Bioclimatic conditions of the Lower Silesia region (South-West Poland) from 1966 to 2017

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Abstract
This work analyses the temporal and spatial characteristics of bioclimatic conditions in the Lower Silesia region. The daily time values (12UTC) of meteorological variables in the period 1966–2017 from seven synoptic stations of the Institute of Meteorology and Water Management (IMGW) (Jelenia Góra, Kłodzko, Legnica, Leszno, Wrocław, Opole, Śnieżka) were used as the basic data to assess the thermal stress index UTCI (Universal Thermal Climate Index). The UTCI can be interpreted by ten different thermal classes, representing the bulk of these bioclimatic conditions. Stochastic autoregressive moving-average modelling (ARMA) was used for the statistical analysis and modelling of the UTCI as well as separately for all meteorological components. This made it possible to test differences in predicting UTCI as a full index or reconstructing it from single meteorological variables. The results show an annual and seasonal variability of UTCI for the Lower Silesia region. Strong significant spatial correlations in UTCI were also found in all stations of the region. “No thermal stress” is the most commonly occurring thermal class in this region (about 38%). Thermal conditions related to cold stress classes occurred more frequently (all cold classes at about 47%) than those of heat stress classes (all heat classes at about 15%). Over the available 52-year period, the occurrence of “extreme heat stress” conditions was not detected. Autoregressive analysis, although successful in predicting UTCI, was nonetheless unsuccessful in reconstructing the wind speed, which showed a persistent temporal correlation possibly due to its vectorial origin. We conclude thereby that reconstructing UTCI using linear autoregressive methods is more suitable when working directly on the UTCI as a whole rather than reconstructing it from single variables.

Keywords UTCI · Biometeorology · Forecasting · ARMA model

Introduction
Bioclimatology finds applications in many fields such as climate change (Wu et al. 2019), health research (Bröde et al. 2018), epidemiology (Di Napoli et al. 2018), military (Galan and Guedes 2019), and urban planning or even to determine the attractiveness of tourist places such as coastal towns or health resorts (Błażejczyk and Kunert 2011b; Ge et al. 2017). However, at a time when meteorological weather forecasts can be modelled anywhere on the planet, there are still many locations that do not possess historical records of meteorological measurements. Forecast for these regions, often including cities or attractive areas, therefore relies purely on extrapolation from the modelled data. The Lower Silesia region accounts for about 20% of all health resorts in Poland to which tourists and the sick go in order to recover or improve their health conditions. Despite the fact that only a few of those health resorts have historical records of meteorological measurements, all resorts are required to periodically report on the biometeorological conditions in the region so as to obtain standard certifications.

Over the last century, scientists have proposed many different bioclimatic indicators. In a review of these bioclimatic indicators, de Freitas and Grigorieva (2017) showed that 165 indicators may be gathered into eight groups depending on the type and nature of these indicators. The Universal Thermal Climate Index (UTCI) was placed within the group representing an energy balance stress index. Its multivariate component definition makes it a versatile bulk
index for representing comprehensive bioclimatic conditions (de Freitas and Grigorieva 2017). The World Meteorological Organization (WMO) officially promoted the use of UTCI as the most suitable tool for determining bioclimatic conditions at the international symposium in April of 2009 (WMO 2009). In the last decade, Polish scientists have used UTCI in different parts of Poland and they confirmed that this index is well suited for describing the local bioclimatic conditions (Błażejczyk et al. 2010, 2012, 2013; Chabior 2011; Kuchcik et al. 2013; Okoniewska and Więcław 2013; Nidzgorska-Lencewicz 2015; Bryś and Ojrzyńska 2016; Rozbicka and Rozbicki 2016, 2018). UTCI has also been used worldwide. In Europe, for example, Novak (2013) investigated its use for regions of the Czech Republic. From the perspective of tourism, researchers have analysed changes of UTCI in Greece, Luxemburg, and Hungary (Matzarakis and Nastos 2011, 2013; Nemeth 2011). Outside Europe, Bröde et al. (2012b) have made predictions using UTCI in South Brazil, Coutts et al. (2016) in Australia, Maciejczyk et al. (2017) in the Arctic, and Ndetro and Matzarakis (2015) in Tanzania.

In this paper the UTCI was used to determine the biometeorological conditions of the Lower Silesia Voivodeship (south-west Poland). We present a broad statistical analysis of the bioclimatic conditions in terms of the UTCI, and use a stochastic modelling approach to test its reconstruction either as a whole or starting from single meteorological variables that define it. We show how statistics of biometeorological conditions are related to the available synoptic stations in the Lower Silesia region. The significantly strong statistical spatial relationships seem to support the modelling of bioclimatic conditions for those locations that do not have a history of meteorological measurements. However, the stochastic analysis appears to be suitable for modelling the UTCI directly rather than starting from its meteorological components.

Materials and methods

Location and available data

The meteorological data for seven synoptic stations (Fig. 1) used in the article have been provided by the Institute of Meteorology and Water Management (IMGW) by way of the climate R package (Czernecki et al. 2020). Air temperature, water vapour pressure, wind speed, and cloud cover for the years 1966–2017 were used. For the calculation 1200 UTC observations (in total 132,951 observations; 18,993 per station) were used (Błażejczyk and Kunert 2011b). All analysed synoptic stations are part of the WMO database and they fulfil WMO standards (Jarraud 2008) including measurements of the wind speed at a height of 10 m above ground level. Leszno and Legnica stations had gaps of measurements in cloud cover for the years 1966–1977 (about 12% of data for these stations). For the UTCI, calculations gaps for the cloudiness were approximated from the sun’s duration (Bryś et al. 2019).

Universal Thermal Climate index

The UTCI is a function of air temperature, $T_a$ (°C); wind speed, $v$ (m·s$^{-1}$); water vapour pressure, $e$ (hPa); and mean radiant temperature, $T_{mrt}$ (°C) (Błażejczyk et al. 2013):

$$UTCI = f(T_a, v, e, T_{mrt}).$$

The mean radiant temperature was calculated with the Bioklima software (Błażejczyk 1996), which uses the following mathematical relationships:

$$T_{mrt} = \left( \frac{R}{I_{rc} + 0.5L_a + 0.5L_a} \right)^{0.25} - 273$$

where $R$ is the absorbed solar radiation by the human body (W·m$^{-2}$), $I_{rc}$ is the coefficient reducing convective and radiative heat transfer through clothing, $L_a$ is the ground radiation (W·m$^{-2}$), $L_a$ is the atmosphere’s back radiation (W·m$^{-2}$), $s_h$ is the emissivity coefficient for humans (0.95), and $\sigma$ is the Stefan-Boltzmann constant (5.667 $\times$ 10$^{-8}$ W·m$^{-2}$·K$^{-4}$). The absorbed solar radiation ($R$) was calculated using the SolAlt model based on cloudiness (N [%]) and position of the sun (hSI [°]); detailed formulas have been reported by Błażejczyk (2005).

The range of limiting conditions in order for UTCI to be applicable are as follows: wind speed between 0.5 and 20 m·s$^{-1}$ (Novak 2013), air temperature from −50 to 50 °C, mean radiant temperature and air temperature difference $T_{mrt} - T_a$ from −30 to 70 °C, and relative humidity that needs to be higher than 5% (Bröde et al. 2012a). In the analysed period, only the wind speed exceeded the prescribed limiting conditions. About 2% (i.e. 2768 obs.) of the data were greater than 20 m·s$^{-1}$ and about 4% (i.e. 5420 obs.) of the data were lower than 0.5 m·s$^{-1}$. When wind data exceeded the upper limiting conditions, the UTCI reached its utmost limits. Therefore, following Novak (2013), it was decided to cut off wind data at the limiting conditions and include them in the analysis. The calculated UTCI values correspond to the conditions of a man walking at a speed of 4 km/h (which is equivalent to metabolic changes of 2.3 MET). Activities like mountain hiking will represent a higher metabolic rate; thus, people would have a slightly higher perception than the UTCI prediction.

The scale of thermal stress classes was taken from the physiological model proposed by Bröde et al. (2012a), which is shown in Table 1.
Fig. 1 Location of Institute of Meteorology and Water Management (IMGW) stations in Lower Silesia (SW Poland) with heights of the stations in metres above sea level (m a.s.l)

ARMA model

Several works in the literature have reported on the significant relationships between UTCI and various climatic oscillations (Owczarek 2019). For example, there is a significant link between atmospheric circulations (e.g. North Atlantic Oscillation, NAO) and climatic conditions in Poland (Marsz et al. 2019). Since climatic oscillations have successfully been modelled by means of stochastic models, we propose to use AutoRegressive Moving Average models (Maidment and et al 1993) to decompose bioclimatic conditions (according to UTCI) into their fundamental linear components (i.e. temporal correlation and noise).

AutoRegressive Moving Average (ARMA) models (3) have widely been used in hydrology (Salas et al. 1985; Haltiner and Salas 1988; Maidment and et al 1993). ARMA(p,q) stands for Auto-Regressive, AR(p) and Moving Average, MA(q). Consider a time series of \( N \) equally spaced observed data (e.g. temperature) \( y_t \), statistically stationary (i.e. showing no temporal trends), and temporally correlated. An ARMA(p,q) model may be written to represent such series as:

\[
Y_t = \mu + \sum_{j=1}^{p} \phi_j (y_{t-j} - \mu) + \epsilon + \sum_{i=1}^{q} \theta_i \epsilon_{t-j} \quad (3)
\]

with \( p \) autoregressive parameters \( \phi(1), ..., \phi(p) \) and \( q \) moving average parameters, \( \theta(1), ..., \theta(p) \). The noise \( \epsilon_t \) in Eq. 3 is an uncorrelated Gaussian process with zero mean and unit variance (Maidment and et al 1993). Alternatively, the time series can first be detrended, and then standardised by subtracting the mean and then divided by the standard deviation. The standardised data with the removed trend can then be checked for the most suitable ARMA model by computing the sample autocorrelation function (ACF).

Table 1 Assessment scale of UTCI (Havenith et al. 2012)

| UTCI °C  | Heat stress classes       | Number |
|---------|--------------------------|--------|
| UTCI >46| Extreme heat stress       | 10     |
| 46 > UTCI >38 | Very strong heat stress  | 9      |
| 38 > UTCI >32 | Strong heat stress     | 8      |
| 32 > UTCI >26 | Moderate heat stress   | 7      |
| 26 > UTCI >9  | No thermal stress         | 6      |
| 9 > UTCI >0   | Slight cold stress        | 5      |
| 0 > UTCI >−13 | Moderate cold stress     | 4      |
| −13 > UTCI >−26 | Strong cold stress    | 3      |
| −26 > UTCI >−40 | Very strong cold stress | 2      |
| −40 > UTCI    | Extreme cold stress       | 1      |
Table 2  Pearson test correlation of 1200 UTCI values between seven analysed stations

| Stations   | Kłodzko | Legnica | Leszno | Opole | Wrocław | Śnieżka |
|------------|---------|---------|--------|-------|---------|---------|
| Jelenia Góra | 0.85   | 0.90   | 0.89   | 0.87  | 0.90    | 0.82    |
| Kłodzko     | 0.85   | 0.90   | 0.89   | 0.87  | 0.90    | 0.80    |
| Legnica     | 0.94   | 0.90   | 0.94   | 0.94  | 0.81    |         |
| Leszno      | 0.90   | 0.93   | 0.79   |       | 0.79    |         |
| Opole       | 0.92   | 0.79   |        |       |         | 0.81    |
| Wrocław    |        |        |        | 0.81  |         |         |

All p values lower than 0.01

Table 3  Average, minimum, maximum, and amplitude of UTCI values at 12 UTC for the years 1966–2017 in Lower Silesia

| Stations   | Jan  | Feb  | Mar  | Apr  | May  | Jun  | Jul  | Aug  | Sep  | Oct  | Nov  | Dec  | Year  |
|------------|------|------|------|------|------|------|------|------|------|------|------|------|-------|
| Average (°C UTCI) |      |      |      |      |      |      |      |      |      |      |      |      |       |
| Jelenia Góra | −10.8| −8.9 | −5.5 | 2.4  | 11.3 | 15.3 | 18.0 | 18.5 | 12.6 | 5.6  | −3.7 | −9.4 | 3.8   |
| Kłodzko     | −14.9| −11.5| −6.2 | 3.1  | 12.1 | 17.0 | 19.8 | 19.9 | 13.1 | 3.9  | −7.3 | −13.2| 3.1   |
| Legnica     | −14.9| −12.3| −6.6 | 2.9  | 12.3 | 16.2 | 19.5 | 19.6 | 12.7 | 4.5  | −6.2 | −13.0| 3.0   |
| Leszno      | −15.2| −12.7| −7.2 | 2.6  | 12.3 | 16.7 | 20.1 | 19.8 | 12.9 | 4.7  | −6.8 | −13.2| 2.9   |
| Opole       | −11.8| −8.2 | −3.0 | 5.6  | 14.6 | 18.5 | 21.2 | 21.6 | 14.8 | 6.9  | −3.7 | −9.9 | 5.6   |
| Wrocław    | −14.5| −11.4| −5.8 | 3.9  | 13.2 | 17.4 | 20.2 | 20.5 | 13.6 | 5.1  | −6.0 | −12.4| 3.7   |
| Śnieżka     | −43.7| −42.0| −36.0| −26.0| −14.7| −9.5 | −6.3 | −4.2 | −13.9| −23.6| −35.9| −42.1| −24.7 |
| Minimum (°C UTCI) |      |      |      |      |      |      |      |      |      |      |      |      |       |
| Jelenia Góra | −48.1| −47.5| −40.5| −33.7| −23.7| −19.9| −11.0| −15.6| −13.2| −30.7| −42.4| −46.9| −48.1 |
| Kłodzko     | −51.9| −46.5| −42.3| −30.6| −20.6| −16.2| −8.1 | −7.8 | −14.7| −33.4| −40.7| −52.0| −52.0 |
| Legnica     | −46.9| −44.2| −43.8| −33.7| −21.6| −10.5| −11.4| −8.4 | −18.7| −27.3| −43.0| −43.8| −46.9 |
| Leszno      | −47.3| −48.9| −44.4| −36.6| −21.0| −12.9| −7.9 | −11.6| −14.8| −34.6| −38.7| −52.8| −52.8 |
| Opole       | −54.2| −43.0| −41.4| −32.8| −23.4| −10.8| −12.3| −5.0 | −18.5| −30.2| −35.7| −40.0| −54.2 |
| Wrocław    | −52.2| −40.8| −42.6| −35.8| −19.4| −17.0| −8.4 | −7.6 | −13.2| −29.0| −38.0| −45.2| −52.2 |
| Śnieżka     | −72.8| −70.0| −70.0| −63.4| −55.7| −51.4| −44.5| −46.7| −52.9| −60.8| −66.5| −72.0| −72.8 |
| Maximum (°C UTCI) |      |      |      |      |      |      |      |      |      |      |      |      |       |
| Jelenia Góra | 19.0 | 22.7 | 28.0 | 32.6 | 34.6 | 36.2 | 40.3 | 38.5 | 36.8 | 30.4 | 21.8 | 16.9 | 40.3 |
| Kłodzko     | 13.6 | 17.5 | 24.4 | 31.9 | 34.1 | 37.7 | 38.7 | 37.6 | 35.5 | 29.6 | 21.0 | 15.2 | 38.7 |
| Legnica     | 15.7 | 18.6 | 24.2 | 33.3 | 34.2 | 38.1 | 40.2 | 40.6 | 37.3 | 31.8 | 19.8 | 16.1 | 40.6 |
| Leszno      | 11.1 | 20.7 | 22.0 | 31.9 | 34.7 | 37.7 | 40.8 | 41.6 | 36.5 | 29.5 | 20.1 | 11.7 | 41.6 |
| Opole       | 13.1 | 22.8 | 26.9 | 33.6 | 34.4 | 38.6 | 40.9 | 40.1 | 35.5 | 30.1 | 22.8 | 12.6 | 40.9 |
| Wrocław    | 13.0 | 18.1 | 28.0 | 31.6 | 33.4 | 38.0 | 40.3 | 40.3 | 37.7 | 30.0 | 25.0 | 15.5 | 40.3 |
| Śnieżka     | 10.1 | 12.7 | 17.4 | 18.0 | 20.5 | 26.4 | 29.8 | 27.0 | 23.1 | 16.3 | 12.0 | 29.8 |       |
| Amplitude (°C UTCI) |      |      |      |      |      |      |      |      |      |      |      |      |       |
| Jelenia Góra | 67.2 | 70.2 | 68.5 | 66.3 | 58.3 | 56.2 | 51.3 | 54.1 | 49.9 | 61.1 | 64.2 | 63.8 | 88.4 |
| Kłodzko     | 65.5 | 64.0 | 66.8 | 62.4 | 54.7 | 53.9 | 46.8 | 45.4 | 50.2 | 63.0 | 61.6 | 67.2 | 90.6 |
| Legnica     | 62.6 | 62.8 | 68.0 | 67.0 | 55.9 | 48.5 | 51.5 | 49.0 | 55.9 | 59.1 | 62.8 | 59.8 | 87.6 |
| Leszno      | 58.3 | 69.6 | 66.5 | 68.5 | 55.7 | 50.5 | 48.7 | 53.2 | 51.2 | 64.1 | 58.8 | 64.5 | 94.2 |
| Opole       | 67.3 | 65.8 | 68.3 | 66.4 | 57.8 | 49.4 | 53.1 | 45.1 | 54.0 | 60.4 | 58.5 | 52.6 | 95.1 |
| Wrocław    | 65.2 | 58.9 | 70.6 | 67.4 | 52.8 | 55.0 | 48.7 | 47.9 | 50.9 | 59.0 | 63.0 | 60.7 | 92.5 |
| Śnieżka     | 82.9 | 82.7 | 87.4 | 81.4 | 76.2 | 77.8 | 74.3 | 73.7 | 75.9 | 84.0 | 82.7 | 84.0 | 103.0 |
and the sample partial autocorrelation function (PACF) (Brockwell et al. 1991). The sample ACF is defined as:

\[
R(t, s) = \frac{E[(Y_t - \mu)(Y_s - \mu)]}{\sigma^2},
\]

where \(t\) and \(s\) are indexing the time series and \(k = t - s\) is the lag at which the correlation is calculated.

The PACF is defined by the equation:

\[
\alpha(k) = \text{corr}(Y_{t+1} - E_{Y_{t+1}}(Y_{t+1}), Y_t - E_{Y_{t+1}}(Y_t))
\]

where:

\(E_{Y_{t+1}}(Y_t)\) is best mean square predictor of \(Y_t\).

If, for example, ACF (4) is nonzero only at lag zero and PACF (5) tails off at lag 2, then the most suitable model is ARMA(0,2), which is coincident with an MA(2). On the other hand, if PACF is nonzero only at lag 0 and ACF tails off at lag 1 for example, then the best suitable model is ARMA(1,0), which is AR(1). Nonzero ACF and PACF up to a certain lag will otherwise define an ARMA \((p,q)\) model. The purpose of having fitted a suitable ARMA model is to use it in order to decompose the standardised signal into its correlated and uncorrelated components (Brockwell and Davis 2016). Similarly, the ARMA model can then be used for generating a statistically equivalent time series as well for forecasting. The goodness of the model can be examined for example by using the Akaike Information Criteria (AIC) (Akaike 1974), or better still by the modified AIC called AICc which also accounts for overfitting and overparameterisation (Brockwell et al. 1991). AICc is defined as:

\[
AICC(p, q) = N\ln(\hat{\sigma}^2) + \frac{2(p + q + 1)N}{(N - p - q - 2)},
\]

where \(\hat{\sigma}^2\) is the maximum likelihood estimator of the noise variance, \(N\) is the number of observations, and \(p, q\) are...
the autoregressive and moving average ARMA parameters, respectively.

For each meteorological component (air temperature, vapour pressure, cloudiness, and wind speed) and the computed UTCI from the daily data, we divided the entire record into homogeneous periods showing an almost linear trend, which could then be easily removed. The next step in the decomposition process was to remove the seasonality by subtracting the monthly mean as computed by averaging out the daily data within the same month. Data were then standardised and the most ARMA(p,q) were estimated using the R software (Team and et al. 2013). The estimated autoregressive model was then used for generating new data.

Results

Annual and seasonal variability of UTCI in Lower Silesia for the years 1966–2017

Six out of the seven presented stations show comparable biometeorological conditions. The UTCI annual average values are the highest in Opole in 70% of the times for the analysed period (1966–2017) (Fig. 4).

UTCI values oscillate for the seven stations almost synchronously, which reflects the high Pearson correlation coefficients computed between all stations (Table 2). The high correlation coefficients confirm the comparability of UTCI oscillations in the studied region. Table 3 shows that UTCI values can become extreme (i.e. according to the classification given in Table 1), reaching high values during winter and low values during summer. However, apart from Śnieżka station, the occurrence of such extremes is generically very low (see Fig. 3). Additionally, the monthly picture offered by Fig. 2 for all stations confirms that there are only few values representing cold stress in summer and heat stress in winter. The case of Śnieżka station needs some further discussion which will be had in the next section. Here, it suffices to say that the frequency and yearly distribution of the frequent extreme UTCI conditions is probably ascribable to its geographical location, elevation, and aspect ratio (Figs. 3 and 4).

ARMA results

The results of the ARMA model are presented only for the air temperature in Wrocław for the sake of clarity and synthesis. However, all model results are presented in Table 4. All time series were divided into three almost equally long periods: 1966–1983, 1984–2001, and 2002–2017 to which linear trends were fitted. As far as temperature at Wrocław station is concerned, goodness of fit returned $R^2=0.197$, $R^2=0.552$, and $R^2=0.732$ for the respective aforesaid time periods. The computed linear trends for each period and at each station were thus used to detrend the series (Fig. 5) (Maidment and et al. 1993).

The next step in the decomposition process was standardisation, which we obtained by subtracting the daily mean, here assumed to be equal to the monthly one, and then dividing it by the standard deviation of the corresponding month. In doing so, we assumed that daily changes are negligible compared with monthly ones, and the resulting process also allowed removing the effect of seasonality. After standardisation, we reasonably assumed the statistical stationarity and homogeneity within the three time periods and then computed both ACF and PACF for the whole length of the series. Both ACF and PACF are shown in (Fig. 6).

ACF tails off gradually over several lags, where as PACF becomes 0 almost immediately after lag 1. This suggests that an autoregressive model order 1, namely AR(1), could be sufficient to remove all correlations in the signal thereby
Table 4 ARMA model proposal for the analysed period of 1966–2017 for all components and UTCI

| Station      | Parameter     | Model       | AIC   | Model Par |
|--------------|---------------|-------------|-------|-----------|
| Wrocław     | Temperature   | AR          | 0.187 | \(p = 1; q = 0\) |
|              | Cloudiness    | ARMA        | 0.747 | \(p = 2; q = 3\) |
|              | Wind speed    | –           | –     | –         |
|              | Vapour pres.  | AR          | 0.451 | \(p = 4; q = 0\) |
|              | UTCI          | AR          | 0.650 | \(p = 4; q = 0\) |
| Klodzko      | Temperature   | AR          | 0.294 | \(p = 1; q = 0\) |
|              | Cloudiness    | ARMA        | 0.872 | \(p = 4; q = 2\) |
|              | Wind speed    | –           | –     | –         |
|              | Vapour pres.  | AR          | 0.452 | \(p = 4; q = 0\) |
|              | UTCI          | AR          | 0.684 | \(p = 3; q = 0\) |
| Jelenia Góra | Temperature   | AR          | 0.310 | \(p = 1; q = 0\) |
|              | Cloudiness    | AR          | 0.773 | \(p = 4; q = 0\) |
|              | Wind speed    | –           | –     | –         |
|              | Vapour pres.  | AR          | 0.478 | \(p = 4; q = 0\) |
|              | UTCI          | ARMA        | 0.699 | \(p = 2; q = 4\) |
| Legnica      | Temperature   | AR          | 0.304 | \(p = 2; q = 0\) |
|              | Cloudiness    | –           | –     | –         |
|              | Wind speed    | –           | –     | –         |
|              | Vapour pres.  | AR          | 0.426 | \(p = 3; q = 0\) |
|              | UTCI          | AR          | 0.674 | \(p = 4; q = 0\) |
| Leszno       | Temperature   | AR          | 0.280 | \(p = 2; q = 0\) |
|              | Cloudiness    | –           | –     | –         |
|              | Wind speed    | –           | –     | –         |
|              | Vapour pres.  | AR          | 0.466 | \(p = 4; q = 0\) |
|              | UTCI          | AR          | 0.636 | \(p = 4; q = 0\) |
| Opole        | Temperature   | AR          | 0.287 | \(p = 1; q = 0\) |
|              | Cloudiness    | ARMA        | 0.870 | \(p = 3; q = 4\) |
|              | Wind speed    | –           | –     | –         |
|              | Vapour pres.  | AR          | 0.454 | \(p = 2; q = 0\) |
|              | UTCI          | AR          | 0.685 | \(p = 3; q = 0\) |
| Śnieżka      | Temperature   | AR          | 0.302 | \(p = 2; q = 0\) |
|              | Cloudiness    | ARMA        | 0.740 | \(p = 2; q = 3\) |
|              | Wind speed    | –           | –     | –         |
|              | Vapour pres.  | AR          | 0.542 | \(p = 2; q = 0\) |
|              | UTCI          | ARMA        | 0.779 | \(p = 3; q = 2\) |

Missing models of cloudiness are due to gaps in the missing data which did not allow for a stochastic model obtaining the uncorrelated residuals and good correspondence between the modelled and sample data (Fig. 7). For a specific station, the AR(1) scored an AICc value of 0.1871, which suggests a good performing model (Sakamoto et al. 1986). The present model can also be made to generate new data, which must be de-standardised and summed according to the original monthly mean and linear trend in order to obtain the statistically equivalent time series (Fig. 8) to the real data. It is important to appreciate how the predicted temperatures (in red) are all contained within the grey belt, which has a width that is equal to ±1 standard deviation (\(\sigma^1\)). The \(\sigma^1\) according to so-called three-sigma rule of thumb statistically represent at least 70% of the measured data (Wheeler et al. 1992). Thus, the red signal is clearly just one possible realisation of the stochastic process (Fig. 8).

Whilst the proposed linear stochastic approach was shown to be successful in decomposing all time series into deterministic and noise components, this was not the case for the wind speed. For this variable (Table 4), the decomposition of the time series did not lead to satisfactory results for any ARMA model order that we tested. This may have been caused by the vectorial origin of the variable itself, where changes in wind direction with similar
Fig. 5 Eight years moving average of temperature in Wroclaw for 1966–2017, with three linear trends for three homogeneous periods.

Fig. 6 Autocorrelation and partial autocorrelation functions of detrended and standardised signal of air temperature in Wroclaw; the discontinuous blue line indicates the confidence interval below which autocorrelation is statistically insignificant.

Fig. 7 Example of ACF residuals (red line, level of confidence interval) of AR(1) model for air temperature in Wroclaw (left) and comparison with theoretical quantiles, the red dashed line represents the ideal distribution of data (right).
magnitude might have produced ambiguity in the data. This generates some spurious temporal correlation, which cannot simply be removed by linear autoregressive models. The UTCI was then computed from the data (blue line in Fig. 8) with the purpose of comparing it with its stochastic model, or with the one obtained from single stochastic models for each meteorological component. Figure 8 shows that fitting a stochastic model on the UTCI after applying the decomposition steps already described produces a stochastic model that successfully removes all correlations and separates the noisy component from the correlated one (green line). This model was built using all UTCI data up to 2017 and then using 2018 data as a prediction.

We also tried to compute the UTCI starting from the stochastic models of each single meteorological component including the wind speed, of which not all correlations could successfully be removed as already described. This resulted in a fluctuating signal (red line in Fig. 8) very similar to the green one in terms of visual appearance in the time domain. This would also result in similar probability density
distributions, even though the autocorrelation function might be substantially different (Fig. 9).

Discussion

The average annual UTCI values in the Lower Silesia region range from 2.9 °C in Leszno to 5.6 °C in Opole (Table 3). Slightly higher values can be found in the literature. Rozbicka and Rozbicki (2018) showed that the annual average ranged from 3.5 to 9.3 °C for the period 1998–2015. According to Mąkosza (2013), the average UTCI values in the Lubuskie province change between 6.1 °C in Zielona Góra and Gorzów Wielkopolski and 8.1 °C in Słubice. Blażejczyk et al. (2014) calculated an annual UTCI value of 4.1 °C in Warsaw and 5.7 °C in Kołobrzeg, for the period 1991–2000. However, those studies were carried out over shorter periods and in more recent years, where the influence of ongoing climatic changes may have affected the result, thus explaining the slightly higher values. This notwithstanding, all studies correspond to the same heat stress class of “slight cold stress.” The situation for Śnieżka is significantly different, it being a mountain station, where cold stress at low temperatures is considerably increased by the high wind speeds (Bröde et al. 2012a). The Śnieżka Mountain has the most commonly used hiking trails in Karkonosze and knowledge of the local bioclimate can be useful for supporting future tourism in the area. Due to frequent high wind speeds, the average UTCI value is as low as −24.7 °C. It is worth stressing that cutting off the wind speed to 20 m·s⁻¹ (Novak 2013), which we imposed in order for the UTCI formula to be applicable, has not affected the interpretation of UTCI in terms of thermal comfort. For those regions, the limiting wind speed of 20 m·s⁻¹ already represents high cold stress classes that require additional protective measures, especially from the wind (Błażejczyk 2011a). This is an important piece of information especially for tourism applications, particularly if such a combination of meteorological events leading to extreme cold happens during the spring and summer seasons. Most of the time, tourists might be unprepared for exposure to such extremes (e.g. as occurred in Śnieżka in May where for the analysed period, 30% of the thermal conditions corresponded to strong cold classes (Fig. 2). These findings may also have applications in analysing the bioclimate in arctic windy conditions (Araźny et al. 2019). Each station shows a weak upward trend for UTCI, which is in line with the air temperature and solar radiation trends that occur in Wroclaw for the analysed period (Bryś 2010, 2013). All synoptic stations also show UTCI seasonal patterns that reflect the Polish annual climate (Marsz et al. 2016, 2019). Two heat waves were recorded for the “very strong heat stress” class in 1994 and in 2015. For example, for Opole in 1994, the heat wave persisted for 6 days, i.e. from July 28 to August 2. In Wroclaw, Leszno, and Legnica, the heat wave was also classified as “very strong heat stress” and lasted 4 days, i.e. from July 29 to August 1. In Jelenia Góra and Klodzko, values were 1–2 °C UTCI below the “very strong heat stress” class threshold. In 2015, a strong heat wave lasted from of August 7–12 in Opole, while it was cooler by 5–6 °C of UTCI in other cities. In both heat waves, Jelenia Góra and Klodzko had the lowest values of UTCI. The 2015 heat wave was also presented for Warsaw by Rozbicka and Rozbicki (2018) where the period August 3–16 was analysed. The number of “strong heat stress” class events for all stations in the analysed period was 1452, which corresponds to a relative frequency of about 1%. Therefore, events leading to heat stress are rather rare and we can assume that in the studied area there is low risk of thermal comfort disruption caused by thermal classes of the warm type (Bröde et al. 2012a). As far as cold thermal classes are concerned, there were 5613 observations of “extreme cold stress” in Śnieżka (i.e. 29% of the time), and 1 observation in Leszno and Legnica in 1996 (0.005%). “Very strong cold stress” occurred 7288 times (5.5% of all station observations) in 5406 days over 52 years. In terms of individual stations, 457 times (2.5%) occurred in Jelenia Góra, 722 times (4%) in Klodzko, and 664 times (3.5%) in Legnica and Leszno, 661 times (3.5%) in Opole, 339 times (1.5%) in Wroclaw, and 3878 times (20%) in Śnieżka. In summary, “extreme cold stress” represents 4.3% of all observations (mainly in Śnieżka), “very strong cold stress” 4.8%, “strong cold stress” 14.8%, and “moderate cold stress” 22.6%. The “slight cold stress” class occurred with a frequency of 17.4%; “no thermal stress” 29.7%, which was the most common thermal class for the analysed period and area, “moderate heat stress” 4.9%, and “strong heat stress” and “very strong heat stress” 1.5% (Fig. 3). These results are similar to those registered in other parts of Poland (Kuchcik et al. 2013; Blażejczyk et al. 2014; Rozbicka and Rozbicki 2018).

We performed a stochastic modelling of the meteorological variables and of the UTCI, using the results for air temperature in Wroclaw station as an example. Removing the trends (Fig. 5) and seasonality was necessary in order to use the ARMA models (Fig. 7). The ARMA models were estimated according to the sample auto- and partial-correlation functions (Fig. 6). All models were successful in removing all correlations from noise for all components except for wind speed (Table 4), as shown for example by the comparison with theoretical quantiles for the temperature signal (Fig. 7). As shown in Fig. 8, the prediction underestimates the actual air temperature which is the result of a very warm year in 2018 compared with the past 52 years. The modelled UTCI signal correctly oscillates within the ±σ₁ variability band as the calculated one (blue line) up
Conclusions

This study analysed the bioclimatic conditions of Lower Silesia (SW Poland) for the period 1966–2017. A long-term analysis of the bioclimate of Lower Silesia showed many similarities to other parts of Poland (Kuchcik et al. 2013; Makosza 2013; Blażejczyk et al. 2014; Rozbicka and Rozbicki 2018). The most favourable biometeorological conditions occur between April and October. The most common thermal class is “no thermal stress,” which is also consistent with cases found in the literature. In the case of windy conditions as in Śnieżka located at the top of the mountain, calculation of the UTCI requires that wind speed be cut off at its uppermost limiting value. Although this may well be questionable as it introduces a strong nonlinearity and discontinuity in the resulting time series, its final effect on UTCI may still be correct if the index falls into those classes representing extreme stress conditions. This was the case for the stations analysed in this study, even though we would still recommend that this forced approach should be verified on a case-by-case basis. Forecasts for the air temperature and UTCI for Wrocław were presented using a comparison of the measured data with those of the corresponding stochastic models. However, the presented ARMA modelling approach has shown itself not to be applicable for wind speed, specifically in successfully removing all temporal correlations from the residuals. Accordingly, the UTCI calculated from the single modelled components failed to reproduce some of the linear statistical properties of the real signal, that is, its temporal autocorrelation. On the contrary, the autocorrelation model of the UTCI signal seemed successful and can thus be used for reconstruction and forecasting purposes. This work paved the way for future studies that aim, for instance, not just at clarifying the propagation of the temporal correlation across the formula for the UTCI, but also at reconstructing the dynamical system governing regional bioclimatic conditions.

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References

Akaike H (1974) A new look at the statistical model identification. In: Selected Papers of Hirotugu Akaike. Springer, pp 215–222
Aráni A, Wyszyński P, Przybyłak R (2019) A comparison of bioclimatic conditions on franz jøsef land (the arctic) between the turn of the nineteenth to twentieth century and present day. Theor Appl Climatol 137(3):2623–2638. https://doi.org/10.1007/s00704-018-20276-y
Błażejczyk K (1996) BioKlima 2.6. Institute of Geography and Spatial Organization (http://www.igipz.pan.pl/Bioklima-zgik.html), [Online; accessed 19-01-2019]
Błażejczyk K (2005) MenEx2005 - the updated version of man-environment heat exchange model. https://www.igipz.pan.pl/tl_files/igipz/ZGiK/opracowania/indywidualne/blazejczyk/MENEX_2005.pdf, [Online; accessed 19-01-2019]
Błażejczyk K, Bróde P, Fiala D, Havenith G, Holmér I, Jendritzky G, Kampmann B, Kunert A (2010) Principles of the new Universal Thermal Climate Index (UTCI) and its application to bioclimatic research in European scale. Miscellanea Geograph 14(2010):91–102. https://doi.org/10.2478/mgrsd-2010-0009
Błażejczyk K (2011a) Assessment of regional bioclimatic contrasts in poland. Miscellanea Geograph-Region Stud Dev 15:79–91. https://doi.org/10.2478/v10288-012-0004-7
Błażejczyk K, Kunert A (2011b) Bioclimatic principles of recreation and tourism in Poland (in Polish), vol 13
Błażejczyk K, Epstein Y, Jendritzky G, Staiher H, Tinz B (2012) Comparison of UTCI to selected thermal indices. Int J Biometeo 56(3):515–535. https://doi.org/10.1007/s00484-011-0453-2
Błażejczyk K, Jendritzky G, Bróde P, Fiala D, Havenith G, Epstein Y, Psikuta A, Kampmann B (2013) An introduction to the universal thermal climate index (UTCI). Geogr Pol 86(1):5–10. https://doi.org/10.7163/GPol.2013.1
Błażejczyk K, Kuchcik M, Błażejczyk A, Milewski P, Szmyd J (2014) Assessment of urban thermal stress by UTCI–experimental and modelling studies: an example from Poland. DIE EREDE–J Geograph Soc Berlin 145(1-2):16–33. https://doi.org/10.12854/erde-145-3
Brockwell PJ, Davis RA, Fienberg SE (1991) Time series: Theory and Methods: Theory and Methods. Springer Science & Business Media
Brockwell PJ, Davis RA (2016) Introduction to time series and forecasting. Springer, Berlin
Bröde P, Fiala D, Błażejczyk K, Holmer I, Jendritzky G, Kampmann B, Tinz B, Havenith G (2012a) Deriving the operational procedure for the Universal Thermal Climate Index (UTCI). Int J Biomete-rol 56(3):481–494. https://doi.org/10.1007/s00484-011-0454-1
Bröde P, Krüger EL, Rossi FA, Fiala D (2012b) Predicting urban outdoor thermal comfort by the universal thermal climate index utci—a case study in southern brazil. Int J Biomete-rolog 56(3):461–470
Bryš K, Bryš T, Glogowski A (2019) Long-wave radiation balances of the south-west poland. In: Es3 web of conferences, EDP sciences, vol 116, pp 00013
Chabior M (2011) Selected aspects of the bioclimate of Szczecin (in Polish). Prace Stud Geogr 47:293–300
Couuts AM, White EC, Tapper NJ, Beringer J, Livesley SJ (2016) Temperature and human thermal comfort effects of street trees across three contrasting street canyon environments. Theor Appl Climatol 124(1-2):55–68. https://doi.org/10.1007/s00704-016-1832-8
Czernecki B, Glogowski A, Nowosad J (2020) Climate: An r package to access free in-situ meteorological and hydrological datasets for environmental assessment. Sustainability 12(1). https://doi.org/10.3390/su12010394, https://www.mdpi.com/2077-1312/12/1/394
Di Napoli C, Pappenberger F, Cloke HL (2018) Assessing heat-related health risk in europe via the universal thermal climate index (utci). Int J Biomete-rolog 62(7):1155–1165. https://doi.org/10.1007/34
de Freitas CR, Grigorieva EA (2017) A comparison and appraisal of a comprehensive range of human thermal climate indices. Int J Biomete-rolog 61(3):487–512. https://doi.org/10.1007/s00484-016-1228-6
Galan JC, Guedes J (2019) Applicability of heat stress index in the context of military work: Pilot study. In: Occupational and Environmental Safety and Health. Springer, pp 313–322. https://doi.org/10.1007/978-3-030-14730-3_34
Ge Q, Kong X, Qi J, Zheng J (2017) Application of UTCI in China from tourism perspective. Theor Appl Climatol 128(3-4):551–561. https://doi.org/10.1007/s00704-016-1731-z
Haltiner JP, Salas JD (1988) Development and testing of a multivariate, seasonal arma (1, 1) model. J Hydrol 104(1-4):247–272
Havenith G, Fiala D, Błażejczyk K, Richards M, Bröde P, Holmér I, Rintamaki H, Benschabat Y, Jendritzky G (2012) The UTCI-clothing model. Int J Biomete-rolog 56(3):461–470
Jarraud M (2008) Guide to meteorological instruments and methods of observation (wmo-no. 8), vol 29. World Meteorological Organisation, Geneva. https://www.wmo.int/pages/prog/www/IMOP/CIMO-Guide.html
Kuchcik M, Błażejczyk K, Szmyd J, Milewski P, Błażejczyk A, Baranowski J (2013) Potencial leczniczy klimatu Polski(in Polish). Wydawnictwo Akademickie SEDNO Spółka z oo
Maciejczyk M, Brón A, Opyrchał M (2017) Changes in aerobic performance, body composition, and physical activity in polar explorers during a year-long stay at the polar station in the arctic. Int J Biomete-rolog 61(4):669–675. https://doi.org/10.1007/s00484-016-1244-6
Maidment DR et al (1993) Handbook of hydrology, vol 9780070.
McGraw-Hill, New York
Marsz AA, Styszyńska A, Krawczyk WE (2016) Long-term fluctuations of annual discharges of the main rivers in Poland and their association with the Northern Atlantic Thermohaline Circula-tion(in Polish). Przegląd Geogr 88(3):295–316
Marsz AA, Styszyńska A et al (2019) Course of winter temperatures in Poland in the years 1720–2015(in Polish). Prace Geogr 2018(155):85–138
Matzarakis A, Nastos PT (2011) Human-biometeorological assessment of heat waves in Athens. Theor Appl Climatol 105(1-2):99–106. https://doi.org/10.1007/s00704-010-0379-3
Matzarakis A, Rammelberg J, Junk J (2013) Assessment of thermal bioclimate and tourism climate potential for central Europe—the example of Luxembourg. Theor Appl Climatol 114(1-2):193–202. https://doi.org/10.1007/s00704-013-0835-y
Milani E, Andrade M, Diniz C (2017) Generalized normal arm model applied to the areas of economy, hydrology, and public policy. Commun Stat-Simul Comput 46(7):5819–5835. https://doi.org/10.1080/03610918.2015.1100736
