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Homogeneity Assessment and Correction Methodology for the 1980-2022 Daily Temperature Series in Padua, Italy

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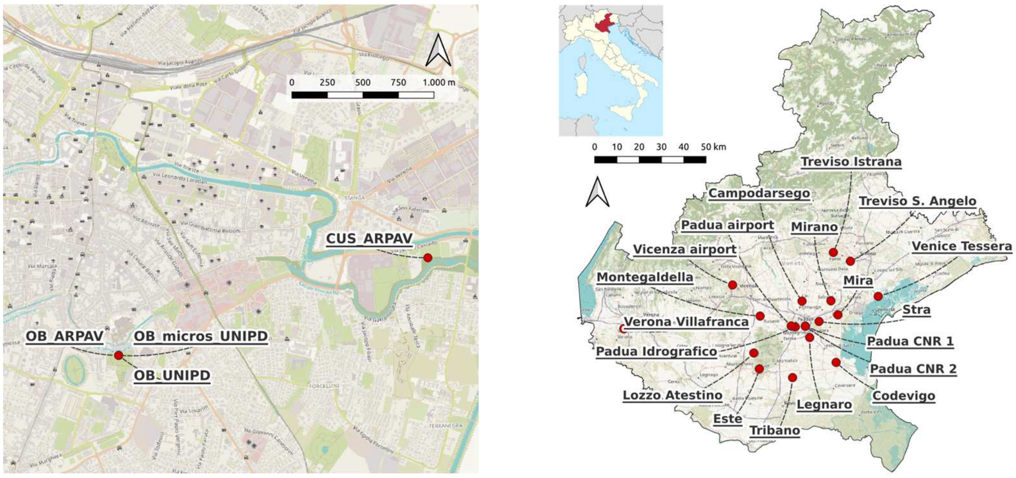
Abstract: Meteorological observations over the last four decades are of paramount importance to investigate the ongoing climate change. The assessment of the reliability of any climatic time series is thus mandatory to draw correct conclusions. This evaluation involves homogeneity tests to detect artificial discontinuities whose identification is facilitated by metadata availability. In this work, daily minimum and maximum temperature measurements collected in Padua, Italy, between 1980 and 2022, are examined. Hourly observations began in 1993 and since the aim is to study long term behavior of the temperature, the focus is on daily averages and extremes. Over this period, the weather station of Padua center underwent many changes, in location or instrument; therefore, some tests have been used to identify and remove the effects of these variations and obtain a homogeneous time series. The homogeneity tests applied must be able to identify change-points both in the middle and at the extremes of the series. Some well-known absolute tests have been applied to investigate shift in the mean value: Standard Normal Homogeneity test (SNH), Buishand U and range tests, Pettitt test, F-test, STARS. Some relative tests have been applied too, which are generally more reliable than absolute tests, because they consider the information from neighboring stations. As relative tests rely on the homogeneity and quality of the reference series, several nearby stations and two reanalysis datasets (ERA5 and MERIDA) have been considered, to enhance the picture of the local situation and provide more robust conclusions. The applied tests identify change-points in the years in which a change in instrument or location of the station have occurred, confirming that these changes have compromised the homogeneity of the series. The sub-series obtained splitting the observations in correspondence of these change-points have been homogenized with respect a selected period; corrections must be applied also to future measurements to extend the time series properly.

Keywords: homogeneity tests; daily temperature series; correction methodology; climate change.

1. Introduction

Temperature observations in Padua have a very long history, being one of the oldest continuous series in the world with regular measurements starting in 1725 [1] and some sporadic records taken even before [2]. The modern observations in the city center, from 1980 to present day, were started by the University of Padua at the historical Botanical Garden. In 1993 the original weather station was substituted and since 2000 measurements have been under the control of ARPAV (Regional Agency for Environmental Protection of Veneto), when the weather station was changed again and translated of some meters in the Botanical Garden. In 2019 the station was relocated ~2 km away in a less urban environment (see Figure 1a).



(**a**) (**b**)

Figure 1. Locations of the meteorological stations considered in this study: (**a**) Padua city center; (**b**) Veneto region.

Hence, over the 1980-2022 period, some inhomogeneities in the temperature records can arise because of the changes of instrument and relocation. The availability of the metadata in combination with statistical methods provides the most complete and effective way to identify inhomogeneities, with the final aim to bring out the climate signal from human interventions.

The statistical methods used for this scope are commonly known as *homogeneity tests*, which are widely described in the literature [e.g., 3,4]. A possible classification divides *absolute* from *relative tests*: the former use the series itself while the latter use the information from neighboring stations, called *reference stations*, supposedly homogeneous. The most common type of shifts, i.e., in the mean, was considered in this study, defined as "differing average climatic levels over a multi-annual duration" [5]. Several studies [e.g., 6] recommend applying relative homogeneity tests when one or more reliable reference stations are available, with high level of correlation with the test station. Relative tests are generally more powerful and reliable than absolute ones [3], but their result highly depends on the quality of the reference series; consequently, they have to be used with at least one absolute test to detect possible inhomogeneities in the reference series. On the other hand, relative tests cannot deal with concurrent changes in both the test and the reference stations, as it happens when climate variations occur. However, if the aim is to assess the presence of artificial change-points in the time series because of changes in the instrument and/or location, then relative tests can indubitably help.

The evaluation of the reliability of the temperature series of Padua is essential to investigate climate change in the last decades in the Mediterranean region, a hotspot due to the enhanced warming trend [7]. Therefore, the aim of this study is to assess the presence of change-points in the modern Padua daily temperature time series, obtained by composing different records over the last forty years. In the modern era, four different records are available, which are almost complete and whose metadata (location, instruments) are known. Starting from 1980, daily minimum and maximum temperatures have been continuously recorded while, sub-daily measurements began only later, in October 1993; hence, the focus has been on the daily observations.

The consequent homogenization of the observations allows the extension of the time series in the future once the procedure to blend new observations into the adjusted time series is known. Besides, as homogeneity tests sometimes fail to provide unique results, or have limited reliability, this analysis offers the possibility to evaluate them in presence of a clear knowledge of the metadata.

2. Materials and Methods

In this study, daily minimum and maximum temperatures over the period January 1980 – December 2022 are considered, collected in the station located in the Padua center. Four main periods can be distinguished:

1. January 1980 – December 1993: observations collected at the Botanical Garden by the University of Padua (hereinafter referred to as *OB_UNIPD*), using a SPIGE mechanical thermohygrograph (measurements were copied from the strip chart into a log) and, from 1984 to 1990, two SPIGE minima and maxima glass thermometers. On 24 October 1990 modern electronic instruments were installed and observations were sampled automatically at unknown intervals [1];
2. October 1993 – November 2001: observations sampled every hour (it is unknown whether instantaneous or mean values) collected with a new instrument at the Botanical Garden by the University of Padua (*OB_micros_UNIPD*);
3. May 2000 – 10 March 2019: observations sampled every 15 minutes (instantaneous values) collected with a new instrument at the Botanical Garden, some tens of meters far with respect to the previous sensors, by ARPAV (*OB_ARPAV*);
4. 11 March 2019 up to present: on 11 March 2019 the station was relocated ~2 km east, in the University Sports Center (*CUS_ARPAV*), where it is located nowadays.

The overlapping intervals between these periods are extremely short, or even absent. Quality checks were not applied before the homogeneity tests, as the measurements were already validated by means of automatic and manual procedures by ARPAV. In Table 1 the record availability for each station is reported.

Table 1. Daily temperature datasets for the center of Padua in the period 1980-2022.

Station shortname	Longitude	Latitude	Elevation	Data availability
OB_UNIPD	11.8805	45.3993	12 m	1 Jan 1980 – 31 Dec 1993 (99.6%)
OB_micros_UNIPD	11.8805	45.3993	12 m	1 Oct 1993 – 30 Nov 2001 (91.0%)
OB_ARPAV	11.8805	45.3993	12 m	1 May 2000 – 10 Mar 2019 (100.0%)
CUS_ARPAV	11.9085	45.4050	12 m	11 Mar 2019 – 31 Dec 2022 (99.9%)

Because of the shortness of the overlapping periods, it is not possible to find specific transfer functions between the different datasets, to build a single homogeneous series. Therefore, a new series was composed simply merging the datasets one after the other (so from 1 January 1980 to 30 September 1993 data are from *OB_UNIPD*, from 1 October 1993 to 30 April 2000 from *OB_micros_UNIPD*, from 1 May 2000 to 10 March 2019 from *OB_ARPAV* and from 11 March 2019 from *CUS_ARPAV*) and the presence of change-points by means of homogeneity tests was verified.

Eight absolute homogeneity tests were selected: the Standard Normal Homogeneity test (SNH) for a single break [8], the Buishand U and range test [9], the Pettitt test [10], the F-test [11], the STARS (Sequential T-test Analysis of Regime Shifts) [12], the cpt.mean [13] and the Von Neumann ratio (VN) test [14]. Only VN test does not give information on the timing of the change-point. The others are timing-specific tests, but they don't have the same sensitivity in all parts of the time series, as they are based on different principles. The SNH test is more sensitive to breaks near the beginning or the end of a series, while the Buishand and the Pettitt tests detect more easily breaks in the middle [15]. The F-test is one of the best performing absolute test, able to identify a change-point even if a trend in the series is present [3,4]. The STARS method also works well in the presence of a trend, although it requires the setting of certain parameters, i.e., the significance level and cutoff length, that have to be optimized after several trials. The STARS algorithm finds the most likely significant change-point (based on a t-test), splits the series at that point and searches for further changes in each segment, repeating iteratively the procedure until no more change-points are detected or the sub-time series become smaller than the minimum cutoff length [12]. The cpt.mean algorithm detects changes in the mean using an exact or approximate method, which can identify either a single or multiple change-point. The PELT (Pruned Exact Linear Time) method [16] was chosen, which is exact and quick, using the *asymptotic* penalty, which provides a compromise between lots of small changes and no changes at all.

However, there are some limits in the applicability of these tests: first of all, except the STARS and cpt.mean-PELT methods, they can detect a single change-point in the time series. Secondly, with the exception of the F-test, STAR and cpt.mean-PELT, the mean-shift tests may not work properly if there is a trend in the series and a change-point can be incorrectly identified in the proximity of the middle of the series. Therefore, it is important to check if a trend in the test series is statistically significant and, in such a case, to interpret the results of the homogenization tests critically. To determine whether or not a trend exists in a time series the Mann-Kendall trend test was used. Being a non-parametric test, there is no underlying assumption about the normality of the data [17-19].

All the methods were applied using R and are summarized in Table 2, while in Table 3 the coordinates and data availability for all the stations used with the relative tests are reported (see also the map in Figure 1b).

Table 2. Homogeneity tests and their R implementations used in this study. Absolute and relative classification is reported.

R package	Test	Function	Abs./Rel.
trend 1.1.5	SNH	snh.test	Abs.
	Pettitt	pettitt.test	Abs.
	Buishand U	bu.test	Abs.
	Buishand Range	br.test	Abs.
DescTools 0.99.47	Von Neumann ratio	VonNeumannTest	Abs.
strucchange 1.5-3	F-test	Fstats	Both
changepoint 2.2.4	cpt.mean	cpt.mean	Both
rshift 2.2.2	STARS	Rodionov	Both
climatol 4.0.0	Climatol	homogen	Rel.

Table 3. Daily temperature availability for the reference stations.

Station shortname	Longitude	Latitude	Elevation	Data Availability
Padua Idrografico	11.8716	45.3912	13 m	1 Jan 1986 – 31 Dec 1996 (50.9%)
Padua airport	11.8483	45.3953	13 m	1 Jan 1980 – 29 Dec 1990 (98.8%)
Padua CNR 1	11.9290	45.3931	10 m	10 Apr 1984 – 31 Dec 1986 (51.4%)
Padua CNR 2	11.9290	45.3931	10 m	29 Oct 1993 – 29 Dec 2008 (78.3%)
Codevigo	12.1000	45.2430	0 m	18 Feb 1992 – 31 Dec 2022 (99.6%)
Tribano	11.8490	45.1860	4 m	1 Jan 1996 – 31 Dec 2022 (100.0%)
Mira	12.1177	45.4353	5 m	5 May 1992 – 31 Dec 2022 (99.9%)
Campodarsego	11.9137	45.4948	15 m	1 Jan 1993 – 31 Dec 2022 (100.0%)
Legnaro	11.9524	45.3467	10 m	17 Jul 1991 – 31 Dec 2022 (99.3%)
Este	11.6606	45.2244	12 m	1 Feb 1980 – 31 Dec 1999 (78.4%)
Lozzo Atestino	11.6307	45.2893	15 m	1 Jan 1985 – 31 Dec 1996 (79.3%)
Stra	12.0084	45.4107	9 m	28 Jan 1985 – 31 Dec 2004 (88.1%)
Mirano	12.0797	45.4930	10 m	1 Jan 1988 – 30 Nov 2004 (100.0%)
Montegaldella	11.6710	45.4383	22 m	1 Apr 1993 – 31 Dec 2004 (98.6%)
Treviso Istrana	12.1013	45.6887	41 m	1 Jan 1980 – 31 Dec 2022 (98.6%)
Treviso S. Angelo	12.1978	45.6508	17 m	1 Jan 1980 – 31 Dec 2022 (97.0%)
Venice Tessera	12.3519	45.5053	2 m	1 Jan 1980 – 31 Dec 2022 (99.8%)
Vicenza airport	11.5167	45.5667	39 m	1 Jan 1980 – 29 Feb 2008 (98.1%)
Verona Villafranca	10.8881	45.3964	72 m	1 Jan 1980 – 31 Dec 2022 (98.8%)

Concerning relative tests, two reanalysis datasets were also considered as reference time series over the whole period: ERA5 and MERIDA. The ERA5 reanalysis, produced by the *Copernicus Climate Change Service* (C3S) at ECMWF [20], represents the state-of-the-art in the field of global meteorological reanalysis, and the time series was extracted in the grid point closest to Padua. ERA5 has a horizontal resolution of 31 km and the pixel selected has to be at the same altitude of Padua, not containing the near Euganean Hills, located south-west of the city center. The ERA5 synthetic station was used because of its reliability as it well captures the mean and extreme temperatures in particular in plain regions of Italy [21] and being the most complete.

The Meteorological Reanalysis Italian Dataset (MERIDA) is a reanalysis product developed for Italy and surrounding areas which use ERA5 as initial and boundary conditions for the numerical simulations conducted with the Advanced Research core of the Weather Research and Forecasting (WRF-ARW) mesoscale model [22]. Simulated data are provided on a 7 km horizontal resolution grid

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at hourly steps and exploit observations (temperature and precipitation) from the meteorological stations of the Regional Agencies for Environmental Protection (ARPA), not assimilated by ERA5, distributed throughout the national territory. These data are continually validated by the agencies but are cross-validated again in this context through spatial and temporal consistency criteria [22], and the weather stations meet the WMO guidelines. MERIDA covers the most recent period, from 1990 to present, but only the 1993-2022 period was used because the unbroken observations performed by most of the ARPAV stations located in the area of interest, and assimilated by the model, started from 1993.

All the homogeneity tests, both absolute and relative, were applied to monthly anomalies time series calculated with respect to the 30-year period 1993-2022 to detect more precisely the timing of the change-points.

Among the relative tests, the R package Climatol [23] was also applied, developed by the Spanish State Meteorological Agency (AEMET), that performs quality control, homogenization and infilling of missing data in a set of daily series of any climatic variable. The homogenization is based on the SNH test [8], considering reference stations to detect inhomogeneities in the test series: when the SNH test statistics are greater than a prescribed threshold, the series is split at the point of maximum SNH, moving all data before the break to a new series that is incorporated into the data pool. This procedure is performed iteratively, splitting only the series with the higher SNH values at every cycle, until no inhomogeneous series is found. As the core test, SNH test was originally designed to detect no more than a single change-point in a series; to overcome this problem, the test was first applied to stepped overlapping temporal windows, and then to the complete series. Finally, the method infills missing data in all homogeneous series and sub-series. Details on the package can be found in [23]. As reference stations to be used by the algorithm, fourteen stations within a 25 km radius from Padua were selected (top of Table 3) and farther five stations of the Italian Air Force selected because of their longer available time series (last five rows of Table 3) (Figure 1b). The ERA5 time series was added, instead MERIDA was not, because it is a derived product obtained from ERA5 and the stations themselves. To infill the missing data and compute the homogeneity tests, the algorithm does not use the proximity criterion but evaluates the correlation between datasets. The stations selected are all located on a plain terrain, but the algorithm was also successfully applied to orographically complex areas, e.g., Spain and Southern Italy [23,24].

3. Results

3.1. Absolute tests

The results of the absolute tests applied to the maximum and minimum temperatures in Padua are reported in Table 4. Tests are performed over the 1980-2022 period using monthly anomalies with respect to 1993-2022 climatology. STARS and cpt.mean tests require input parameters which provide sensibility thresholds for the number of change-points and they can be quite sensitive to these choices. For STARS, a cutoff length has to be selected, that is the minimum length of a subdivision of the time series needed to confirm that a change-point is present at a given time. Since a potential change-point is in March 2019, when the station was moved, a value less than ~3.5 years had to be chosen, i.e., before the time series ends, otherwise the algorithm would not be able to detect it. Therefore, several trials were made in the range 12-42 months (i.e., 1-3.5 years) and the most frequent change-points the algorithm provided were selected. Similarly, in cpt.mean test a penalty value controls the maximum number of potential change-points. An "elbow plot" was used to find the most reliable penalty value: the number of changes decreases as the penalty value increases, until it becomes constant. A value on the last part of this curve was selected to reduce change-points induced by noise. Nonetheless, both cpt.mean and STARS tests retrieved many change-points, in particular for maximum temperature, most of them caused by the noise in the time series and without any specific meaning. This was assessed by the comparison of the results with metadata.

Table 4. Results of absolute tests applied to monthly minimum and maximum temperatures in Padua over the period 1980 – 2022.

Test	Change-points	
	Minimum temperature	Maximum temperature

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SNH[1]	Feb 2000	Mar 2000
Pettitt[1]	Feb 2000	Mar 2000
Buishand U[1]	Feb 2000	Mar 2000
Buishand Range[1]	Feb 2000	Mar 2000
Von Neumann ratio[1]	yes	yes
F-test[1]	Feb 2000	Mar 2000
cpt.mean[2]	Mar 2000	Apr 1982 Mar 2000 Apr 2003 Aug 2003 Feb 2011
STARS[3]	Sep 1987 Jul 2013 Mar 2020	Jul 1985 Apr 2000 Jan 2004 Sep 2006

[1] p-value < 0.01.
[2] The package does not calculate traditional p-values directly related to the changes.
[3] p-value ≤ 0.01 and cutoff length in the range 12-42 (i.e., 1-3.5 years).

The only change-point found by all the absolute tests is at the beginning of 2000 (February-March) for both minimum and maximum temperatures. This result can be referred to the time at which the change and relocation of instruments took place, i.e., between April and May 2000. However, further analysis is required to confirm this finding.

3.2. Relative tests

Relative tests make use of reference stations and study the difference between the test and the reference datasets. Therefore, they required the selection of one or more datasets recorded continuously over the same period of the Padua time series. A few stations apart from Padua have observations over the whole 1980-2022 period (see Table 3). But, these series may present change-points not related to climate, but to substitution of sensors, maintenance, presence of vegetation, etc. For example, some relative tests were applied to the monthly differences between Padua and Legnaro, which is one of the stations most similar to Padua (see Table 5) and for which the maintenance history is known. Results indicate a change-point in the minimum temperature anomalies in the first months of 2002, that corresponds to the change of the station's radiation shield material from metal to plastic in May 2002. As expected, the tests are sensitive to change-point not related to any climatic signal.

For this reason, in the absence of certain and complete metadata, the reanalysis datasets were considered as references for relative tests. Firstly, the data extracted from these products have to be reliable. Therefore, their robustness was checked by comparing the Pearson correlation coefficients and the Root Mean Square Errors (RMSE) obtained coupling the reference time series and the Padua observations. In Table 5 these indicators are reported for ERA5, MERIDA and some stations listed in Table 3 for which data are available over 1993-2022. Some observations go even further back in time, but the time frame common to all datasets was selected to have a reliable comparison.

Table 5. Pearson correlation coefficient (c_Pearson) and RMSE obtained comparing Padua daily observations to the ones of other stations and to reanalysis data over 1993-2022. In parenthesis the values obtained after having removed the seasonal components (using R package "stlplus").

Datasets over 1993-2022	Minimum temperature		Maximum temperature	
	c_Pearson	RMSE (°C)	c_Pearson	RMSE (°C)
ERA5	0.980 (0.866)	2.25	0.986 (0.904)	1.48
MERIDA	0.987 (0.912)	1.17	0.990 (0.926)	1.28
Campodarsego	0.982 (0.911)	2.47	0.995 (0.965)	1.01
Legnaro	0.986 (0.923)	1.83	0.994 (0.962)	0.93
Codevigo	0.983 (0.904)	1.76	0.991 (0.936)	1.22

Mira	0.983 (0.915)	2.25	0.992 (0.953)	1.08
Tribano [1]	0.985 (0.912)	1.88	0.992 (0.946)	1.23
Treviso Istrana	0.983 (0.898)	1.86	0.991 (0.936)	1.37
Treviso S. Angelo	0.987 (0.919)	1.56	0.991 (0.941)	1.26
Venice Tessera	0.990 (0.929)	1.22	0.986 (0.908)	1.62
Verona Villafranca	0.982 (0.884)	2.06	0.987 (0.908)	1.50

[1] 1996-2022.

All the correlations coefficients are very high, even excluding the seasonal components of the time series, and the MERIDA reanalysis shows a clear improvement with respect to ERA5. RMSE for minimum temperature from MERIDA is even the best among all cases. On the other hand, RMSE of maximum temperature from MERIDA shows no improvement with respect to the stations, but it is still comparable. Overall, these indicators support the idea of using MERIDA time series as reference for the relative tests. However, since MERIDA covers only the 1993-2022 period and not knowing the maintenance history of the Air Force stations (which also have some gaps), there was no choice but using ERA5 to explore the whole 1980-2022 period to evaluate the presence of change-points around 1993, the first time the instrument changed. In Table 6 and 7 the results of the relative tests using ERA5 and MERIDA as reference, respectively, are reported.

Table 6. Relative tests results for monthly temperature series in Padua using ERA5 as reference, over 1980 – 2022.

Test	**Padua-ERA5 Change-points**	
	Minimum temperature	**Maximum temperature**
F-test	Jun 2018 [1]	Apr 2000 [2]
cpt.mean	Feb 1991 [2] Jun 2004 [2] Mar 2019 [2]	Aug 1980 [2] Apr 1983 [2] Feb 1993 [2] Apr 2000 [2]
STARS	May 1983 [3] Mar 1991 [3] Jul 1996 [3] Oct 2000 [3] Apr 2019 [3]	May 1983 [3] Dec 1990 [3] Feb 1994 [3] May 2000 [3] Sep 2003 [3]

[1] p-value < 0.01.
[2] The package does not calculate traditional p-values directly related to the changes.
[3] p-value ≤ 0.01 and cutoff length in the range 12-42 months (i.e., 1-3.5 years).

Table 7. Relative tests results for monthly temperature series in Padua using MERIDA as reference, over 1993 – 2022.

Test	**Padua-MERIDA Change-points**	
	Minimum temperature	**Maximum temperature**
F-test	Nov 2018 [1]	Apr 2000 [2]
cpt.mean	Nov 2018 [2]	May 1996 [2] Apr 2000 [2] Aug 2003 [2]
STARS	Aug 1996 [3] May 2016 [3] Apr 2019 [3]	Jun 1996 [3] Oct 1998 [3] May 2000 [3] Sep 2003 [3] Jan 2004 [3] May 2015 [3]

[1] p-value < 0.01.
[2] The package does not calculate traditional p-values directly related to the changes.

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[3] p-value ≤ 0.01 and cutoff length in the range 12-42 months (i.e., 1-3.5 years).

Once again, cpt.mean and STARS identified many change-points but most of them are disregardable and not linked to climatic signals or changes in the station. Additionally, the Climatol package, which use all the available observations, even the very sparse ones (reported in Table 3), was also applied. Climatol identified two change-points for minimum temperature in May 1991 and April 2019 and three change-points for maximum temperatures, in May 1983, May 1994 and May 2000.

In conclusion, the relative tests applied to Padua time series quite agree in identifying two change-points for minimum temperature in 1991 and 2019, and three change-points for maximum temperature in 1983, at the end of 1993/beginning of 1994, and in 2000. The timing of some change-points has more variability with respect to the others, as the tests not always agree on the precise month they occurred and meteorological variability overlaps with the signal affecting the outcome of the tests. Nonetheless, the exact months of these change-points were identified according to the station metadata changes. The main difference with the absolute tests is that the latter also indicated a change-point for minimum temperature in February or March 2000. This change-point is probably fictitious, i.e., an artifact caused by the trend present in the time series. Indeed, both for monthly minimum and maximum temperatures the Mann-Kendall test detects significant trend (p-value < 0.01) over the 1980-2022 period. Since a trend could sometimes deceive some homogeneity tests, leading to the indication of a fictitious change-point usually in the middle of the time series, and since no relative test has detected the 2000 timing, this change-point for minimum temperature was excluded. The final selected change-points are reported in Table 8.

Table 8. Summary of the change-points identified by the absolute and relative tests for the Padua minimum and maximum time series over the period 1980-2022.

	Change-points	
	Timing	**Cause**
Minimum temperature	24 Oct 1990	Instrument change
	11 Mar 2019	Location change
Maximum temperature	1 Jan 1984	Instrument change
	1 Oct 1993	Instrument change
	1 May 2000	Instrument and location change

3.3. Homogeneization

Once the change-points have been identified, the sub-periods have to be corrected to homogenize the time series. As the overlapping windows (Table 1) are very short or absent, the Climatol package was used again. *OB_ARPAV* was chosen as reference with respect the other time series have to be corrected to, because it is the longest available homogeneous series. The current station *CUS_ARPAV* wasn't considered because the location is supposed to be temporary and the station could be relocated again in the future. For minimum temperature three homogeneous subperiods are available: i.e., Jan 1980 – Oct 1990 (1), Nov 1990 – Feb 2019 (2) and Mar 2019 – Dec 2022 (3), and (1) and (3) should be corrected to make them homogeneous with respect to (2). For the maximum temperature, four homogeneous subperiods are available: i.e., Jan 1980 – Dec 1983 (1), Jan 1984 – Sep 1993 (2), Oct 1993 – Apr 2000 (3), May 2000 – Dec 2022 (4). In addition, (1), (2) and (3) should be corrected to make them homogeneous with respect to (4). Climatol allows the reconstruction, back and forward in time, of the sub-time series identified by splitting the time series by means of the change-points, to cover the whole period 1980-2022. In this way, the time series overlap enough to perform a proper comparison and calculate transfer functions. These transfer functions are evaluated as previously done for older Padua observations [25]: they are the least square interpolation polynomials obtained comparing, month by month, one time series with the other, excluding measurements exceeding 10^{th} and 90^{th} percentiles of the series of daily differences between the two series. Results are reported in Table 9 and 10 for minimum temperature, and in Table 11, 12 and 13 for maximum temperature.

Table 9. Transfer functions from *OB_UNIPD* of the period 1 Jan 1980 – 23 Oct 1990 to *OB_ARPAV* for minimum temperature.

1980-2022	*OB_UNIPD* (1 Jan 1980 – 23 Oct 1990) to *OB_ ARPAV*	
Month	**Tmin (°C)**	**r²**
January	Y = 0.9768 · X - 0.44	0.991
February	Y = 0.9847 · X - 0.26	0.957
March	Y = 0.9500 · X - 0.07	0.953
April	Y = 0.9640 · X - 0.09	0.948
May	Y = 0.9882 · X - 0.34	0.943
June	Y = 1.0136 · X - 0.69	0.942
July	Y = 0.9961 · X - 0.30	0.915
August	Y = 1.0010 · X - 0.38	0.926
September	Y = 0.9416 · X + 0.52	0.946
October	Y = 0.9443 · X + 0.14	0.970
November	Y = 0.9408 · X - 0.11	0.977
December	Y = 0.9408 · X - 0.35	0.968

Table 10. Transfer functions from *CUS_ARPAV* to *OB_ARPAV* for minimum temperature.

1980-2022	*CUS_ARPAV* to *OB_ARPAV*	
Month	**Tmin (°C)**	**r²**
January	Y = 0.9701 · X + 0.28	0.968
February	Y = 0.9913 · X + 0.39	0.921
March	Y = 0.9781 · X + 0.65	0.910
April	Y = 0.9915 · X + 0.79	0.906
May	Y = 1.0328 · X + 0.43	0.904
June	Y = 1.0617 · X + 0.02	0.909
July	Y = 1.0380 · X + 0.54	0.872
August	Y = 1.0403 · X + 0.52	0.884
September	Y = 0.9749 · X + 1.36	0.910
October	Y = 0.9735 · X + 0.99	0.934
November	Y = 0.9682 · X + 0.70	0.954
December	Y = 0.9758 · X + 0.32	0.939

Table 11. Transfer functions from *OB_UNIPD* of the period 1 Jan 1980 – 31 Dec 1983 to *OB_ARPAV* for maximum temperature.

1980-2022	*OB_UNIPD* (1 Jan 1980 – 31 Dec 1983) to *OB_ ARPAV*	
Month	**Tmax (°C)**	**r²**
January	Y = 0.9938 · X + 0.65	0.996
February	Y = 0.9803 · X + 0.84	0.978
March	Y = 1.0032 · X + 0.70	0.980
April	Y = 1.0160 · X + 0.40	0.975
May	Y = 1.0117 · X + 0.27	0.977
June	Y = 0.9983 · X + 0.46	0.975
July	Y = 0.9992 · X + 0.46	0.967
August	Y = 1.0147 · X + 0.04	0.971
September	Y = 0.9868 · X + 0.69	0.969
October	Y = 0.9731 · X + 0.80	0.971
November	Y = 0.9529 · X + 0.97	0.973
December	Y = 0.9675 · X + 0.89	0.959

Table 12. Transfer functions from *OB_UNIPD* of the period 1 Jan 1984 – 30 Sep 1993 to *OB_ARPAV* for maximum temperature.

1980-2022	*OB_UNIPD* (1 Jan 1984 – 30 Sep 1993) to *OB_ ARPAV*

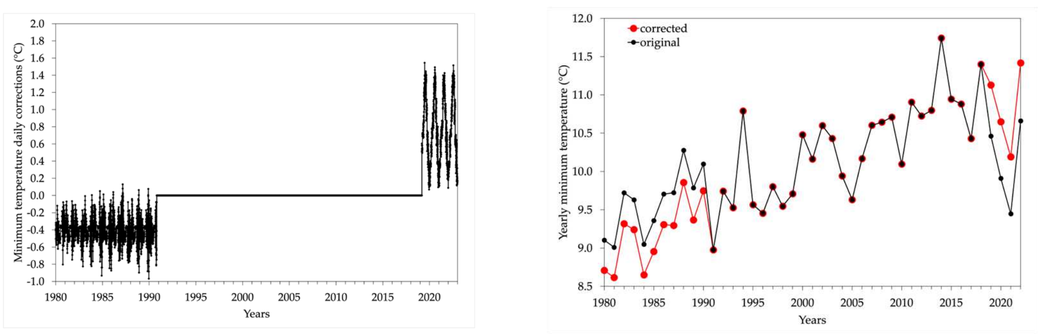
Month	Tmax (°C)	r^2
January	Y = 1.0010 · X - 0.31	0.992
February	Y = 0.9739 · X - 0.02	0.969
March	Y = 0.9979 · X - 0.13	0.968
April	Y = 1.0112 · X - 0.34	0.966
May	Y = 1.0088 · X - 0.38	0.971
June	Y = 1.0044 · X - 0.33	0.968
July	Y = 1.0047 · X - 0.27	0.960
August	Y = 1.0274 · X - 0.92	0.962
September	Y = 0.9983 · X - 0.26	0.962
October	Y = 0.9742 · X + 0.01	0.964
November	Y = 0.9490 · X + 0.21	0.964
December	Y = 0.9611 · X + 0.00	0.951

Table 13. Transfer functions from *OB_micros_UNIPD* to *OB_ARPAV* for maximum temperature.

1980-2022	*OB_micros_UNIPD* to *OB_ ARPAV*	
Month	**Tmax (°C)**	**r^2**
January	Y = 1.0401 · X - 0.15	0.997
February	Y = 1.0661 · X - 0.29	0.988
March	Y = 1.0795 · X - 0.44	0.988
April	Y = 1.0900 · X - 0.72	0.983
May	Y = 1.0831 · X - 0.80	0.986
June	Y = 1.0748 · X - 0.77	0.985
July	Y = 1.0738 · X - 0.77	0.975
August	Y = 1.0836 · X - 1.02	0.977
September	Y = 1.0703 · X - 0.71	0.980
October	Y = 1.0546 · X - 0.48	0.982
November	Y = 1.0238 · X - 0.05	0.983
December	Y = 1.0410 · X - 0.17	0.972

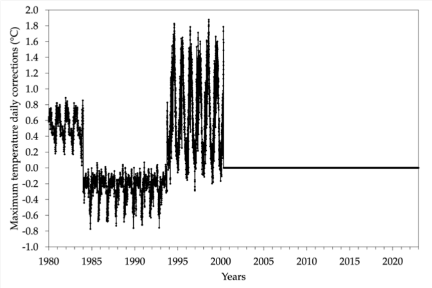
More measurements are expected to be included to extend the time series and keep it up to date. Therefore, the use of the transfer functions is the more practical and immediate way to include future observations from *CUS_ARPAV*. Minimum temperature values must be converted in the future using the transfer functions of Table 10, while future maximum temperatures do not need correction.

In Figure 2a the daily corrections to the minimum temperature are shown, with most of them ranging from -1.0°C to +0.1°C in Jan 1980 – Oct 1990 and +0.1°C to +1.5°C in Mar 2019 – Dec 2022. Figure 2b compares the yearly values of both the corrected and the original time series.

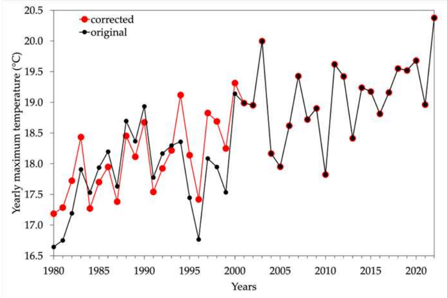


(**a**) (**b**)

Figure 2. (**a**) Daily corrections applied to minimum temperature; (**b**) Yearly mean of the original time series (black) and the corrected one (red).



(**a**)



(**b**)

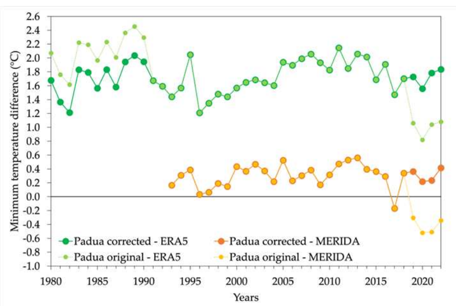
Figure 3. (**a**) Daily corrections applied to maximum temperature; (**b**) Yearly mean of the original time series (black) and the correction (red).

Figure 3 shows the same analysis but for the daily corrections of the maximum temperature, with most of the corrections of the Jan 1980 – Dec 1983 period ranging from +0.2°C to +0.9°C, of the Jan 1984 – Sep 1993 period ranging from -0.8°C to +0.0°C and of the Oct 1993 – Apr 2000 period ranging from -0.3°C and +1.9°C.

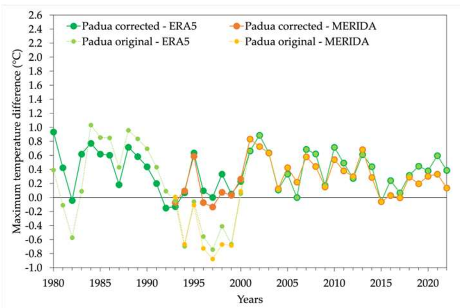
4. Discussion

Change-points in the monthly time series of minimum and maximum temperatures in Padua have been investigated with absolute and relative tests. Results showed two change-points for the minimum temperatures, in 1991 and 2019, and three change-points for maximum temperatures, in 1983, 1993 and 2000. By applying the R package Climatol to the sub-time series identified by the change-points, they have been extended back and forward, to have a consistent overlapping window of more than forty years, between 1980 and 2022, from which it was possible to calculate the transfer functions and homogenize the 1980-2022 time series with respect to the central period, 2000-2019, when *OB_ARPAV* was active.

Lastly, the yearly differences between the Padua and ERA5 temperature time series over 1980-2022 and between the MERIDA one, over 1993-2022, for both the original and corrected time series, were calculated. Results are reported in Figure 4a and 4b for minimum and maximum temperatures, respectively. As already shown in Section 3.2, ERA5 has a larger bias than MERIDA for minimum temperature. The corrected Padua time series exhibits a more coherent behavior in the first and last years with respect to the original one. The range of the differences between the original Padua minimum temperature series and ERA5 is 3.3°C, that decreases to 1.0°C after correction. Considering MERIDA, the range decreases from 1.1°C to 0.7°C (Figure 4a). Regarding maximum temperatures, there is a strong improvement after correction in the 1980-1993 period using ERA5 as reference dataset, and in the 1993-2000 period using both ERA5 and MERIDA. The range of the differences between the original Padua time series and ERA5 is 1.8°C, while after correction the range is 1.2°C; considering MERIDA, the range decreases from 1.7°C to 1.1°C (Figure 4b). Overall, the corrections applied to the Padua time series, for both minimum and maximum temperatures, provide more consistent differences with respect to the reanalysis products, exhibiting more stable evolutions.



(**a**)



(**b**)

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Figure 4. (**a**) Difference of yearly minimum temperatures between the Padua, original and corrected, and ERA5 time series over 1980-2022 (green) and between MERIDA over 1993-2022 (orange); (**b**) the same but for maximum temperature. The continuous lines highlight the zero.

The effect of these corrections on the overall trend was also explored. Considering the monthly anomalies time series over the 1993-2022 period, the slopes of the linear regression are reported in Table 14, while the slopes calculated over the whole 1980-2022 period are shown in Table 15. The slopes of the Padua corrected time series are closer to the reanalysis datasets in all cases except for maximum temperatures over the 1980-2022 period, for which the original slope was already consistent with ERA5. This confirms the goodness of the corrections to the Padua time series.

Table 14. Slopes of linear regressions for the Padua original and corrected time series and MERIDA over the period 1993-2022.

1993-2022	Slopes (°C/decade)	
	Minimum temperature	**Maximum temperature**
Padua original	+0.31 ± 0.08	+0.61 ± 0.09
Padua corrected	+0.48 ± 0.08	+0.40 ± 0.09
MERIDA	+0.46 ± 0.07	+0.39 ± 0.09

Table 15. Same of Table 14 but for ERA5 and the period 1980-2022.

1980-2022	Slopes (°C/decade)	
	Minimum temperature	**Maximum temperature**
Padua original	+0.35 ± 0.05	+0.52 ± 0.06
Padua corrected	+0.54 ± 0.05	+0.48 ± 0.05
ERA5	+0.49 ± 0.05	+0.50 ± 0.06

5. Conclusions

In this paper, the daily minimum and maximum temperatures recorded in the city center of Padua, Italy, from 1980 to 2022 have been examined. Four main different sub-periods are present in this time frame, determined by change of instruments or location or both. Fortunately, the dates of these changes are known, as well as the spatial coordinates of each new location. The application of the most used and performing absolute and relative homogeneity tests allow to identify the timing of the artificial change-points caused by these changes, not related to climatic signals. Two change-points were found for minimum temperature, in 1991 and 2019, and three change-points for maximum temperature, in 1983, 1993 and 2000, all supported by changes in the metadata.

Once the homogeneous sub-periods have been identified, the complete, homogeneous time series by means of monthly transfer functions have been obtained. Since the overlaps between the sub-time series are very short or absent, the Climatol algorithm provided by R [23] has been used to extrapolate the values of all the time series over the entire 1980-2022 period. In this way, very long overlapping periods have been obtained to calculate the transfer functions which also allow the blending of future measurements.

A comparison of the differences between the original and corrected Padua time series with the ERA5 and MERIDA reanalysis datasets confirms that the obtained reconstructions are reliable and more coherent with the modern warming trend. The meteorological observations of Padua have a very long history, as daily minimum and maximum temperatures are available since 1774 and daily mean values since 1725. Previous works reconstructed and homogenized the observations with respect to the XVIII – mid XIX century period [1,2]. A future work will address the problem of homogenizing observations before 1980 to the modern era to add new records correctly and continue the nearly 300-year time series, thus exploring the entire transition from the pre-industrial to the modern era.

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