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RESEARCH

Temporal resolution of climate pressures on façades in Oxford 1815–2021

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Abstract

Changes in climate will exert increasing pressure on heritage, so standard climate metrics need to be tuned to heritage threats. Historical meteorological records are commonly available as monthly summaries, with few offering daily observations as daily readings may not have been taken or yet digitised. As data averaged over longer intervals misses short weather events, we investigate the extent to which temporal resolution is important for assessing climate pressures on façades. The Radcliffe Meteorological Station, Oxford, UK, provides the longest continual record of daily temperature and precipitation measurements in the UK. We use this record to assess the role of temporal scale in heritage climate parameters relating to (i) sunshine and warmth, (ii) rainy days and (iii) freezing events. Where there is a linear relationship between daily and monthly scale data, monthly observations can be interpolated as heritage climate parameters. However, for the majority of parameters, daily data was required to capture the variability in the datasets. We argue for the increased availability of daily observations to help assess the threat of climate to heritage.

1 Introduction

Climate change is increasingly affecting our heritage. There is growing evidence that the twenty-first century will exert enhanced pressures on our buildings (Sabbioni et al. 2010; Leissner et al. 2015). Many of the standard metrics used in climate science are not well suited to represent the processes that affect material heritage, as these do not capture the specific components of weather that damages materials. Neither do they capture the spatial or temporal scale of these processes (Brimblecombe 2014). The need to tune environmental and climate parameters to represent threats to heritage was recognised in the early 2000s. The European NOAHs ARK project (Sabbioni et al. 2010) was developed as a response to the increasing recognition of climate as a driver of heritage damage, marking a notable shift in heritage research away from pollution threats. This led to the concept of heritage climatology (Brimblecombe 2010), which directly addresses the relationship between climate processes and heritage. Heritage climate parameters most often tune traditional meteorological variables to the context of the heritage threat (Brimblecombe and Richards 2022; Hernández-Montes et al. 2023).

High spatial resolution of available climate data has been seen as necessary in representing potential damage (Cacciotti et al. 2021). The spatial scale of past observations and modelled projections needs to relate to heritage for the outcomes to be relevant (Richards and Brimblecombe 2022a). However, the issue of time resolution has had less of a focus. Perhaps it is not widely seen as an issue because damage accumulates over many years before becoming evident. This can lead to the use of annually averaged or summed meteorological data (Hernández-Montes et al. 2023) or model output (Bonazza et al. 2009), which may fail to recognise limits imposed by temporal resolution. Climate data with a high spatial resolution is seen as necessary as data averaged

Highlights 1. Assess the role of temporal scale on heritage climate pressures
2. Compare heritage climate parameters derived from daily and monthly data
3. Daily observations are needed to capture variability in heritage pressures

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over larger intervals has lower variability and will impose a structure on the data that limits the presence of extremes within the dataset. As extremes can cause substantial impact to building materials, these are of particular interest to the heritage community.

Daily meteorological observations are needed for many heritage climate parameters if they are to capture events such as rain days or the number of days where a particular temperature threshold is crossed. Climate models provide outputs at a daily resolution, with some being used to assess change in heritage climate over the next century (Orr et al. 2018; Richards and Brimblecombe 2022b; Brimblecombe and Richards 2022). We also need to understand past exposures of materials, yet many historical climate records are only available at a monthly resolution. For example, the World Climate Normals dataset provides monthly data (World Meteorological Organization 2020) and the recent Rainfall-rescue project (Hawkins 2021; Met Office 2022) used some 16,000 volunteers to help transcribe > 65,000 pages of monthly rainfall observations from UK and Ireland over the period 1677 to 1960 for over 5000 sites including Abergeldie Castle, Guildford Royal Grammar School, Park Hall estate, Kidderminster and Looe Railway station (https://docs.google.com/spreadsheets/d/1W2SUDvzevnzhUmUjfr31XXd8WODAFCoZpeBliOebVBs/edit#gid=1874162311).

Researchers in other fields, such as hydrology and agronomy, have faced similar challenges acquiring daily outputs from monthly records—particularly for precipitation due to its variability over time and space. Deterministic models tend to have poor spatial resolution, so stochastic models have been used to generate probabilistic outcomes of weather series (Gregory et al. 1993). Markov chains have been widely used to determine daily estimates from monthly averages or totals (Srikanthan and McMahon 2001). They have been used to simulate daily precipitation amounts (Wan et al. 2005; Sadiq and Sadiq 2014; Li and Shi 2019), daily river discharge from monthly precipitation and temperature data (Schuol and Abbaspour 2007) and to resolve crop model inputs (Geng et al. 1986; Jones and Thornton 2000). Bayesian approaches (Costa and Fernandes 2017) and probability distributions (Piantadosi et al. 2009) have been used in capturing flood occurrences. Such approaches are uncommon in heritage science, perhaps because they lead to probabilistic outputs rather than identifying specific times when damage is likely to occur.

This study brings together approaches used in climate, heritage and environmental sciences, applying them to the long daily meteorological record from the Radcliffe Meteorological Station in Oxford, UK. This paper aims to (i) investigate the role of temporal resolution in heritage climate parameters and (ii) identify heritage climate parameters that could be calculated from monthly datasets. While this study asks a theoretical question about temporal scale, it has important implications for how researchers undertake meteorological observations, and the archiving resolution of climate model outputs so the resultant data are useful for understanding heritage conservation.

2 Data and method

2.1 Study site

2.1.1 Radcliffe meteorological station

We used the Radcliffe Meteorological Station records, available at https://www.geog.ox.ac.uk/research/climate/rms/daily-data.html. The station is located in Green Templeton College, Oxford, UK, (51.7612°N, 1.2640°W) at 63 m above sea level. It has the longest continual record of daily temperature and precipitation in the UK, and one of the longest globally. These daily measurements have been recorded since 1813 (temperature) and 1827 (rainfall), with detailed metadata on the type and positioning of equipment (Burt and Burt 2019).

Daily minimum and maximum temperatures were recorded from 1815. Before 1849, temperature readings were taken from unscreened thermometers. From 1849 to 1878, measurements were collected from within a wooden screened, ventilated “penthouse” structure until it was replaced with a Stevenson screen. Minor corrections have been applied by the Radcliffe Meteorological Station to pre-1925 measurements to account for differences in exposure (Burt and Burt 2019). Until 1852, the rain gauge was located at roof level, resulting in higher rain volumes being recorded. Therefore, temperature observations from 1815/2021 and rainfall observations from 1852/2021 (times and dates in this paper follow ISO 8601) are used in our analysis.

Daily sunshine hours have been recorded since 1921 using a Campbell-Stokes sunshine recorder, located on the roof of the Radcliffe Observatory tower until 1976, when it was moved to the roof of the Engineering Science building (Burt and Burt 2019). Day length was calculated using the 2021 sunrise and sunset times for Oxford from *timeanddate* (https://www.timeanddate.com/sun/uk/oxford).

Meteorological data is often skewed, so we used non-parametric statistics such as Theil-Sen slopes (Hollander et al. 2013) to represent change over time along with the Kendall τ statistic (Vannest et al. 2016) and the Wilcoxon signed rank test (Woolson 2008) to compare parallel records.

2.1.2 Oxford, UK

Oxford is home to a wealth of built heritage, with the centre structured around historic College and University buildings. Many are constructed from Jurassic oolitic limestones, including Wheatley and Headington stone (Arkell 1947). The stone facades have periodically required extensive repair and restoration, with the latest extensive phase occurring in the 1960s (Oakeshott 1975). The effect of pollution on the deterioration of Oxford's built heritage has been much researched (Viles 1996; Viles and Gorbushina 2003; Thornbush and Viles 2005; Sternberg et al. 2010; Wilhelm et al. 2021). However, there has been less of a focus on monitoring deterioration as a response to climate pressures.

2.2 Heritage climate parameters

We calculated a range of heritage climate parameters using temperature, precipitation and sunshine as these were available for many years at a daily resolution. Wind speed was recorded as monthly mean measurements (Burt and Burt 2019), so important parameters such as wind-driven rain have not been included. We focus on three aspects of heritage climate: sunshine and warmth, rainy days and freezing events. This approach enables us to capture a range of climate processes that have posed a threat to heritage in the Oxford area over many decades.

2.2.1 Sunshine and warmth

Solar irradiation increases the temperature of stone surfaces above air temperature, inducing steep thermal stress gradients in the outer layers of the stone (Bonazza et al. 2009; Smith et al. 2011b; Al-Omari et al. 2019). Moderate levels of light and warmth may encourage plant growth, although in some cases prolonged UV exposure or high temperatures can inhibit growth.

Sunshine hours: Sunshine hours have recently been argued to be a key environmental parameter in determining deterioration of façades (Hernández-Montes et al. 2023). The Radcliffe record includes daily sunshine hours for more than a hundred years (1921–present).

Degree days: In this study, warmth is represented using the concept of degree days, which are calculated as:

$$DD_{Th} = \sum \left(T_D - T_{Th}\right) \tag{1}$$

where the sum accumulates only when $T_D > T_{Th}$, T_D being the daily temperature and T_{Th} the threshold temperature.

We focus on two temperature thresholds, 5°C and 15°C. The 5-degree day parameter is used because temperature is an important factor in microbial colonisation on stone façades, which can result in algal greening (Gaylarde 2020). Micro-organisms can erode stones such as limestones and are "a principal factor of toning down new stonework" (Arkell 1947, p160). They are able to photosynthesise, respire and grow at near freezing temperatures, i.e. between 1 and 5°C (Häubner et al. 2006; Karsten et al. 2014).

The threshold temperature of 15°C was chosen to represent the growth of ivy (*Hedera helix*). Ivy can have a bioprotective role (e.g. Viles et al. 2011; Sternberg et al. 2011) with "the leaves act[ing] like little tiles which shed the water off" (Arkell 1947, p158). Ivy is a southern-temperate species that develops fruit when the warmest months are > 13°C (Metcalfe 2005) and is cultivated in greenhouses at 20°C (Pollet et al. 2009). This temperature threshold of 15°C would also be suitable for other damage forms such as insect attack (Brimblecombe and Lankester 2013).

2.2.2 Rainy days

Monthly rain days: Rain days are defined in the Radcliffe dataset as a day with ≥0.2 mm of rain. The number of rain days (n_{RD}) is a key parameter in the wetting of building surfaces and greening of façades. As neither rain days nor precipitation (P, mm) can take negative values, a power function ($n_{RD,m} = aP_m^{\,b}$, where a is a coefficient and b is a fitted exponent, and subscript "m" is the month) seemed a sensible representation to correlate the observations.

Periods of deep wetting: Prolonged periods of wetness can result in sub-surface wetting of porous building materials and encourage biological growth (Smith et al. 2011a; McCabe et al. 2013). Deep wetting can drive salt penetration into the stone (Sass and Viles 2010). While this process may delay the onset of surface decay, the severity can be greater due to increased surface or substrate heterogeneity (Sass and Viles 2010). Here, we consider a prolonged period of wetness to be ≥ 4 days of rainfall ≥0.2 mm. The length of wet spells is difficult to define, and in climatology this is done on a probabilistic basis (Bärring et al. 2006), but this seemed poorly related to heritage. Here, we chose a period of 4 days, which would ensure building surfaces remained wet for a substantial amount of time, yet give the possibility of several spells each month for statistical analysis. If a wet spell occurs over a monthly boundary, it is attributed to the end month. Various approaches including the use of Markov chains were used in modelling the number of 4-day rain spells, but in the end a simple approach assuming a Poisson distribution proved successful.

Scheffer index: The Scheffer index (Scheffer 1971) is commonly used to estimate the risk of fungal attack on wooden structures (e.g. Lisø et al. 2007; Hygen et al. 2011; Curling and Ormondroyd 2020; Richards and Brimblecombe 2022b; Brimblecombe and Richards 2022). While stone buildings dominate in Oxford, the city has a number of structures with significant timber elements, such as the Oxford University Cricket Club Pavilion. The index can also be an indicator for algal growth on stone façades (Gaylarde 2020).

The Scheffer index is expressed in the equation:

$$\mathrm{Sch} = \sum_{\mathrm{Jan}}^{\mathrm{Dec}} \left[\left(T_{\mathrm{m}} - 2\right)\left(n_{\mathrm{RD,\,m}} - 3\right) \right] / 16.7 \tag{3}$$

which represents the sum over 12 months for the product of the monthly mean temperature (T_m) and number of days in the month with ≥0.2 mm of rain (n_{RD}). The original Scheffer index defines a rain day as ≥0.3 mm, but we determined n_{RD} to be the number of days in the month with ≥0.2 mm of rain to match the Radcliffe rain gauge threshold and to follow the common definition of a rain day (American Meteorological Society 2022). An index value of less than 35 or more than 65 is associated with a low and high risk of fungal attack, respectively (Scheffer 1971). It is only the rainfall that requires a daily resolution, as the temperature parameter uses the monthly mean temperature.

2.2.3 Freezing events

Deep frost days: Colder temperatures can cause freezing processes to penetrate deeper into the core of a structural element. Permeable stones are particularly susceptible, with local Doulting stone being known to split under deep frosts of −5°C. Unfortunately, this stone has often been used in repairs, e.g. the pinnacles on Tom Tower in Christ Church College, Oxford (Curthoys 2017). Here, we calculate frost intensity simply by determining the number of days when $T_{min} \le -5$°C.

Freezing events: These are the freeze part of a freeze-thaw cycle and are counted on a daily basis when $T_{max} >$ 0°C and $T_{min} < 0$°C during any given day, although in small pores water might not freeze at 0°C (Ruedrich et al. 2011). Although low temperatures increase the chance of a freeze event, very low temperatures mean the freezing persists reducing the number of freeze-thaw events. Therefore, a Gaussian curve:

$$n_{\mathrm{Fz}} = a_1 e^{-\frac{1}{2}\left(\frac{T_{\mathrm{m}} - a_2}{a_3}\right)^2} \tag{4}$$

is applied, where n_{Fz} is the number of freezing events in a month, a_1, a_2 and a_3 represent three least-squares fitting parameters and T_m is the monthly mean temperature. The distribution of freezing events across a year was used to assess their seasonality. We arbitrarily chose a second-degree polynomial to fit the seasonality curves.

Wet frosts: A wet frost occurs when a rainfall event is followed by a frost. These are likely to be particularly damaging for building materials as the surface layers would contain high levels of moisture, so when frozen can impose high levels of stress. The chronology of rainfall and the freezing event is important in determining if a wet frost has occurred—but wet frosts are difficult to establish using daily data. If we simply looked for days with both rainfall and a minimum temperature below 0°C, the frost could have occurred in the early morning before the rainfall (though not snow), and so no wet frost would have occurred. Therefore, we determine wet frosts to have occurred when it rains (when T_D>0°C) on a given day and then the minimum temperature falls below 0°C on the following day.

3 Results and discussion

3.1 Warmth and sunshine

3.1.1 Hours of sunshine days

Figure 1a shows the hours from sunrise to sunset in Oxford. The maximum recorded hours are slightly less than the daylight hours, as the Campbell-Stokes sunshine recorder will not record very weak sunlight when the sun is close to the horizon. The mean daily values for the 30-year periods at the start and end of the sunshine record 1921/1950 and 1992/2021 are shown as lines. These are considerably less than the maximum values as some days were cloudy and others completely overcast. More than two-thirds of 365 individual daily averages are higher in the recent 30-year period (Wilcoxon signed rank test significant p<.0001), probably an indicator of climate change (Burnett et al. 2014), and potentially a reduction in pollution haze events.

Between 1921 and 2021, the total hours of sunshine each year shows a slight increase (Fig. 1b) of 1.64±0.52 h a^{-1} expressed as a Theil-Sen slope. Although this sounds small,

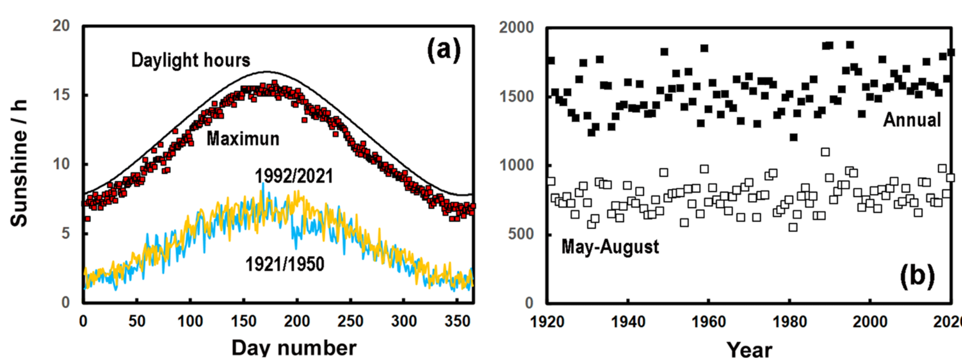


Fig. 1 **a** Curve showing the length of daylight in Oxford (black line) and the maximum hours of sunshine on a given day of the year from the Radcliffe record 1921/2021. Lines show the values for 1921/1950 (blue) and 1992/2021 (yellow). **b** Observed trend in annual and May to August sunshine hours

it amounts to an increase of more than 160 h each year over a century. Similarly, the sunnier months (May to August) show a slight increase (Fig. 1b) in hours of sunshine over the record (0.59±0.35 h a^{-1}). Indeed, the Radcliffe station recorded its sunniest May in 2020 with 331.7 h of sunshine, 173% of the average of 192 h (SoGE 2020). In 2022 (not included in this analysis) January, August, October 2022 were respectively the 6th, 6th and 1st sunniest months on record (SoGE 2022).

Our analysis suggests there is little problem in using monthly amounts rather than the sum of daily amounts for assessing sunshine hours. This could be a useful heritage climate metric as it could use datasets with a monthly resolution. However, translating the number of daily sunshine hours into thermal stresses experienced by stone surfaces is complex (Bonazza et al. 2009), and resultant stresses are likely related to rapid temperature changes, rather than overall sunshine exposure. This is reflected in Arkell's book on Oxford Stone (1947), "In Oxford blistering is usually worse on south walls than on north. [...] south walls consequently suffer worst because they experience the greatest temperature changes." (p 153). Capturing solar-induced stresses would require data at high temporal resolution (subhourly) as infrared energy causes very steep temperature/stress gradients within the outer 10 mm of exposed limestone (Smith et al. 2011a). Indeed, in desert environments, rocks have been found to experience temperature changes up to 10°C $\min^{-1}$ over 1-s intervals (McKay et al. 2009). While this is likely to be an extreme rate of temperature change, it highlights the potential stress that direct sunlight could cause on Oxford façades (Bonazza et al. 2009). Consequently, while sunshine hours are relatively insensitive to being recorded at a daily or monthly resolution, it can be difficult to translate this parameter meaningfully to damage on stone façades.

3.1.2 Heritage degree days

The 5-degree day (Section 2.2.1) results for algal growth show a very clear linear relationship with mean monthly temperature for the warm months April to October (Fig. 2). The relationship is so strong for these months that the regression shows the number of degree days to be simply the product of the days in the month and the mean temperature minus 5°C. For example, for August, the regression equation is $DD_{5,8}$=31T−155, showing that the coefficient is the number of days in the month, and the intercept is the number of days in the month multiplied by the threshold. By contrast, the regression equation for January is $DD_{5,1}$=8.632T−2.518.

The annual 5-degree days (units °C day) are calculated as:

$$\begin{aligned} DD_5 = 8.632T_1 + 9.3984T_2 + 18.836T_3 + 26.948T_4 \\ + 30.843T_5 + 30T_6 + 31T_7 + 31T_8 \\ + 30T_9 + 29.813T_{10} + 19.397T_{11} \\ + 11.738T_{12} - 1162.2 \end{aligned} \tag{5}$$

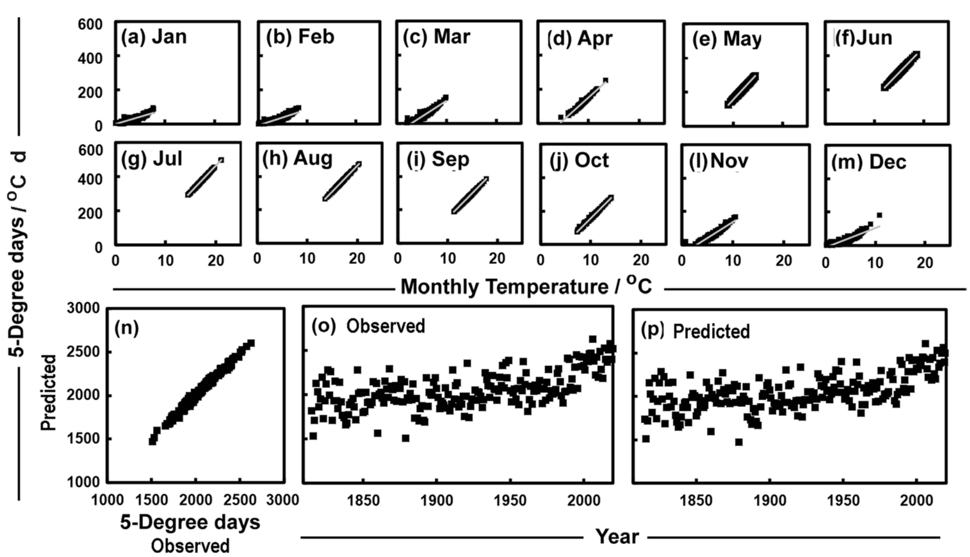


Fig. 2 **a**–**m** Relationship between observed 5-degree days and average monthly temperatures for the period 1815/2021, with grey lines from linear regression. **n** Predicted 5-degree days as a function of observed degree days. **o** Trend in observed number of 5-degree days for the entire year from 1815/2021. **p** Trend in predicted degree number of 5-degree days from 1815/2021. Note: the monthly linear regression equations are: Jan, $DD_{5,1}$=8.632T − 2.518; Feb, $DD_{5,2}$= 9.3984T − 9.2189; Mar, $DD_{5,3}$=8.836T − 55.411; Apr, $DD_{5,4}$=26.948T − 119.18; May, $DD_{5,5}$=30.843T − 152.96; Jun, $DD_{5,6}$=30T − 150; Jul, $DD_{5,7}$=31T − 155; Aug, $DD_{5,8}$=31T − 155; Sep, $DD_{5,9}$=30T − 150; Oct, $DD_{5,10}$=29.813T − 140.75; Nov, $DD_{5,11}$=19.397T − 58.351; Dec, $DD_{5,12}$=11.738T − 12.851

Most of the contribution to the annual values for 5-degree days arises from the summer months where monthly temperatures completely describe 5-degree days. This means that there is an excellent agreement (r^2=0.99) between the annual predicted and observed values (Fig. 2n), with a slope close to unity (0.98) and a small intercept (41°C day). Climatologically, this result is unsurprising as degree days are an accumulation of temperature—this makes it a simple task to use monthly data. The observed (Fig. 2o) and predicted trends (Fig. 2p) over time show almost identical Theil-Sen slopes of 2.05±0.24 and 2.09±0.24 °C day a^{-1}, an increase reflecting a warming climate.

As the calculation of degree days rejects values less than the threshold, the predicted degree days are only valid when all the daily values in a month exceed the threshold. Therefore, as the temperature threshold increases, there is a weaker relationship between days and months. When considering the 15-degree days to represent accumulating biomass such as for ivy growth, the linear relationship is clear for the warm months of July and August, but weaker for the cooler months (Supplementary Information Fig. S1). This suggests that when translating degree day parameters into a heritage context, daily data are more likely to be required when considering high temperature thresholds.

Future increases in temperatures will likely strengthen the relationship between monthly temperatures and degree days. However, increases in extreme temperatures may produce environmental conditions too harsh for organisms to reproduce or survive, altering the balance of protection and deterioration that these species currently generate for heritage buildings (Metcalfe 2005; Häubner et al. 2006).

3.2 Rainy days

3.2.1 Monthly rain days

In contrast to sunshine hours and 5-degree days, we found the correlation between the monthly rainfall totals and the number of monthly rain days is not strong, with regression coefficients (r^2) to the power function (Eq. 4) ranging from as little as 0.48 for June and 0.66 for February (Fig. 3a–m). Accumulating the monthly predictions allows an estimate of the annual prediction which is compared with observations as shown in Fig. 3n. The predicted values are somewhat greater with an average 185±18 compared to that for the observed values of 166±19. As with many fitted parameters, the variance tends to be smaller with the predicted data, though not markedly so here. The trend in the observations is 0.076±0.030 a^{-1} compared to the predicted value of only 0.051±0.031 a^{-1}.

The variability in rainfall event characteristics poses a challenge within a heritage context as the same monthly total of rainfall could drive two very different processes of deterioration depending on how the rain fell, e.g. short isolated spells of heavier rain can drive surface deterioration, while prolonged rainfall with little drying time between spells will promote deeper wetting of the stone, with deeper areas requiring longer to dry out (Sass and Viles 2010). Furthermore, drying of walls will likely take longer in months with lower temperatures and higher humidities. Therefore, while broad trends of rain days can be identified from monthly totals, they can obscure the implications for damage mechanisms.

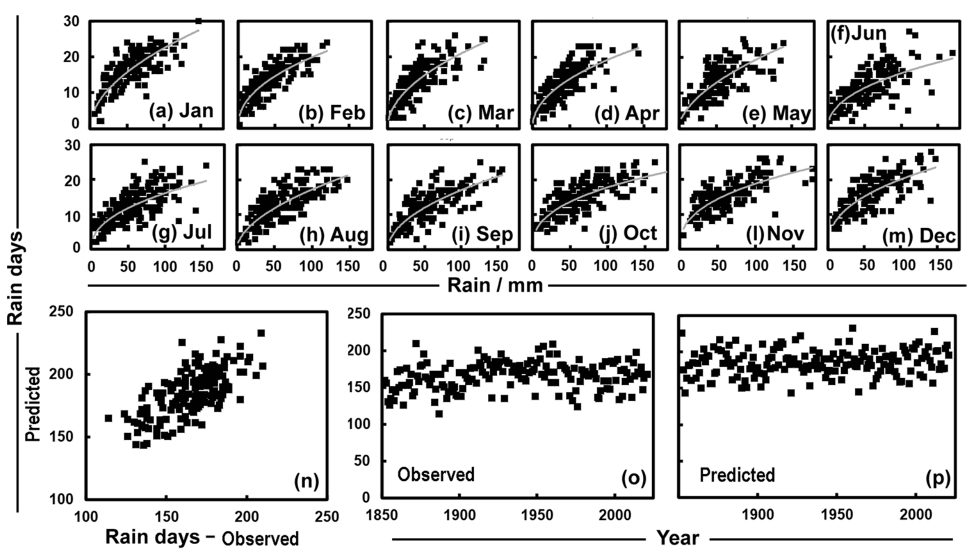


Fig. 3 **a–m** Monthly rain days as a function of the monthly rainfall totals with the fitted power function shown as grey curves. **n** Predicted annual rain days as a function of the observed number. **o** Trend in observed annual rain days. **p** Trend in predicted annual rain days. Note, the power functions are Jan, $n_{RD,1}$=2.0792$P^{0.5166}$; Feb, $n_{RD,2}$= 2.5302$P^{0.4475}$; Mar, $n_{RD,3}$=2.1176$P^{0.4976}$; Apr, $n_{RD,4}$=2.2623$P^{0.4639}$; May, $n_{RD,5}$=1.4476$P^{0.5598}$; Jun, $n_{RD,6}$=1.9971$P^{0.4438}$; Jul, $n_{RD,7}$=2.0351$P^{0.4484}$; Aug, $n_{RD,8}$=1.4325$P^{0.54}$; Sep, $n_{RD,9}$=1.6599$P^{0.5055}$; Oct, $n_{RD,10}$=3.0772$P^{0.5377}$; Nov, $n_{RD,11}$=3.1728$P^{0.3863}$; Dec, $n_{RD,12}$=3.142$P^{0.4032}$

Fig. 4 **a** Scheffer index calculated from predicted rain days as a function of the Scheffer index calculated using the observed meteorological values and **b** changes in the Scheffer index over time

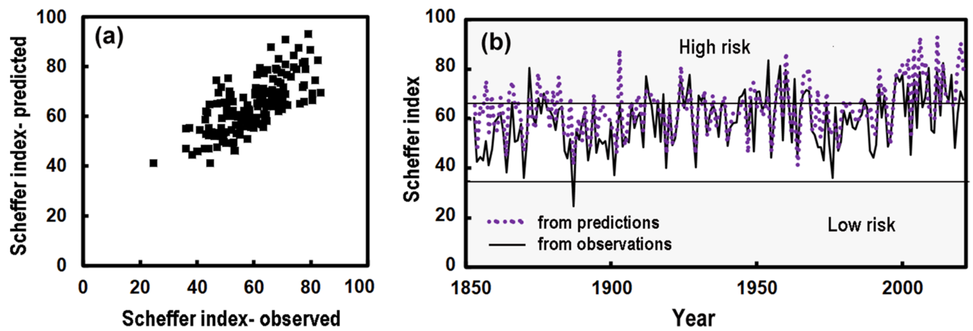


Table 1 Number of years of each risk type associated with the observed and modelled Scheffer index. Percentage of years is given in brackets

		Observed		
		Low (<35)	Medium (35–65)	High (>65)
Modelled	Low (<35)	0 (0)	0 (0)	0 (0)
	Medium (35–65)	1 (0.60)	80 (47.62)	11 (6.55)
	High (>65)	0 (0)	30 (15.86)	47 (27.38)

3.2.2 Scheffer index

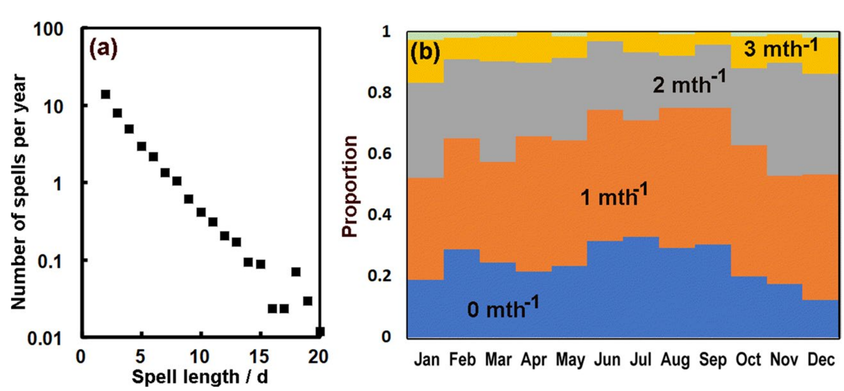
The Scheffer index for deterioration shows good agreement between the observed and modelled values (Fig. 4a), with a slope from the origin close to unity (1.06) and reasonable correlation (Kendall $\tau = 0.526$). However, there is large variability around the predicted regression line, e.g. the observed Scheffer index of 50.11 has a predicted value of 49.05 in 1 year, yet in another year the observed index of 50.88 is predicted as 75.39.

Figure 4b shows that the trend of the predicted Scheffer index broadly tracks the observed data but does not capture many of the extreme values. Figure 4b modelled results more commonly over-predict ($n = 116$) than under-predict ($n = 53$). When converting the Scheffer index into a risk category (Table 1), our results found that the modelled and observed risk results did not correspond in nearly a quarter (23%) of years within the time period studied. Of the years where risk categories do not align, 60% (31 years) were over-estimates. As environmental conditions can drive significant differences in algal growth on limestone within a 12-month period (Cabello Briones and Viles 2018; unpublished thesis by Crawford 2007, as cited by Smith et al. 2011a), the modelled index could result in under- or over-estimates of greening.

3.2.3 Periods of deep wetting

Figure 5a shows the frequency of rain spells of different durations. For prolonged periods of rain (≥4 days), just a few occur each month (Fig. 5b). This means we are unable to construct a meaningful relationship between the number of wet spells and monthly rain metrics. This highlights how climate events that occur infrequently, yet are important for heritage, can be lost when only monthly data are available. We calculate that on average there are 1.21 ± 0.08 wet spells per month. If we assume these are randomly distributed and follow a Poisson distribution, the number of months with no wet spells would be 606 compared to the 497 observed 1852/2021. However, the Poisson distribution would suggest that 736 months would be found with just one wet spell, while 815 were observed, while for two spells in a month 446 are predicted and 542 observed. It suggested that rain days cluster together slightly more than would be expected from a random distribution. While agreement between observed and predicted was imperfect, it suggested that

Fig. 5 **a** Number of spells of rain of a given length over the period 1852/2021. **b** The proportion of wet spells (≥4 days of ≥0.2 mm) each month 1852/2021. The smaller light areas at the top represent >3 spells mth^{-1}



Markov or probabilistic approaches might be useful in heritage climatology in the future.

3.3 Freezing events

3.3.1 Deep frost days

Figure 6a shows the number of days (n_{-5}) each year when the minimum temperature recorded fell below −5 °C. The number declines throughout the period (−0.035±0.005 a^{-1}), which represents a reduction of about nine extremely cold days a year between 1815/2021. For each year, the number of frost days is variable yet often small, although there are some years such as 1895, 1947 and 1962 which have a high number of frost days.

Our approach assesses number of days with freezing across a year using a multi-linear regression:

$$n_{-5} = 27.51 - 0.07871T_1 - 0.9457T_2 - 0.07871T_3 - 0.2507T_{10} - 0.3725T_{11} - 1.124T_{12} \quad (6)$$

where T_n is the mean temperature of the month defined by the subscript number (October to March). The regression has a multiple r^2 value of 0.6827, and the six colder months have a regression coefficient significant at $p<.025$. As shown in the inset to Fig. 6a, the predicted values are typically too high in years that have warmer winters, so the parameterisation using Eq. 6 is not satisfactory. This shows that using monthly data is problematic as there are just a few events even in the winter months, so correlating freeze events with individual monthly temperatures is difficult (as shown above with rain spells).

3.3.2 Freeze events

The fitted Gaussian curve for the winter months (November to February) of 1815/2021 (Fig. 6b) agrees well with the number of observed winter freeze events (inset Fig. 6b). The slope is close to unity (0.97) when the linear fit is constrained to pass through the zero-intercept. Over the winter periods 1815/2021, there is agreement between the mean number of predicted events (31.53±8.84 a^{-1}) and observed events (31.50±10.38 a^{-1}), but unfortunately the standard deviation, and thus the variance, is lower in the predicted data.

The non-winter freezing events (March–October) pose a problem because while there are only a few each year (12.1±7.2 a^{-1}), they are markedly over-predicted (23.9±3.9 a^{-1}) by the Gaussian function. This is because the function has a long tail (as seen in Fig. 6b) which means that predicted freezes are probable even for higher monthly temperatures, i.e. above 9°C.

Accurately capturing the number of freeze-thaw events is important as small numbers of such events can drive

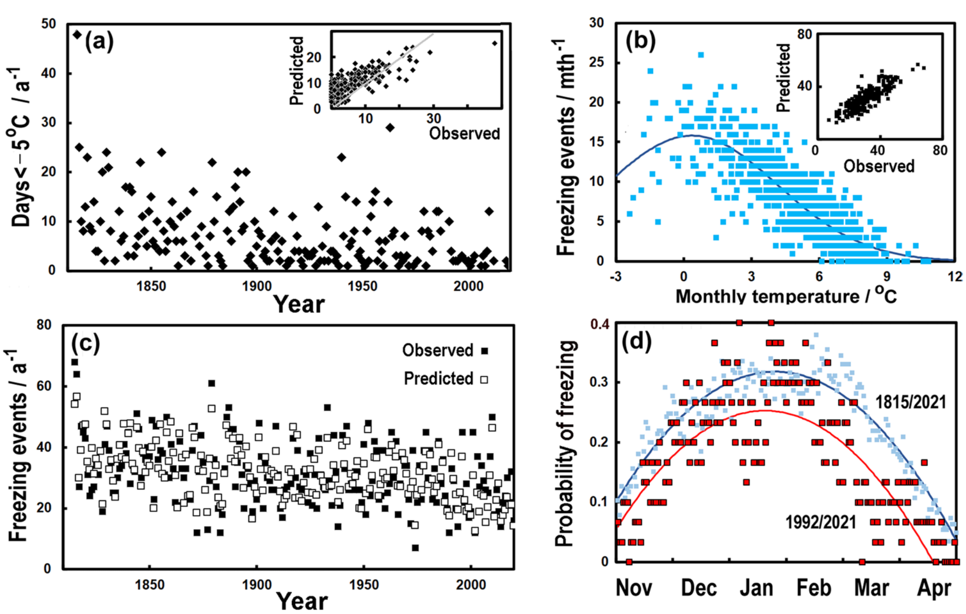


Fig. 6 **a** Number of days each year with minimum temperatures below −5 °C. Inset shows the predicted number of days below −5 °C as a function of those observed. **b** The total number of freezing events each month (Nov–Feb) for the whole record 1815/2021 and a Gaussian best fit (Eq. 4) where a_1 = 15.82±0.08, a_2 = 0.358 ±0.027 and a_3 = 3.81±0.013. Note that a_2 which represents the offset is close to zero degrees as might be expected. Inset shows the predicted annual number of freezing events as a function of those observed. **c** The predicted number (open squares) and observed number (black squares) of freezing events changes over time for the whole record 1815/2021. **d** The probability of November–April freezing days 1815/2021 (blue) and 1992/2021 (red) with curves fitted as second order polynomials

deterioration of stone, with materials with open porosity values of >10% being the most susceptible (Martínez-Martínez et al. 2013). For example, Cotswold limestone samples experienced mass loss after being exposed to 12 freeze-thaw cycles in an archaeological site in Oxfordshire (Cabello Briones 2016; data extracted from Fig. 6.16). A local oolitic limestone (Elm Park) suffered significant mass loss and surface softening after the equivalent of 1 year of shallow freeze-thaw events (Coombes et al. 2018). Therefore, the overprediction in the modelled results might be greater than the number of freeze-thaw occurrences required to cause damage.

Our results also show that the number of freezing events has declined in both the observed and predicted values (Fig. 6c) with a trend in freeze events of -0.106 ± 0.016 a^{-2} as a Theil-Sen slope. This is small but amounts to a reduction of about 10 annual events over a century, which is likely to mean a reduction in frost damage. When using the observed daily data, it is also possible to see changes in the seasonality of the freeze events. Figure 6d shows the probability of a freeze occurring on a given day of the year (29th Feb omitted), with the fitted polynomial suggesting that not only are the values for 1992/2021 smaller than 1815/2021, but the peak occurs 3 days earlier (20th January compared to 23rd January). Even small changes in seasonality can have implications for the management of buildings due to set maintenance and closure periods. However, these subtle changes in seasonality would be obscured when using monthly data.

3.3.3 Wet frosts

As shown in Fig. 7, the number of wet frosts declined across the record (-0.039 ± 0.009 a^{-2}), but the use of monthly data to infer daily events was unsuccessful (inset to Fig. 7). Here, the requirement for two sets of daily variables resulted in errors that rendered an outcome of little value.

Given that wet frosts require a specific sequence of weather events (i.e. rain followed by frost), even daily data may not have sufficient resolution for this metric. When using daily data, there could be a delay of up to 48 h between the rainfall and the freezing event. Furthermore, if a day had a minimum temperature that was below zero and it had rained, we would not know if the rain had come before or after the frost, and so our current methodology using daily data might not capture such events properly.

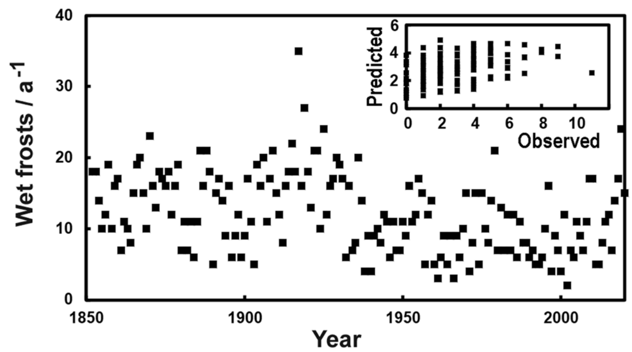


Fig. 7 Wet frosts (days of rain followed by freezes). Inset shows the predicted wet frosts as a function of those observed

3.4 Summary discussion

Our results show that the ability to calculate heritage climate parameters from monthly data is highly dependent on the nature of the climate processes the parameters draw upon. For parameters that have a broadly linear relationship between daily and monthly totals, daily data can be accurately inferred from monthly data (e.g. Fig. 1). Even though individual events are not captured by the monthly data, the cumulative nature of these events means that daily and monthly timescales can be interpolated. This finding is helpful as it means these heritage climate parameters with linear characteristics can be calculated for the many datasets where only monthly measurements have been recorded or digitised. These metrics rely on simple cumulative functions, but many useful metrics are more complex than this. Additionally, these linear parameters, such as sunshine hours and 5-degree days, capture a simplistic understanding of processes that cause deterioration of heritage and therefore, while they could be calculated for many monthly-only datasets, they do not capture rapid deterioration processes, e.g. sub-hourly fluctuations in stone surface temperature. Correlating metrics such as freeze events or rain days from monthly observations can be especially difficult if events are rare.

Where parameters using one climate metric had a more complex relationship such as between daily events and their monthly frequency, the monthly scale data captured the broad trends within the parameter, but with smaller variance (Figs. 3, 4, and 6). When considering temperature within the context of heritage climate, the inclusion of a set threshold (e.g. freezing events and degree days) to transform the variable into a binary occurrence can make the scaling of this parameter across time challenging. Similar outcomes were found for the Scheffer index, which combines a daily metric with a monthly metric (Eq. 3).

When parameters combine multiple daily values (e.g. wet frosts), or require a sequence of events (e.g. wet spells), the parameters were difficult to calculate using monthly data. As these heritage climate parameters are perhaps some of the most useful for predicting damage, this result highlights the need for sub-monthly (e.g. daily or hourly) weather records and reanalysis datasets to understand climate-induced deterioration on built heritage. Therefore, access to meteorological observations at a minimum of a daily resolution is required. This will help address the current imbalance between the feasibility of calculating a heritage climate parameter and its applicability to heritage damage.

4 Conclusion

Our findings have important implications for how researchers assess meteorological observations and design climate models, so that the resultant data are useful for understanding heritage change. Where possible, recording meteorological observations at a daily (or sub-daily) resolution will help heritage scientists understand the threat climate poses to heritage. High temporal resolution is especially important for assessing the impact of pressures that can cause damage after a small number of events. Now that so many weather stations are automatic, we hope that high-resolution, digital records will become increasingly available. Reanalysis datasets could help provide sub-monthly resolution data for historical records (such as ERA5 reanalyses). In a similar vein, this work also highlights the value of climate model projections available at a daily resolution, rather than just monthly or yearly averages.

Further research is needed to (i) establish a more effective calibration process for monthly datasets or incomplete records and (ii) assess the extent to which changes or extremes in heritage climate parameters can be seen as damage to heritage buildings and sites. This will require judicious use of archival material such as estate accounts and budgets, or stone masons' records might provide useful insights into change of building materials.

The impact of future climate change on heritage requires us to understand climate pressures on heritage materials. We show that cumulative processes (e.g. sunshine hours, degree days) can be well captured from monthly data. Broad trends in daily events (e.g. rain days, freezing events) could be captured where calibration was possible using daily observations. However, the variance, extremes and infrequent events were difficult to assess, so individual years of enhanced threat are not well represented, although averages are typically well estimated.

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Code availability Data can be provided upon reasonable request.

Author contribution Conceptualisation - J.R; statistical analysis and figure preparation - P.B.; formal analysis, investigation and writing—review and editing - P.B. and J.R. All authors reviewed the manuscript.

Data Availability Data can be provided upon reasonable request.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication The authors consent for this material to be published. No other consents are required.

Conflict of interest The authors declare no competing interests.

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