calculate the normal degree days above (CDD) or below (HDD) any base as follows:

$$N\,\bar{D}^{\pm} = N\,[l^*(\mp x_0)\sqrt{N}\sigma_m \pm (t - b)] \tag{7}$$

where $\bar{D}^+$ are degree days above a base (i.e. Cooling Degree Days) and $\bar{D}^-$ are degree days below a base (i.e. Heating Degree Days), N is the month length in days, σ_m is the standard deviation of monthly average temperature (which was calculated in our case from the average monthly temperatures over several years as available), b=18°C is the base, and x_0 and l^* the so-called truncation point and truncation coefficient, which are related empirically and after Thom [1966] calculated with an exponential approximation as follows:

$$x_0 = \frac{b-t}{\sqrt{N}\sigma_m} \quad (8)$$

$$l^*(x_0) = 0.34e^{-4.7x_0} - 0.15e^{-7.8x_0} \quad (9)$$

$$l^*(-x_0) = l^*(x_0) + x_0 \quad (10)$$

3 A statistical measure of climates similarity

3.1 The 1-Dimensional two sample Kolmogorov-Smirnov test

The Kolmogorov-Smirnov test is a commonly used and relatively simple non-parametric statistical test. It can be used to examine if a sample comes from a known distribution, or to examine if two samples come from the same unknown distribution. Our use is the later: to compare climates from two different places and periods, using samples of 30 years. In its basic univariate case, the Kolmogorov-Smirnov statistic D is defined as the maximum vertical distance between the cumulative distribution functions of the two samples. This is illustrated in figure 3 for the cumulative distribution of the 30 annual aridity indices of the climate of Paris from 2071 to 2100 and the climate of the southern Italian city Barletta from 1961 to 1990 respectively (aridity indices computed using the results of the HadRM3H model simulation.)

The basic idea of the test is the following. When one draws two samples of numbers according to a given probability distribution f, the cumulative distribution curves of the two samples will both tend to fall around the same PDF curve of f. Thus, if one cannot expect D to be exactly 0, one can expect it to be small. But when one draws two samples according to very distinct probability distributions, respectively f and g, the cumulative distribution curves of the two samples will tend to fall around the PDF curves of respectively f and g. If these curves are well apart, one can expect the statistic D to be close to 1. To illustrate with an extreme case, if numbers drawn according to f are known to lie within [1, 2] and numbers drawn according to g are in [3, 4], then certainly the distance will be 1.

Monte-Carlo simulations allow to compute empirically the frequency distribution p of the K-S statistic D for two samples of 30 drawn from the same distribution f to any useful precision. The key to the K-S test is that p does not depend too much on the shape of f itself. Thus, the K-S is non parametric, as no assumption need to be made on the unknown distribution[1]. Figure 4 displays the distribution according to the literature.

[1] Fasano and Franceschini [1987] show for the 2- and 3-dimensional case the correlation between the multiple variables to be the sole dependency.

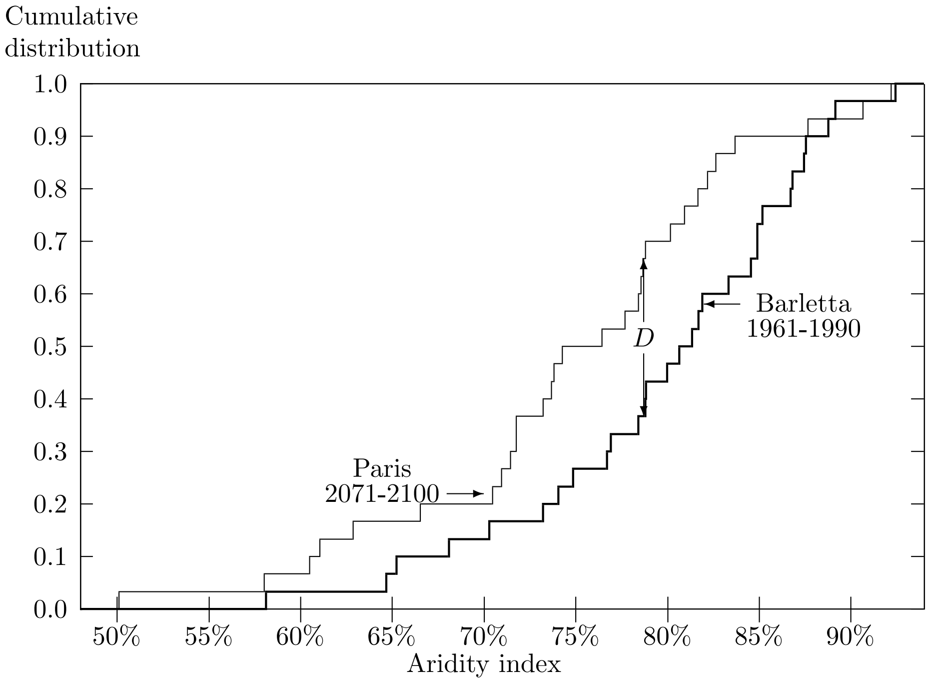


Figure 3: Cumulative Probability Distributions of the Aridity index for Paris (2071–2100) and the southern Italian city Barletta (1961–1990), data from HadRM3H model. The Kolmogorov-Smirnov statistic D is the maximum vertical distance between the two curves.

The Kolmogorov-Smirnov distance D allows to compute an absolute measure of similarity between two samples, using statistical testing theory. In technical language, the probability that two samples drawn from the same distribution have a K-S statistic at least as a great as D is called the p-value. For example, the p-value of two identical samples ($D = 0$) is $p = 1$. When the p-value is small there is reason to reject the hypothesis that the two samples come from the same distribution. On the contrary, the larger p, the more reason there is to believe (or accept the hypothesis) that the two samples where indeed drawn from the same distribution.

3.2 The 2-D and 3-D Kolmogorov-Smirnov test

The classical K-S test exposed above deals with real-valued variables (i.e. is 1-dimensional). However, we characterize climates with three indicators, so we have to test the joint probability distribution of the triple (AI, HCC, CDD). Generalization is not trivial because in higher dimensions there is no obvious total ordering relation, so the notion of cumulative distribution is not immediately applicable. We used Peacock [1983], Fasano and Franceschini [1987] generalization of the K-S test for two and three dimensions.

In the case of two-dimensional samples, each data point is a pair of numbers, such as (AI, CDD) for example. Peacock [1983] approach is best understood graphically, as illustrated in figure 5 for the combination of annual Aridity Index and annual Cooling Degree Days over 30 years of the climate of Paris from 2071 to 2100 and the climate of Barletta, Italy, from 1961 to 1990. It replaces the

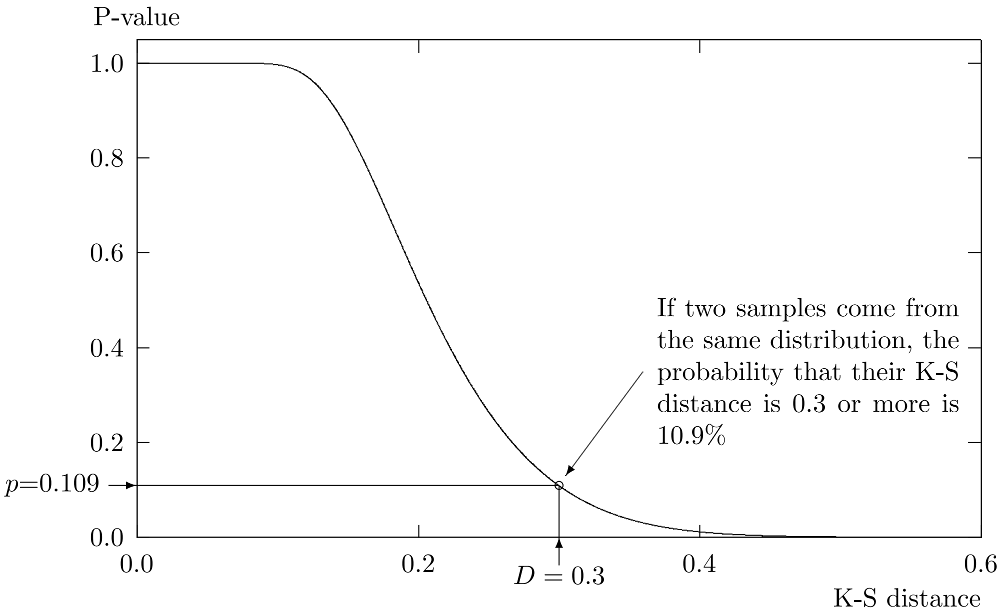


Figure 4: The p_{value} as a function of the K-S statistic D after Press et al. [1992]. It measures on an absolute scale (between 0 and 1) how likely it is for two samples to be drawn from the same distribution i.e. in our case, how well the two climates, as described by the indicator, correspond.

cumulative probability distribution with a description of the integrated probability in each of the 4 quadrants around a given *reference point* (x,y) of the sample. Practically, each data point of the sample is successively used as the reference point. For each such reference point, the relative frequencies for the two samples are calculated in each quadrant, as the ratio of the number of data points in the quadrant to the total number of data points. Finally, The K-S statistic D between two samples is the maximum difference of the relative frequencies in the 4 quadrants, when considering successively all data points as the reference point.

Generalizing the 2-dimensional version of the K-S statistic D to the 3-dimensional case is straightforward. Each data point is a triple, for example (AI,CDD, HDD). These data points can be seen as a cloud in the 3-dimensional space. There are 8 octants in the space around each data point instead of 4 quadrants in the plane. The K-S statistic D between two sample distributions is taken as the maximum difference of the relative frequencies when considering the 8 octants around and all data points.

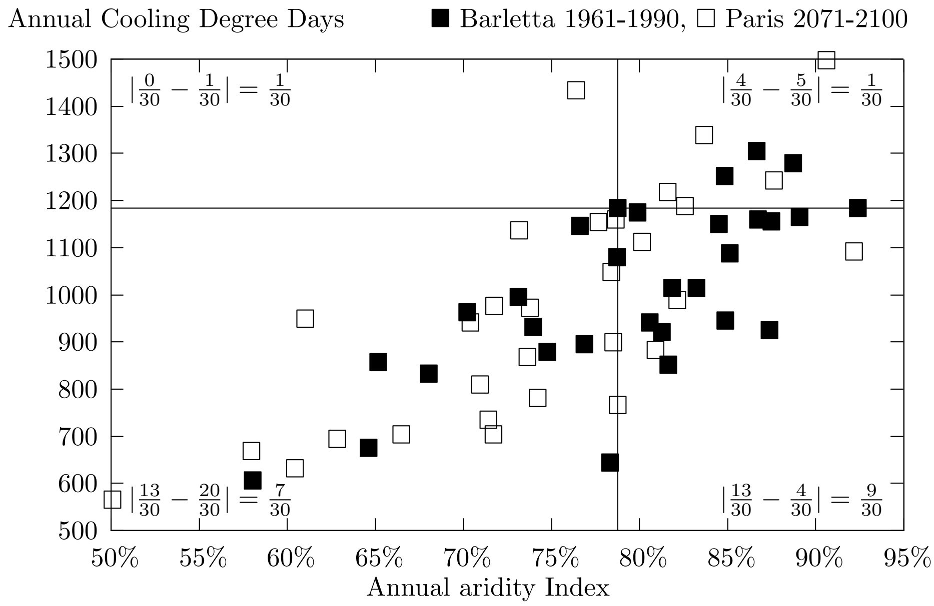


Figure 5: Spatial distribution of the combination of the two climate indicators annual Aridity Index and annual Cooling Degree Days from 30 years for Paris (2071–2100) and the southern Italian city Barletta (1961–1990), data from HadRM3H model. The Kolmogorov-Smirnov statistic D is the maximum difference of the integrated probabilities of the two distributions in the 4 quadrants around each data point. The figure displays this calculation with one data point as a reference. To find the maximum the same calculation is performed for all data points.

For statistical testing, the translation of the K-S statistic D into the p_{value} in the multi-dimensional cases is based on the same Monte-Carlo methods as in the 1-dimensional case. Technically, given a distance D measured between two tested samples, the p_{value} is the probability that the K-S distance between two samples randomly drawn from the same distribution is greater than D. It describes how well the two samples are similar, or could come from the same probability distribution. In other terms, the p_{value} is the likelihood that the two samples are two realizations from the same probability distribution. In our case, it also means how well two climates, as described by multiple indicators, coincide. Technical details on the probability distributions used in the 2- and 3-dimensional cases are shown Appendix A.

3.3 Analogue Filtering, Selection and Visualization

The selection of the best current analogue to a city's future climate amounts to searching for a local minimum in D. We used the two additional filters.

First, only grid points in the model with a p_{value} greater than 0.5 were considered acceptable for further evaluation. Locations that reject the "same climate" hypothesis at a 50% confidence level were not acceptable. According to the usual practice of statistical testing at 95%, this is a quite low confidence level. But the purpose is not to test for all analogs, only to simplify further computations by filtering out a large fraction of grid cells. When no grid cell is acceptable, the search simply fails.

Second, we penalized narrow optima by applying a lowpass spatial filter before minimizing the D field. The filter combined the score of a cell with a 0.5 weight, with the score of its four cardinal neighbors located at plus or minus 0.5° latitude/longitude, using a 0.125 weight. Neighbors were obtained by interpolation when the datagrid made it necessary. The justification for this smoothing is heuristic. The analogue is meant to represent a climate to readers who have a fuzzy mental representation of European climates. This goal is better accomplished when the optimum is within a large region of good analogues.

The optimum was found using exhaustive search, as this is nonconvex optimization with a finite, computationally tractable number of points (one per grid cell). Compared to Hallegatte et al. [2007], no further heuristic arbitration between candidate optima was needed. The smallest smoothed K-S statistic at an acceptable location was considered the best analogue. It was then possible to name the analogue according to the closest meteorological station or city.

Based on this method, two kinds of maps were drawn. The first kind is the “climate analogues” map, shown Figure 7. It shows where one can find today the future climate of a given city, by mapping the K-S statistic D on a regular grid of Europe, at the resolution of the original dataset, using interpolation when the original dataset is not on a rectangular grid. Appendix C discusses why we choose to display D instead of the p-value. This kind of map allows to check visually the quality of the "best" analogue, which is necessary since it involves nonconvex local minimization.

A second kind of map is the "climate relocation" map. It is obtained by selecting a set of cities, and displaying where their best analogue lies on a common map of Europe, see Figure 8. These maps allow to communicate the directions and order of magnitude of climate changes expected over the course of the century. They also convey a disturbing feeling of otherworldliness by mapping the cities well away from their actual location. In order to convey the uncertainty related to climate simulations, it is important to always show several such maps obtained by different models or emissions scenarios.

4 Application

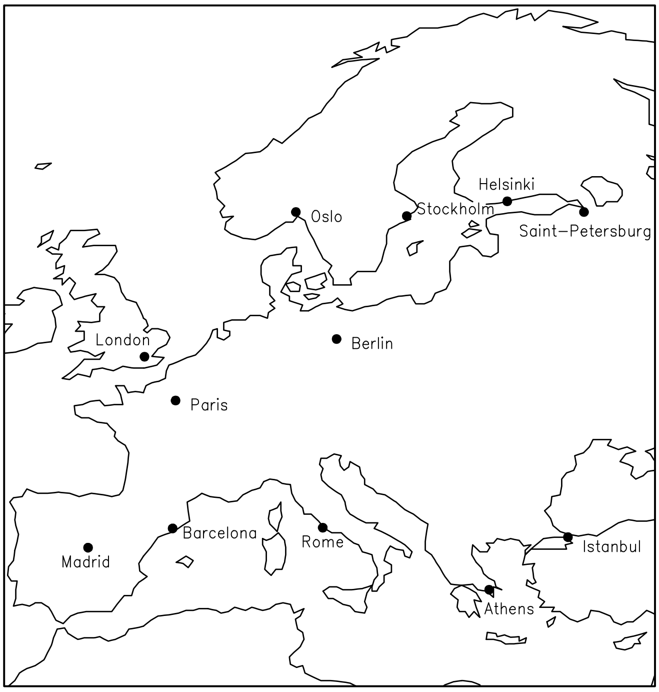


Figure 6: Cities examined in this paper

4.1 Data and implementation

The method was implemented in Fortran, using g77 with the GrADS, NetCDF and CDO libraries. For cities coordinates, we took the list of stations from the Global Historical Climatology Network 2 dataset. The code uses resources from Press et al. [1986], is released under the GPL and available from the CIRED web site[2]. It can be parameterized to examine most big cities in Europe. For this paper, we examined analogues for 12 large European cities: Athens, Barcelona, Berlin, Helsinki, Istanbul, London, Madrid, Oslo, Paris, Rome, Saint-Petersburg and Stockholm, as shown Figure 6.

The key inputs needed are regional 2D fields of mean monthly surface temperatures and precipitations. Data should be at relatively high spatial resolution, about 50 km grid. It should cover two 30 years spans, in order to compare the present and the future climates. Finally, it should cover a reasonably wide latitudinal zone, since warmer climates are to be found southward.

We used two climate simulation datasets from models of the PRUDENCE project. One is the ARPEGE-Climate model from CNRM/Météo-France, a global circulation model with a variable horizontal resolution of up to 50km in Europe. The other is the HadRM3H model from the Hadley Center, a regional model with a 50-km resolution, forced by the global circulation model

[2]http://www.centre-cired.fr

HadAM3. Both models simulate a warming over Europe with an increase in precipitation in the North and a strong drying over the Mediterranean. The global warming predicted by the HadRM3H model is stronger than the one from the ARPEGE model but both lie within the range of the IPCC predictions. They both provided monthly mean temperatures and precipitations over 30 years in the present climate (1961–1990) and the projected future climate (2071–2100).

4.2 Comparing two versus three indicators

We compared empirically the results of the method as described above, based on a 3-dimensional K-S test using three indicators (Aridity Index and both Degree Days), with a simplified version using only two indicators (and a 2-dimensional K-S test). There are three possible ways to pick two indicators out of three, but theoretically it is hardly defensible to throw away the Aridity Index and keep only the two temperature-based indicators. This is why we tested only (AI, HDD) and (AI, CDD).

Figure 7, based on the HadRM3H model simulation, allows to compare for Paris and Saint-Petersburg the climate analogues maps computed with three and two indicators. Logically, it can be seen that the former is like the fuzzy intersection of the later two.

The analogue location selected by the 3D test is also relatively good when tested with the 2-dimensional criteria, whereas the converse is not necessarily true. For example for Paris, the testing method with all 3 indicators found the best climate analogue close to the small Spanish city of Badajoz at the Spanish-Portuguese border with a p_{value} of 90%. This location also evaluates to a p_{value} of 100% in the 2-dimensional test with Aridity Index and Heating Degree Days as well as a p_{value} of 75% in the 2-dimensional test with Aridity Index and Cooling Degree Days.

Also, the best analogue with (AI, CDD) may be a poor one when seen with (AI, HDD) or vice versa. In the same example, the locations of the best analogues found by either of the 2-dimensional tests (for the test with Aridity Index and HDD located in the Black Sea and for the test with Aridity Index and CDD close to the Spanish city of Ciudad-Real) evaluate to a p_{value} of 0% in the other test. This example is representative of all 12 examined cities, see Appendix B.

In short, the results are not only theoretically but also empirically more satisfying using 3 indicators, and since the supplementary computational cost is modest, there is no reason to use just 2. We did not look beyond three, but in some case this may be useful, because in many case there are several analogues approximately as good as each other. See for example all dark gray areas in Figure 7 for cities like Paris and Saint-Petersburg. Possible extensions, to name only a few, would be for example an indicator for seasonality to account for urban adaptation to seasonal variations, elevation in order to consider climatic particularities at different altitudes or distance to the sea to take into account marine influences, which might not be well reproduced by models with a 50-km resolution.

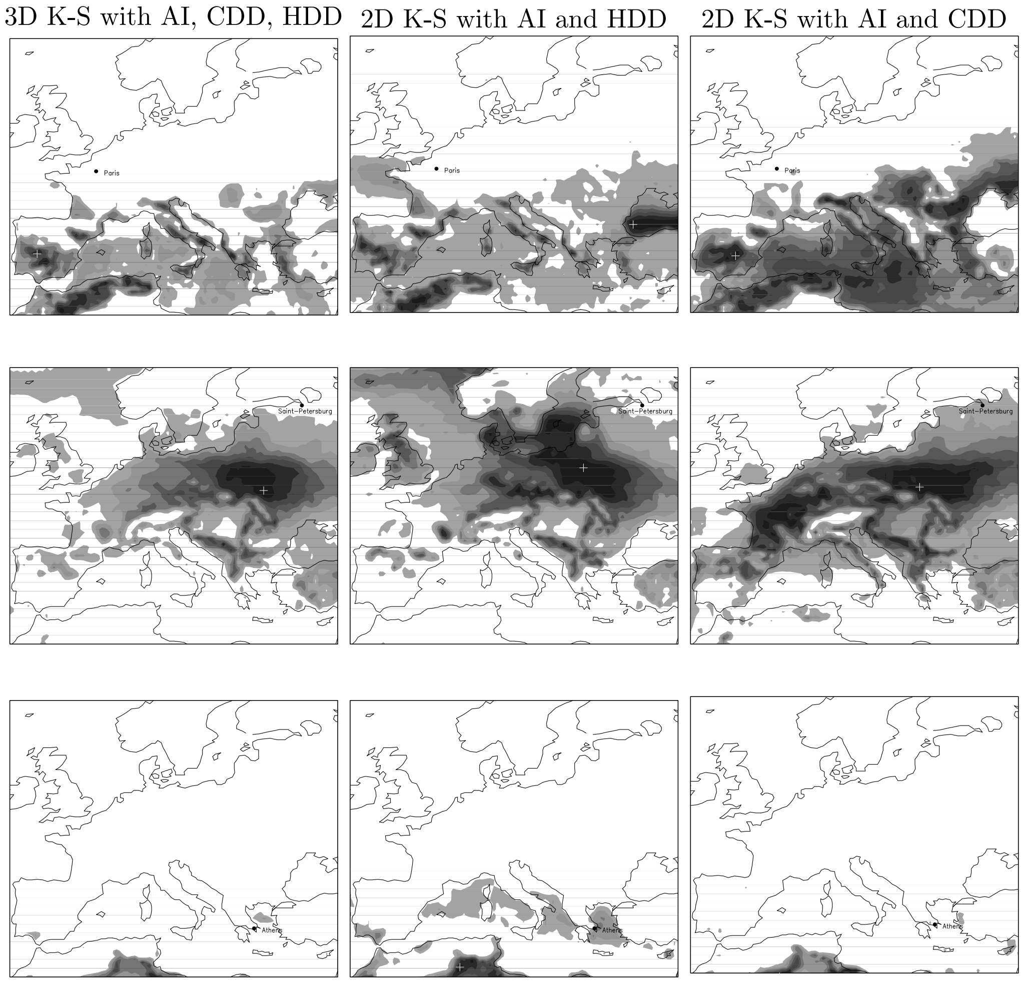
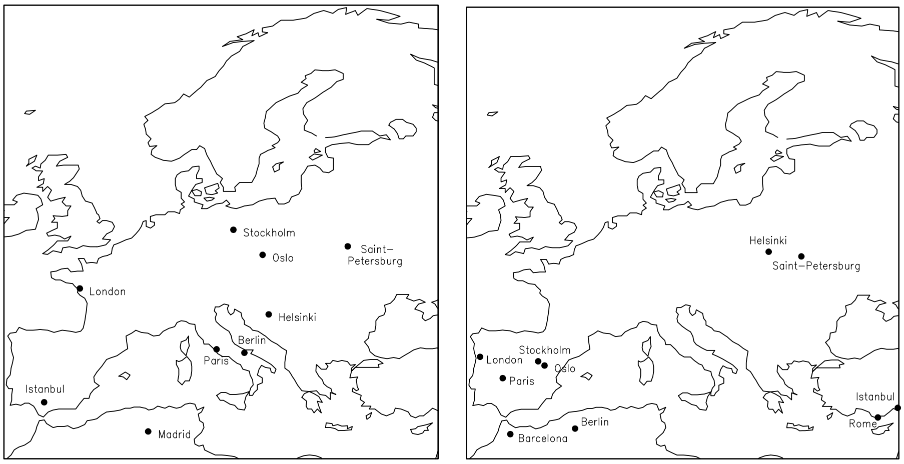


Figure 7: Comparison of the 3-dimensional K-S statistic results (with Aridity Index, HDD and CDD) and the two 2-dimensional K-S statistic results (with Aridity Index and HDD/CDD respectively) for Paris, Saint-Petersburg and Athens. Respective city's actual location indicated on each map along with a white cross for the best climate analogue (if existent). (HadRM3H model simulation)



(a) Analogues: ARPEGE

(b) Analogues: HadRM3H

Figure 8: Relocation of European climates at the end of the 21st century, analogues found with the ARPEGE and the HadRM3H dataset in a global warming scenario.

4.3 Climate relocation maps

Variability in the prediction of future climate arising from the stochastic nature of climatic processes is accounted for, but deeper uncertainties remain. Climate relocation maps can be used to compare the output of climate models and to understand the differences between climate change simulations better. Figure 8 compares the analogues found for the different datasets: the ARPEGE and HadRM3H models projecting global warming. Figure 6 was the reference map of actual locations of the examined 12 cities in Europe.

Comparing the analogues found in the case of the ARPEGE and HadRM3H models, which are two leading climate simulations model, allow to see the extend of the remaining uncertainty in climate change prediction for Europe. Both models however agree in showing a clear southward drift in the climate analogues. This supports the expected effect of global warming on European local climates towards the end of the century, under the A2 greenhouse gases emission scenario.

5 Conclusion

We described a method to analyze the results of climate simulation models, improving on Hallegatte et al. [2007]. It is based on the concept of climate analogues, i.e. finding a City B whose present climate statistically corresponds to the simulated future climate of an evaluated City A. This provides an intuitive visualization of climate change effects on urban areas, by replacing the change of climate (in time) with a change of a city's location (in space). Through the use of several models and scenarios, this approach also allows to clarify the extend of the uncertainty in climatic change predictions, and in their effects on urban areas.

Climates were characterized using three annual indicators: Aridity Index, Heating Degree Days and Cooling Degree Days. These indicators can readily be computed from monthly precipitation and temperature datasets. To compare climates, we compared 30-years time series of these indicators using the two sample tri-dimensional Kolmogorov-Smirnov tests. We found that using 3 instead of only 2 climate indicators provided an heuristically more satisfying analogue selection, at the cost of a moderate increase in computational complexity.

Using two datasets, analogues for 12 European cities were computed: Athens, Barcelona, Berlin, Helsinki, Istanbul, London, Madrid, Oslo, Paris, Rome, Saint-Petersburg and Stockholm. Two climate simulation models projecting different degrees of global warming for the A2 emissions scenario were used: The ARPEGE model from CNRM/Météo-France and the HadRM3H model from the Hadley Center. Both show a clear southward drift in climate relocation for Europe.

The analogues of Paris are representative of the kind of scientific policy-oriented message this method provides: according to one simulation, Paris could have at the end of the century the climate of Bordeaux. That may not be seen as an adverse change by many stakeholders. However, according to another simulation, Paris could also have the climate of the city of Badajoz in Southern Spain. It is widely held that heat waves and water shortages, which were not considered as a significant problem in Paris only ten years ago, are nowadays reccuring sources of trouble in the Badajoz area. This work illustrates, therefore, how new climate-related problems will appear in numerous cities because of climate change. The related evolution of natural risks has to be managed in the most proactive ways to avoid the repetition of costly surprises like the 2003 heat wave in Europe and its dramatic consequences.

In some cases no suitable analogue for the projected climate of a given city were found. This indicates a lack of the type of climate projected for the city within Europe, at a 50% confidence level. For example, Athens lacks a good analogues on figure 7. It can only be supposed that a suitable analogue might be found further south. An obvious extension of this work would be to search potential analogues not only within Europe but worldwide. Another would be to search the analogue using climatological observation data instead of model-based datasets.

Evidence of this method's communication value comes from its use in teaching and in European popular science and mass media [Kopf et al., 2007, Hallegatte, 2007, Adam, 2007]. In the absence of any fully integrated socio-economic simulations for future scenarios, climate analogues provide a rigorous way to frame the climate change issue on cities and provide an estimate of the extent of uncertainty in the prediction of climatic changes. It allows socio-economic adaptation to different climates to enter the mental model.

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References

David Adam. Heat, dust, and water piped in from Scotland. Welcome to London 2071. Climate change map sends 12 capitals further south. Warning to planners on future design of cities. *The Guardian*, May 15th 2007. URL `http://environment.guardian.co.uk/climatechange/story/0,,2079750,00.html`.

Roy Darwin, Marinos Tsigas, Jan Lewandrowski, and Anton Raneses. World agriculture and climate change: Economic adaptations. Technical Report AER-703, U.S. Department of Agriculture, June 1995. URL `http://www.ers.usda.gov/publications/aer703/`.

G. Fasano and A. Franceschini. A multidimensional version of the kolmogorov-smirnov test. *Monthly Notices of the Royal Astronomical Society*, 225:150–170, 1987.

S. Fronzek and T.R. Carter. Mapping shifts in crop suitability under a range of sres-based climate. Prudence Progress Report, 6 pp. Draft report. 3rd meeting report, p. 47: http://prudence.dmi.dk/public/Minutes.Wengen03.pdf, January 2003.

Stéphane Hallegatte. Le GIEC réuni cette semaine à Bruxelles. “Accepterons-nous un Paris climatisé à l’américaine ?”. *Libération*, 3 avril 2007. URL `http://www.liberation.fr/actualite/terre/245177.FR.php`. Propos recueilli pas Sylvestre Huet.

Stéphane Hallegatte, Jean-Charles Hourcade, and Philippe Ambrosi. Using climate analogues for assessing climate change economic impacts in urban areas. *Climatic Change*, 82(1–2):47–60, May 2007. doi: 10.1007/s10584-006-9161-z. URL `http://www.centre-cired.fr/forum/article238.html`.

L. R. Holdridge. Determination of world plant formations from simple climatic data. *Science*, 105(2727):367–368, 1947.

Sebastian Kopf, Stéphane Hallegatte, and Minh Ha-Duong. L’évolution climatique des villes européennes. Climat: Comment éviter la surchauffe ? Dossier Pour la Science 54, 48–51, January / March 2007. URL `http://www.pourlascience.com/`.

Robert Mendelsohn and Ariel Dinar. Climate change, agriculture, and developing countries: Does adaptation matter? *The World Bank Observer*, 14(2): 277–293, August 1999.

J. A. Peacock. Two-dimensional goodness-of-fit testing in astronomy. *Monthly Notices of the Royal Astronomical Society*, 202:615–627, 1983.

William H. Press, Brian P. Flannery, Saul A. Teukolsky, and William T. Vetterling. *Numerical recipes – the art of scientific computing.* Cambridge University Press, 1986. ISBN 0-521-30811-9. Includes code in both Fortran and Pascal.

William H. Press, Saul A. Teukolsky, William T. Vetterling, and Brian P. Flannery. *Numerical Recipes in Fortran77: The Art of Scientific Computing.* Cambridge University Press, 2 edition, 1992. ISBN 0-521-43064-X. Includes code in Fortran77.

C. Schaer, P. D. L. Vidale ane C. Frei, C. Haberli, M. Liniger, and C. Appenzeller. The role of increasing temperature variability in european summer heatwaves. *Nature*, 427:332–336, 2004.

H. C. S. Thom. The rational relationship between heating degree days and temperature. *Monthly Weather Review*, 82(1):1–6, 1954.

H. C. S. Thom. Normal degree days above any base by the universal truncation coefficient. *Environmental Data Service, Environmental Science Services Administration, Washington, D.C.*, July 1966.

C. W. Thornthwaite. An approach toward a rational classification of climate. *Geographical Review*, 38(1):55–94, 1948. URL `http://links.jstor.org/sici?sici=0016-7428\%28194801\%2938\%3A1\%3C55\%3AAATARC\%3E2.0.CO\%3B2-O`.

Appendix A: Parameterization of the Kolmogorov-Smirnov tests

To determine the p_{value} corresponding to a value of the 2 and 3-dimensional Kolmogorov-Smirnov statistic D, we derived a set of sample probability distributions from the procedure and data reported in Appendix A and B of Fasano and Franceschini [1987], and calculated the appropriate approximation formulae for each needed sample size (and a variety of correlation coefficients) through third order polynomial interpolations using an appropriate function from Press et al. [1986]. In the 2-dimensional case, data points of the probability distribution for the needed sample sizes were calculated using the polynomial expansion proposed by Fasano and Franceschini [1987] for the 2-dimensional Kolmogorov-Smirnov test. In the 3-dimensional case, the data points for the needed sample sizes were obtained by linear interpolation of the data calculated by Fasano and Franceschini [1987] with Monte Carlo simulations. The range of correlation coefficients covered (in both the 2 and 3-dimensional case) were CC=0, 0.5, 0.6, 0.7, 0.8 and 0.9 as values between 0 and 0.5 do not differ significantly from the uncorrelated $CC = 0$ case[3]. As our calculations with the three climate indicators Aridity Index, HDD and CDD in the 3-dimensional test did not yield partial correlation coefficients exceeding 0.95, the average $\overline{\varrho}$ of the 3 CC could be used [Fasano and Franceschini, 1987]. Table 1 and 2 report the constants of the derived polynomials for the 2 and 3-dimensional case of the main scenario of sample distributions with 30 samples (i.e. annual Aridity Index and Degree Days over 30 years). Sample points and polynomial estimates for the main scenario are furthermore visualized in figure 9 and 10. All polynomials have the form:

$$p_{value}(d) = \begin{cases} 1.0, & \text{if } d < d_{\min} \\ c_1 d^3 + c_2 d^2 + c_3 d + c_4, & \text{if } d \in [d_{\min}; d_{\max}] \\ 0.0, & \text{if } d > d_{\max} \end{cases} \tag{11}$$

CC	$d_{\min}$	$d_{\max}$	c_1	c_2	c_3	c_4
0.0	0.222	0.462	-32.134	52.213	-27.686	4.825
0.5	0.219	0.459	-32.138	51.894	-27.336	4.733
0.6	0.216	0.457	-29.879	49.164	-26.191	4.563
0.7	0.211	0.454	-29.759	48.448	-25.569	4.417
0.8	0.202	0.448	-30.900	48.514	-24.890	4.202
0.9	0.185	0.436	-31.123	46.797	-23.101	3.766

Table 1: Polynomial constants of the probability distribution approximation for the 2-dimensional case

[3] Fasano and Franceschini [1987]

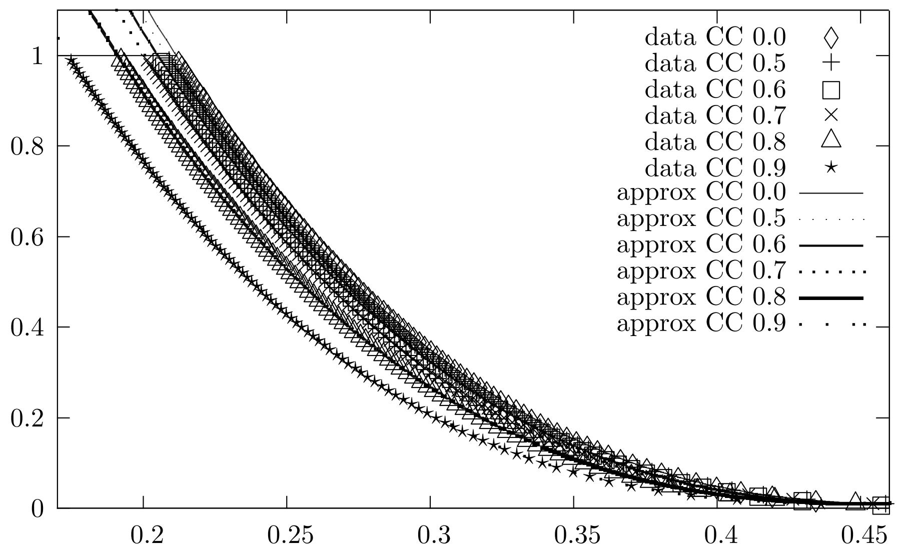

Figure 9: Sample points and polynomial estimates of the probability distribution for the 2-dimensional case

CC	$d_{\min}$	$d_{\max}$	c_1	c_2	c_3	c_4
0.0	0.234	0.468	-26.314	49.131	-28.606	5.334
0.5	0.225	0.467	-37.054	59.458	-31.334	5.450
0.6	0.220	0.464	-35.685	57.477	-30.257	5.240
0.7	0.211	0.458	-36.224	56.879	-29.311	4.984
0.8	0.203	0.454	-49.571	69.975	-33.069	5.239
0.9	0.190	0.443	-56.376	74.752	-33.367	5.023

Table 2: Polynomial constants of the probability distribution approximation for the 3-dimensional case

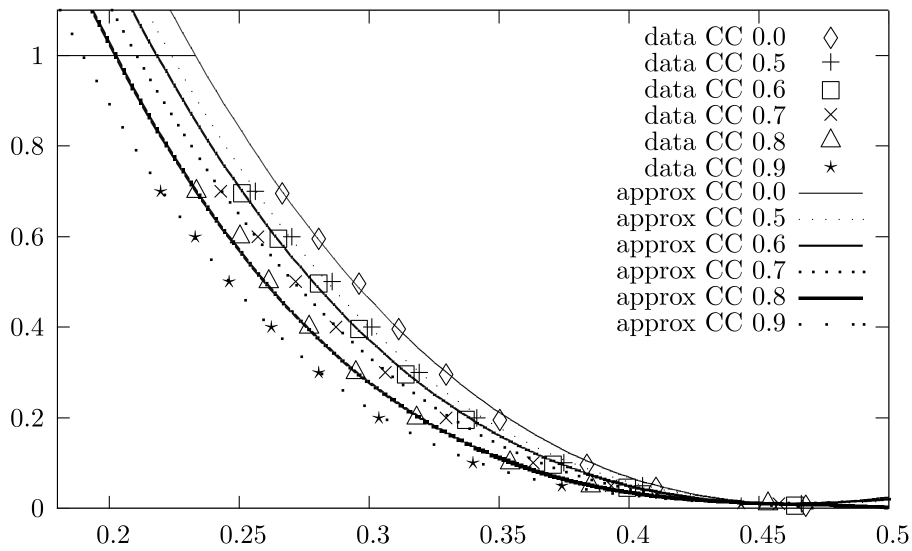

Figure 10: Sample points and polynomial estimates of the probability distribution for the 3-dimensional case

Appendix B: Comparing three versus two climate indicators

We compared the results obtained using a 3-dimensional Kolmogorov-Smirnov test on the 3 climate indicators Aridity Index, Heating Degree Days and Cooling Degree Days with results obtained using only a 2-dimensional test on Aridity Index plus either kind of Degree Days. In a given column, the number is the p-value of the optimal analogue, and the three black rectangular bars display the p-value of same location with respect to the three criteria. Table 3 below allows to check that for the 12 European cities examined in this study, results are as expected:

- Analogues found with the three indicators are not as good as analogues found with only two indicators, in absolute terms. For example, Stockholm has an excellent match ($p \approx 100\%$) with either (AI,CDD) or (AI,HDD), but only a good match (61%) with the complete set of criteria.
- Analogues found with the complete set of 3 criteria, in the first column, are also good analogues when tested with only two criteria. In the left-most column, all 3 black bars are generally high. This shows the good performance of the locations found by the 3-indicators test for all three testing methods.
- The converse is not true. In the middle and right column, it is generally the case that only the bar of the maximized criteria is good. This means that the climate analogue would be rejected when tested with any of the two other set of indicators.

This supports our choice to use three climate indicators instead of only two.

City	3D test	2D test with HDD	2D test with CDD
Athens	no good analogue	El Arfiane 95%	Ghardaia 77%
Barcelona	Ouezzene 100%	Tunis/Carthage 79%	Bordj Bou Arrer 74%
Berlin	Orleans Ville 61%	Cahors 100%	Sremska Mitrovi 91%
Helsinki	Sandomierz 90%	Przemysl 100%	Tours 100%
Istanbul	Karaman 61%	Laghouat 95%	Laghouat 77%
London	Vila Real 90%	Ciudad-Real 100%	Lubny 100%
Madrid	no good analogue	Geryville 63%	El Aliod 77%
Oslo	Teruel 61%	Iasi 100%	Zlynka 100%
Paris	Badajoz 90%	Kumkoy 100%	Ciudad-Real 71%
Rome	Nicosia 61%	Sagres 79%	Djelfa 100%
Saint-Petersburg	Ternopol 100%	Siedlce 100%	Sandomierz 100%
Stockholm	Soria 61%	Oradea 100%	Zlynka 100%

Table 3: Quality of different optima (as measured by p-value) obtained using three or two climate indicators.

Appendix C: Displaying K-S statistic D instead of the p-value

For visualization of the Kolmogorov Smirnov test results, we have chosen to display the K-S statistic D rather than the corresponding p_{value}. The relationship between D and p is obviously monotonous, so mathematically no information is loss, and it does not matter for the location of the optimum best analogue.

Figure 11 illustrates the difference between a D map and a p map. Admittedly, displaying p-values would be more meaningful to the statistician theoretically. But to everyone else, the K-S statistic gives a better visual indication of graduated differences between climates. This is because, as 4 shows, the $p(D)$ function is very nonlinear. Lower values of D give practically $p = 1$, and higher values give $p = 0$. Therefore, displaying p tends to produce more categorical maps of "good" versus "poor" analogues, while displaying D produce more gradual, esthetically pleasing maps. Figure 12 shows the 3-dimensional K-S statistic for all 12 examined cities (HadRM3H model simulation).

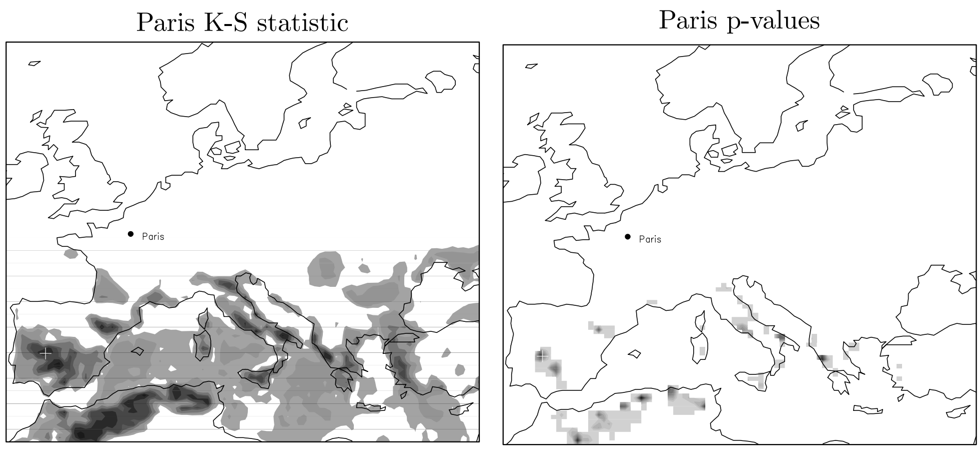

Figure 11: Visualization of the results of the 3-dimensional K-S test (HadRM3H model simulation) by means of visualizing the K-S statistics D and probabilities p_{value} in contrast.

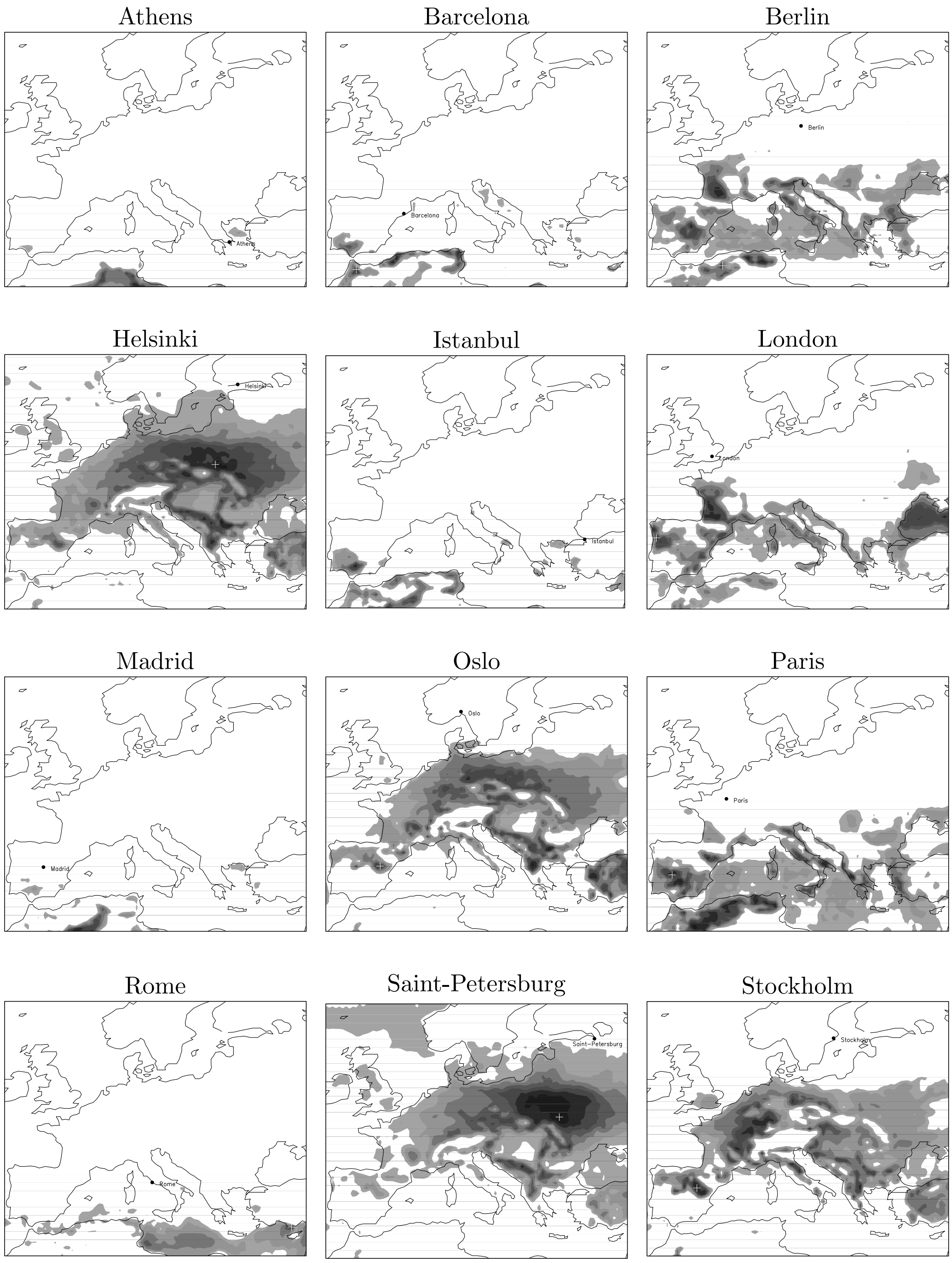

Figure 12: Visualization of the 3-dimensional K-S statistic for all 12 examined cities (HadRM3H model simulation)