



Comparison and Calibration of Climate Proxy Data in Medieval Europe

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Acknowledgments

Researching and writing this senior thesis was singlehandedly the most challenging and rewarding academic experience of my life and I have many people to thank for guiding and supporting me throughout this process.

Thank you, first and foremost, to my two advisors, Professors Peter Huybers and Michael McCormick. Working with you both has been an honor and a pleasure, and our conversations have absolutely made me a better scientist and historian. I sincerely appreciate you both taking time out of your busy schedules to mentor me throughout my entire undergraduate career, offering exciting opportunities and sage advice at every turn. Thank you both for taking on the role of advising this interdisciplinary study and providing insight in a way that urged me to bridge disciplines and think outside of the box.

Thank you to the Earth and Planetary Sciences Department, as a whole, for being my home throughout my time at Harvard and for introducing me to some of the warmest people I have had the pleasure of knowing (and providing lots of free coffee). Special thanks go to Esther James and Annika Quick, our EPS preceptors, for providing academic and emotional support, but most importantly deadlines, to the entire class of thesis writers. Additional thanks go to Chenoweth Moffatt and Maryorie Grande for their unending support and kindness. To my fellow thesis writers, especially my perpetual office mate and accountability buddy, Forrest Lewis, congratulations on completing your theses and job well done! I am so proud to see how much you all have accomplished.

Thank you to Alex More and the Science of the Human Past Initiative at Harvard University. The documentary data collected by SoHP was an invaluable part of my thesis and I am so grateful that you shared this rich data source with me. Members of SoHP have welcomed me into their research community and have treated me as a colleague, pushing me to ask questions and make new connections.

Thank you to the National Oceanic and Atmospheric Association and the Climatic Research Unit for making your data freely and publicly available. In a time when pseudo-science and fake news drive national agendas, publicly providing accurate and unbiased climate data and acknowledging the value of scientific research is more appreciated than ever.

I would be remiss not to thank my many other advisors and mentors who have helped to steer me down the path of earth and climate science: Patrick Ulrich, Jerry Mitrovica, Jim Anderson, and Mike Ranen. To my communities within the Geological Society, the Record Hospital & WHRB, and Dunster House, thank you for listening to me attempt to explain my senior thesis many times and for providing support and an escape when most needed. Finally, thank you to my parents and family for their interest and support, pushing me to pursue research in a field that I find fascinating and meaningful.

Introduction

Despite urbanization and major technological advances which have led to modern comforts, humanity is ultimately composed of denizens of the natural world. As a result, many studies, such as Wu et al. (2014) and Sadori et al. (2016), have demonstrated that societies have often been seriously impacted by natural climate and weather variability throughout history. The effects of climate on society are far-reaching and can impact seemingly disparate sectors, such as the economy, culture, and warfare. Current anthropogenic climate change follows this tendency and its effects on human health and ecosystem well-being, for example through sea level rise, species extinction, or increased drought intensity, will present dire and unprecedented consequences for citizens of modern and future societies (e.g., Fuhrer et al., 2006; McMichael et al., 2006; Cayan et al., 2010; Bosello et al., 2012). However, the full effects and outcomes of climate change on society cannot be wholly understood simultaneously with the changes; a full comprehension of climate-driven societal changes is only obtained after both the climatic and societal events have fully played out.

Though we cannot determine the exact effects that anthropogenic climate change will have on modern humanity, a careful analysis of how a changing climate has affected past societies can help to shape expectations of what might occur societally. Indeed, prior studies have suggested that the rise and fall of certain societies were intimately linked to climate fluctuations and an ability or inability to adapt to these changes (Haug et al., 2003; Buckley et al., 2010; Patterson et al., 2010; Haldon et al., 2014). Additionally, this analysis can assist in the process of formulating strategies to best counter the predicted negative effects of climate change. Using history as a lens through which

we can view the future will allow humanity to learn from past mistakes and more readily tackle the gargantuan problem of anthropogenic climate change. But, to put historical societal responses to climatic changes into context, we must first determine exactly how the climate behaved during that time period (Battipaglia et al., 2010).

The modern, ubiquitous surveillance of Earth’s climate system is a relatively recent phenomenon, particularly intensified after the dawn of the satellite age in the 1950s and 1960s. The current observation of Earth by satellites has provided a myriad of new data that have helped to revolutionize certain scientific fields and have led to exciting breakthroughs in our understanding of the planet (Kansakar and Hossain, 2016). Some instrumental records of climatic phenomena do exist prior to satellite observation. However these instrumental records are highly localized, and even the oldest records do not extend further back than the mid-seventeenth century (Manley, 1974). As a result, determining how the climate behaved during a certain historical period must be achieved through a means other than instrumental observation of climatic phenomena.

Climate Proxies

To determine Earth’s climate prior to instrumental coverage, climate proxies are used. A climate proxy is an archive of climate information that is used to estimate climate conditions prior to the modern period. Many different climate proxies exist, but in a broad sense, climate proxies can be split into two categories: man-made and natural. Until recently, these two categories of climate proxies were considered separately by both historians and scientists.

In this thesis, I will develop a framework to statistically compare and calibrate man-made and natural climate proxies in order to elaborate upon the potential strengths and weaknesses of each class of climate proxy. Through this analysis I hope to outline a methodology for robustly comparing man-made and natural climate proxies and provide new tools and evidence for future interdisciplinary studies of paleoclimate.

Documentary Data

Man-made climate proxies, as the name suggests, are created via human agency and would not exist without the action of historical peoples. A blanket term for man-made climate proxies is “documentary data.” Documentary data includes written sources, such as reports, manuscripts, and records, but also material sources, such as artwork and artifacts (Brázdil, 2000). Figure 1 shows one such example of documentary data in the form of an illuminated manuscript: this fifteenth century French winter scene contains potential clues as to how the climate behaved during the creation of the image. Brázdil et al. (2005) state that the most common form of documentary data are reports of climate written on printed matter, so the label of “documentary data” will henceforth be equated with written descriptions of climate.

Documentary data specifically details either an explicit description of a climatic event or a description of some other event which can be construed to describe climate. A report of a drought is an example of an explicit climate description, whereas a report of a delayed harvest is an example of an interpretable climate description. The climatic cause of an interpretable event can be attributed to more than one climate condition, so this information does

not readily establish the climate regime as precisely as an explicit description otherwise might. Nevertheless, this interpreted information can still help to reveal details regarding the climatic conditions of an era, though often the information revealed is merely what climate can absolutely be ruled out as having caused the event.

Documentary data is a useful climate proxy for several reasons as outlined by both Pfister et al. (1999) and Brázdil (2000). First of all, to the extent that historians can accurately and precisely date the document that records the climate event, this data has high chronological resolution. The dating control of documentary data usually allows for at least annual certainty, though in many cases the specific day and month are known as well. In a similar vein, documentary data is sensitive to events throughout the year. There is no seasonal dependence in documentary data, because, presumably, historical figures were writing throughout the year. Finally, documentary data focuses on climate anomalies and natural disasters. Unusual and extreme events are deviations from the norm and are therefore more likely to be recorded by historical authors.

Despite the strengths of documentary data as a proxy source, there are certain drawbacks to this class of data. First of all, documentary data provides a discontinuous time series of climate observations (Pfister et al., 1999). If an historical author did not feel the need to write about the climate during a certain year, there is no data available for that year and this gap cannot easily be filled via extrapolation. Additionally, an obvious, but key, issue regarding documentary data is that the reports are intimately linked to the location of the author. Rather than providing broad coverage by being evenly distributed



Figure 1: This early 1400s illuminated manuscript from the Très Riches Heures shows a French winter scene. Such manuscripts reveal details about how the climate behaved at the time of creation. Clues are hidden in both the writing and image content.

throughout a region and with the exception of rural monasteries, authors often resided in urban centers. As a result, the climate of these urban locations is disproportionately reported. Perhaps the largest drawback of documentary data, though, is human bias. Document authors view the world relative to

what they are familiar with, so a climate event, which may not in fact be anomalous over a longer time period, could seem particularly unusual over the short course of a lifetime. This could lead that event's severity to be overemphasized by the author. Conversely, if a climate event does not seem unusual relative to the author's experiences, the writer may not mention it at all.

Scientific Paleo Proxies

The other broad class of climate proxies, natural climate proxies, are sources of paleoclimate information produced by and contained within the natural world. These proxies either grow, form, or are deposited annually, and their growth and formation are highly dependent upon the climatic conditions at the time of formation. Examples of natural climate proxies include, but are not limited to, tree rings, ice cores, varved lake sediments, and speleothems. Each of these proxies tells a slightly different story about the climate as a direct result of how each proxy is uniquely formed.

For instance, the width of tree rings, as seen in Figure 2, can be used to estimate temperature and precipitation because a warm or wet year promotes growth and causes wider rings, while a cold or dry year inhibits growth and creates thinner rings (Fritts, 1976). Ice cores and varved lake sediments are both depositional proxies and record climate indices via the law of superposition. Ice cores contain both settled material and atmospheric bubbles trapped within the glacial ice (Dansgaard et al., 1969), while varved lake sediments record both the biological history of the lake, as well as the climatic condition that the sedimentation occurred in (Jenkin et al., 1941). Like tree rings, speleothems

annually grow radially outward and climate conditions such as precipitation and temperature can be inferred from growth rates and stable-isotope analysis (Baker et al., 1993).

The data from a natural paleoclimate proxy, or paleo proxy data, is also a rich source of information on paleoclimate, though in a very different way than documentary data. Unlike documentary data, which consists primarily of anomalous or extreme events, paleo proxy data is more sensitive to long-term trends. While a flash flood may not show up in a paleo proxy record, an unusually wet year more likely would. Another benefit of paleo proxy data is that it provides a quantitative time series of climate conditions. While the documentary record necessarily contains gaps if reports do not exist, paleo proxies will capture climate conditions as long as the conditions for proxy “growth” continue. However, the greatest benefit of paleo proxies is that their formation is ideally free of human bias. These proxies are not wholly free of bias, as their formation can be influenced by natural factors and their scientific analysis and interpretation can certainly be biased, but ultimately paleo proxies do not intrinsically contain the entrenched systematic bias that any man-made climate proxy contains by design.

The archive of paleo proxy data can reveal rich details on paleoclimate, yet there are still certain drawbacks to this natural climate proxy. Most importantly, the signals contained within many paleo proxies are open to interpretation. Using the example of tree rings, we know from seeing a wide tree ring that the climate of that year promoted growth. However, we do not necessarily know what about that year’s climate promoted this growth. As first pointed out by Fritts (1976), temperature and precipitation both influence



Figure 2: Tree rings are one class of scientific paleo proxy which can help to determine the climatic regime throughout the tree's lifetime. Wider rings result from warm or wet years, while thinner rings result from cool or dry years (Fritts, 1976).

tree ring growth. Therefore, a signal derived from tree rings is often a result of temperature or precipitation, but more likely some combination of both. As a result, many studies have been undertaken to determine the sensitivity of tree rings to both of these factors so as to better understand exactly what climate information can be gleaned from this natural archive (Stahle and Hehr, 1984; Heikkinen, 1985; Szeicz, 1997).

Finally, a significant issue with many paleo proxies is that they are by nature often far-removed from the cultural centers where societies are located. These proxies contain an accurate record of natural climate because they are undisturbed by mankind and, ideally, can uninterruptedly continue with their growth or formation. For example, ice cores are a useful paleo proxy, however, most ice cores which contain practical records of climatic conditions are

retrieved from glaciated regions of the world, such as Greenland or Antarctica (Grootes et al., 1993; Petit et al., 1999), and therefore will not readily provide information on the societal response to local climatic changes. As a result, when using paleo proxy data to study the response of societies to a changing climate, distance to cultural centers must be considered, as the weather and depositional climate may vary between the proxy source and society location.

Using proxy data of any sort to help characterize paleoclimatic conditions is a clever means of understanding past climate without having explicit instrumental data. Documentary and paleo proxy data are two archives of information, man-made and natural, historical and scientific, which serve as particularly useful proxies for paleoclimate reconstructions. Though each proxy source has benefits which contribute to a rich understanding of past climate, each source also has significant drawbacks which must be considered throughout analysis. Any study which relies upon only one source of proxy data takes advantage of the benefits of that data source, but also must be sure to recognize and consider the inherent bias contained within the data source as well.

Interdisciplinary Approaches to Climate History

To fully capitalize on the power of both documentary and paleo proxy data, a relatively unexplored but powerful method is to adopt an interdisciplinary approach and use both data sources in tandem. McCormick (2011) labels this interdisciplinary approach of studying climate history as “consilience.” The consilient approach of melding historical and scientific paleoclimate proxy data together can increase the power and precision of paleoclimate estimates,

as the coincidence of an induction from one data source with an induction from another leads to a strong conclusion. Additionally, adopting a consilient approach can allow for calibration of both sources to create a more accurate prediction by addressing bias in one source with data from the other. This interdisciplinary and consilient “climate history” approach offers huge potential gains and insights into describing paleoclimate and ultimately can inform the lessons we learn from past societies and how they responded to climatic changes.

The interdisciplinary approach of considering both documentary and paleo proxy data was pioneered by the French historian Emmanuel Le Roy Ladurie (1929-) in his 1971 book *Times of Feast, Times of Famine: A History of Climate Since the Year 1000* (Ladurie, 1971). In his book, Ladurie sets the stage for studying paleoclimate via an interdisciplinary means by first warning against the anthropocentric bias that climate is imbued with by most historians. Ladurie argues that it is too simplistic to explain an historical event as merely a monocausal result of climatic shifts; he argues that the study of climate history is only possible if the potential sociopolitical causes of an historical change are given thought as well. In this way, Ladurie subordinates the influence of climate on human activity and society to other sociopolitical considerations, emphasizing the importance of analyzing climate alongside other causative factors.

Using tree ring-derived dendro-data in conjunction with wine harvest dates and studying historical reports of alpine glacial advance and retreat, Ladurie corroborates proposed climatic periods in the Medieval era. The climatic theories of the “Medieval Warm Epoch,” proposed primarily from botanical and

meteorological evidence (Lamb, 1965), and the “Little Ice Age,” first suggested from North American glacial evidence (Matthes, 1941) and corroborated by subsequent meteorological studies (Lamb, 1965), are both strengthened by Ladurie’s analysis.

The other seminal contributor to the field of interdisciplinary climate history was the English meteorologist Hubert H. Lamb (1913-1997). Lamb is often considered the first true paleoclimatologist, and his analysis of paleo proxy evidence in conjunction with documentary evidence allowed for the first description of the Medieval Warm Epoch (Lamb, 1965). Unlike Ladurie, Lamb believed that climate had an immense influence on society and that documentary reports responded acutely to changes in climate. Despite this fundamental difference in opinion, Lamb borrows from Ladurie’s framework and methodology in his first book, *Climate: Present, Past, and Future*, and undertakes a more quantitative analysis of paleo proxies to discuss how paleoclimate can inform our understanding of future climate (Lamb, 1972). This analysis is informed by both historical reports and the underlying physics and chemistry of climate science. In his second book, *Climate, History, and the Modern World*, which improved upon strategies and methods from his 1972 work and is considered groundbreaking in the field, Lamb uses many available paleoclimate proxies to give the reader a whirlwind tour of estimated climatic conditions for all notable eras of humanity (Lamb, 1982). Taking a quantitative approach to the methods that Ladurie proposed, Lamb took the next step forward in the study of climate history.

Since the pioneering work of Ladurie in 1971 and Lamb’s huge contributions to the field in 1972 and 1982, the interdisciplinary, consilient approach to

studying paleoclimate through climate history has been adopted by a handful of researchers. Often, researchers in one field will use data from the other field merely as a means of corroboration. Scientists have used history to corroborate their interpretations of a paleo proxy (Battipaglia et al., 2010; Büntgen et al., 2011a; Sadori et al., 2016), or historians have used a paleo proxy time series to confirm their climate-based explanation of an historical event (Chuine et al., 2004; Brázdil et al., 2005, 2010; Pfister et al., 2010). However, the comprehensive and collaborative study of paleoclimate by scientists and historians together has only recently become an accepted and practiced norm. There is much room for work in this little-studied field and huge potential for new knowledge, especially given the availability of personal computing which was not available when Ladurie and Lamb laid their foundation in the 1970s.

Research groups and institutes such as the Initiative for Science of the Human Past at Harvard University (SoHP) in Cambridge, MA are leading the way in the consistent study of climate history. McCormick et al. (2007) analyzed documentary evidence alongside the GISP2 ice core (Groote et al., 1993) to create a statistically robust record of volcanic climate forcing in Carolingian Europe (see Figure 3). Büntgen et al. (2011b) used tree ring data and documentary data to claim that the fall of the Western Roman Empire was aided by many decades of wet conditions, while McCormick et al. (2012) took on the task of reporting the entire climate regime of the Roman Empire with the aid of many documents and paleo proxies. Additionally, Ludlow et al. (2013) statistically analyzed whether volcanism could be linked to widely reported periods of severe cold in Irish historical literature and Camuffo et al. (2000) constructed the seasonality of severe storms in Padova through

historical reports and instrumental measures.

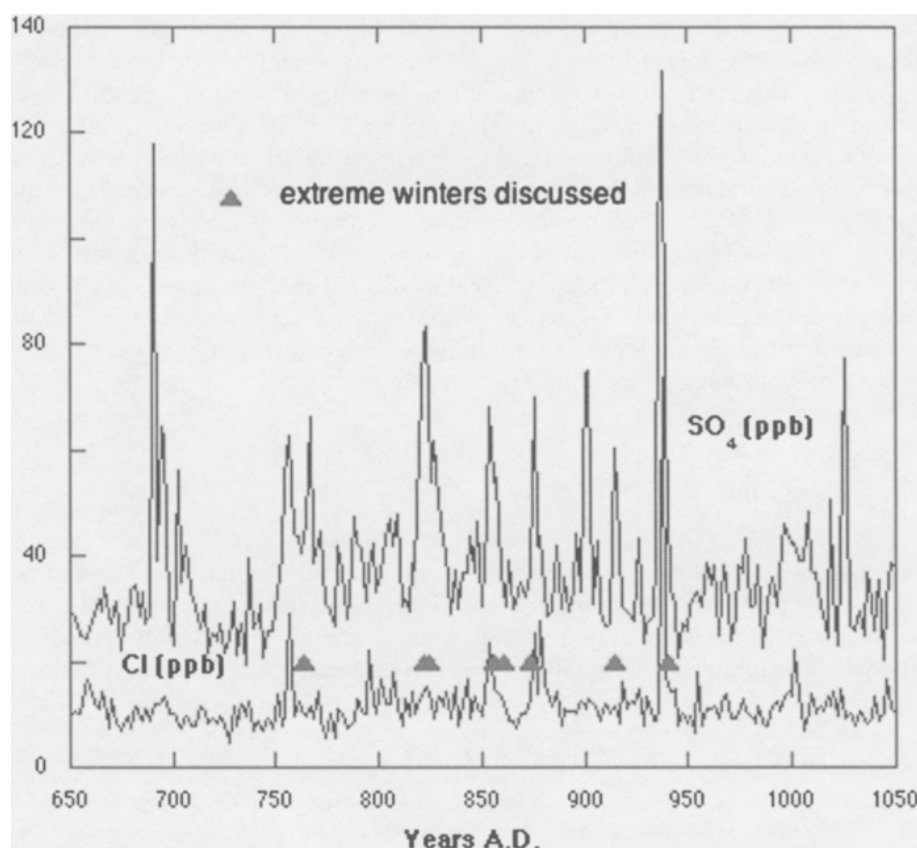


Figure 3: Prior interdisciplinary studies have paved the way for a more robust statistical analysis of documentary and paleo proxy data. Presented here, sulfate and chloride ions covering the period of 650-1050 C.E. from the GISP2 ice core with historically documented multi-regional climate anomalies from McCormick et al. (2007).

Though major steps have recently been taken in the consistent study of climate history, there is still much that can be gained from comparing documentary and paleo proxy data. Prior papers have mainly used data from one source to either confirm or contradict a paleoclimate interpretation concluded from the other source. However, several recent papers indicate the ability

to statistically identify events in both natural and written records in certain specialized situations. This growing evidence suggests the utility of analyzing these two data sets together and creating robust statistical metrics that serve to inform and calibrate both sources. The development of new tools and the examination of more records augments this area of historical science.

In this thesis, I will spatially and temporally compare and calibrate documentary and paleo proxy sources in an effort to clarify the strengths and weaknesses of each source. My primary goal in this analysis is to determine, first and foremost, whether documentary and paleo proxy data are indeed generally comparable in a statistical framework and to elaborate a robust method of doing so.

The first step in this process will be to focus on a location and time period in human history which is equally well-constrained by both documentary and paleo proxy data. This will allow us to maximize the amount of data being analyzed so that any conclusions gained from the analyses can be applied to historical eras with less readily available paleoclimate data. The time period that I will focus on in particular will be the first half of the last millennium, known as the high medieval era, and the geographic focus will be Europe.

A considerable number of diverse paleo proxies exist across Europe that include paleoclimate data for the Medieval period. Data from these paleo proxies and subsequent peer-reviewed climatic reconstructions are freely available through the National Oceanic and Atmospheric Association's (NOAA) online database. In regards to documentary data, a digitized database of climate reports created by SoHP at Harvard and derived from the comprehensive work by Alexandre (1987) provides information on many thousands of climatic

reports from Medieval literature (McCormick and More, 2017a,b). A careful comparison of multiple paleo proxies with the historical reports compiled by Alexandre should allow for the requisite breadth of coverage necessary for comparison in this thesis.

This analysis will compare time series of paleo proxy reconstructions with time series of documentary climate reports and statistically determine whether there is a correspondence between the two data sets. Specifically, I will look at the strength of an historically documented climate event (both in terms of severity and spatial coverage) and determine the likelihood that I will see that event in the paleo proxy reconstructions. Ideally, we should see the reported climatic events within nearby paleo proxy records, depending on the results of a sensitivity analysis and calibration run on each proxy with instrumental records. In comparing the documentary and paleo proxy records we should be able to see how these two data sources differ spatially and throughout time.

By determining how the documentary and paleo proxy data sets differ, we will gain a better idea of how these two sources of data can best augment our understanding of paleoclimate and where our current knowledge and interpretations fall short. An increased knowledge of paleoclimatic conditions will help to put our historical knowledge of societies into context. Better context and understanding will allow for a more useful interpretation of how and why past societies responded to specific changes in climate. The hope is that this information can be used to address the current crisis of anthropogenic climate change by unveiling clues and tips from the past of how to best tackle this significant problem.

Methods

In this section I discuss the methodology and procedures that I undertook in order to obtain the statistics needed to robustly compare historical documentary and scientific paleo proxy sources of paleoclimate information. In summary, the major steps of this analysis consisted of data collection, data formatting, calibration of paleo proxies with instrumental climate data, and the final, crucial statistical comparison of documentary records with the paleo proxies.

Data Collection and Formatting

The requisite data for the statistical analysis of paleo proxy climate reconstructions with Medieval documentary climate evidence were scattered throughout many different databases and required conversion into similar data types and structures for useful comparison. Collecting documentary, paleo proxy, and instrumental data, and subsequently formatting these data to be easily comparable required a fair amount of time and data-massaging.

Climate Reports Database

In 1987, the Belgian climate historian, Pierre Alexandre, published *Le climat en Europe au Moyen Age: contribution a l' histoire des variations climatiques de 1000 a 1425, d' apres les sources narratives de l' Europe occidentale*, a compendium of climate reports gathered from Medieval manuscripts across, primarily, Western Europe (Alexandre, 1987). Alexandre spent years poring over source material in order to compile this collection of more than

four hundred years’ worth of historical reports of climate variation. In doing so, he accomplished the difficult task of collecting these many thousands of climate reports, originating from a plethora of manuscripts, into one cohesive sourcebook.

In the past several years, the Science of the Human Past Initiative at Harvard University (SoHP) undertook the task of creating a digital database of the climate reports contained within Alexandre’s tome (McCormick and More, 2017a,b). For each report, SoHP recorded information on the date, location, certainty, and strength of the climate events, as well as a short description of what exactly was occurring. Creating a shorthand code for the most common climate phenomena, each entry into the database was coded with up to two climate codes. For example, a report that described a particularly cold winter in Paris where the Seine froze for many months may be coded with both the “winter” code and the “freeze” code. SoHP gleaned a huge amount of information from Alexandre’s 1987 work and graciously gave me access to their database for this analysis.

Receiving the digital database as a spreadsheet of tab-separated values, I uploaded the data into the scientific computing software Matlab for analysis and further formatting. The first important modification that I made in the database was translating all location names into latitude and longitude coordinates so that each report could be tied to a specific location and easily mapped. This step was necessary due to typos within the database and identical location names that occur in different countries.

The second important modification that I made in the database was ignoring any reports that did not explicitly describe climate. As discussed earlier,

documentary climate data consists of both explicit climate events, such as a drought, as well as interpretable climate events, such as a bad harvest. Interpretable climate events may come about from an array of different climatic conditions, so to rid this analysis of any guesswork I removed all reports of harvests from the database. After this adjustment, the documentary data consisted solely of climate reports.

From the raw report data, I created time series of the frequency of different climate reports throughout the Medieval era. These time series give an idea of the trend of climate phenomena occurrences across Europe and, particularly, help to identify years that deviate from the norm in terms of the number of reports written.

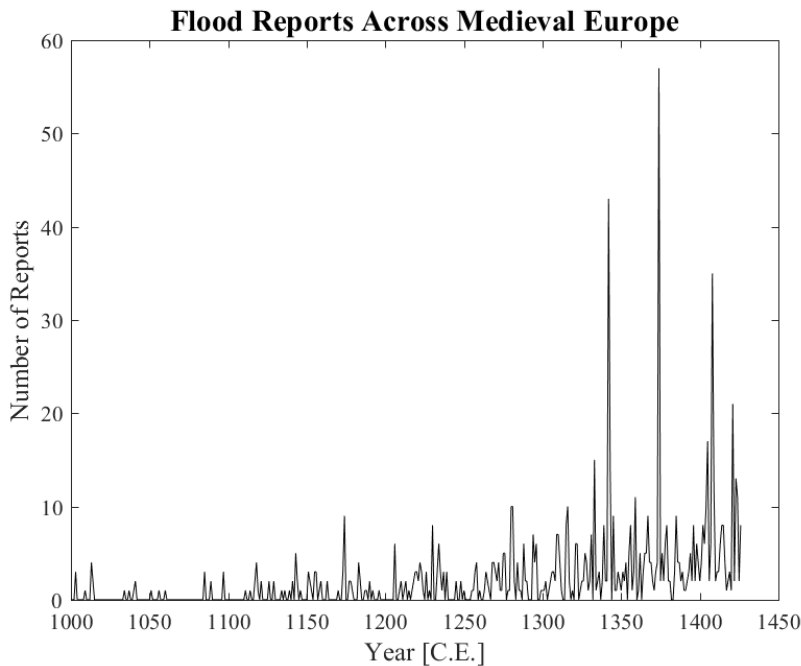


Figure 4: The frequency of flood reports across Medieval Europe. Notice that the average baseline of reports increases as time progresses due to a host of factors including increased literacy, population growth, availability of paper, and better preservation techniques.

As evident from Figure 4, the average annual number of reports increases as we move forward in time from 1000 C.E. to 1425 C.E. At first glance, this marked baseline increase across all major climate phenomena could mistakenly be understood as an increase in the incidence of erratic climate events as the Medieval era progressed. Rather, this baseline increase is a result of a host of factors. In the latter Medieval period, not only did literacy rates increase (Buringh and Van Zanden, 2009), but, as Smail (2013) describes, the relatively expensive and limited supply of parchment was phased out and replaced by cheap and virtually unlimited supplies of paper. This “paper revolution” catalyzed the recording of daily minutiae and revolutionized book manufacturing across Europe. The increasing number of records, reflecting general population growth in Europe until c. 1300 C.E. (Russell, 1958), a shift from oral and memory-based technologies to written documentary ones (Clanchy, 2012), institutional growth, and better preservation conditions all contribute to the average baseline increase of climate phenomena reports. The coincidence of these factors leads to Figure 4’s obvious average upward trend that, if not corrected for, leads to bias and misinterpretation in the analysis of the documentary time series.

This increasing baseline bias across the reference period can be addressed by considering the annual number of reports relative only to the years directly preceding that year. Thus, for example, a peak in the twelfth century with less reports than a peak in the fourteenth century may be relatively more important or unusual because the average baseline is lower further back in history. In order to normalize the report data for relative peak importance, the method of a rolling Z -score was implemented and features heavily in this analysis. The

rolling Z -score calculates the relative anomaly of a certain year's reports as compared to the ten years prior, the recent reference period that historical figures likely would be comparing the present to. If an event is significantly anomalous compared to the prior decade, we assume that the historical figures would make note of it. This window of ten years prior to the year in question is taken to be more useful than five years before and five years after because presumably the historical figure could not know the climatic regime five years into the future.

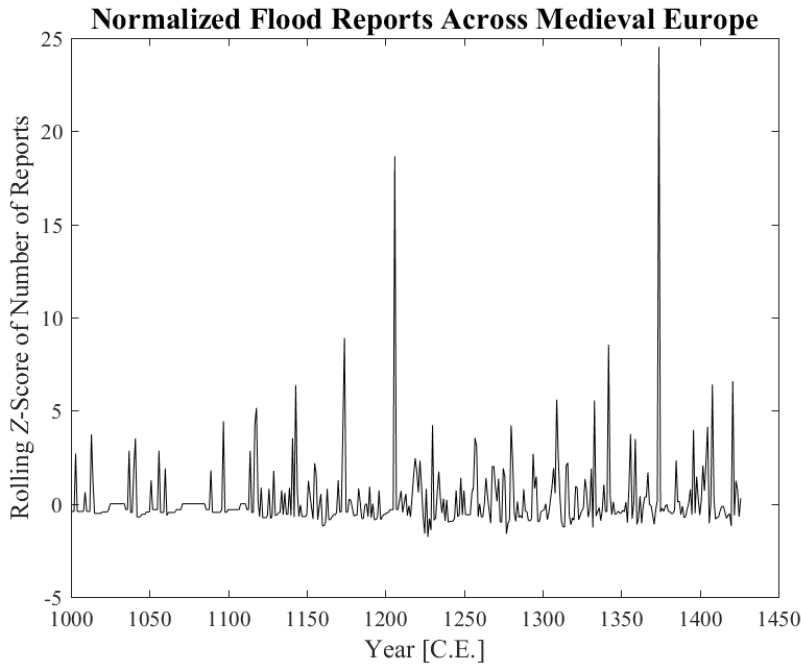


Figure 5: Using the method of a rolling Z -score on the time series of report data allows for a relative comparison of peaks rather than an absolute comparison. This normalization rids the report time series of the bias created by the increasing number of reports generated as time progresses.

Figure 5 shows the time series of flood reports normalized to account for the bias created by the increasing number of reports. Comparing Figure 4 with Figure 5 we see how the rolling Z -score method changes the interpretation

of this time series of flood reports, as peaks are highlighted due to relative deviation from the nearby norm rather than absolute count of reports. For more information on the rolling Z -score, see Appendix A1.

As interesting as a time series of climate reports may be, if we were to consider only reports we may end up counting a single climate event several times. This becomes of particular concern later in the Medieval era when literacy is more widespread. If a severe climate event were to hit a major city like Marseilles, there is almost certainly going to be multiple reports of the event in the many primary source documents and manuscripts from which Pierre Alexandre collected his data.

In order to rid this analysis of double- and triple-counted events, I created a list of criteria for distinguishing individual climate events within the reports. If two reports are from the same calendar year, are within 0.5° latitude and 0.5° longitude of each other, have at least one matching climate event code, and are within the same month, these two reports are lumped into one “event.” If a report was missing any of this information, primarily an issue with the “month” field, this criteria took a conservative approach and created an entirely separate event. Assigning all of Alexandre’s reports to events allowed the data to accurately reflect the frequency of climate phenomena throughout the entire period without fear of counting the same event twice. This time frame of climate event frequency is the data that is most relevant for comparison to the scientific paleo proxies.

Finally, because most European paleo proxy reconstructions generally capture summer, or “growth season” signals (Guiot et al., 2010), the documentary database was trimmed to exclude all events which explicitly occurred outside

of the defined growing season of April through September. This way, we only consider historical documentary climate events which occur in the season when scientific paleo proxy reconstructions are most sensitive to shifts in the climatic regime.

European Paleo Proxies

There are many hundreds of natural paleo proxies across Europe that range from tree rings to ice cores to stalagmites and lake cores. Each of these natural archives contains climate information, however this information is often difficult to interpret and the signal can easily be lost in the noise. Rather than personally analyzing raw data, which might consist of tree ring width or isotopic levels in lake cores, I relied upon published and peer-reviewed climate reconstructions for my proxy data. These reconstructions of climatic phenomena use the raw data to create an estimate of a specific climate condition. They are perfect for comparison against documentary records as they plot anomalies throughout time. Figure 6 shows one such reconstruction: a 2000-year temperature anomaly reconstruction derived from tree ring data collected by Büntgen et al. (2016).

Many climate reconstructions for temperature and precipitation are freely available through the National Oceanic and Atmospheric Association’s (NOAA) paleoclimate website. Narrowing down the search to only include reconstructions that were pertinent to Medieval Europe, I ended up with eleven paleo proxy reconstructions. Of these eleven reconstructions, seven mapped temperature anomalies (Mangini et al., 2005; Larocque-Tobler et al., 2010; Trachsel et al., 2010; Martín-Chivelet et al., 2011; Büntgen et al., 2013; Esper

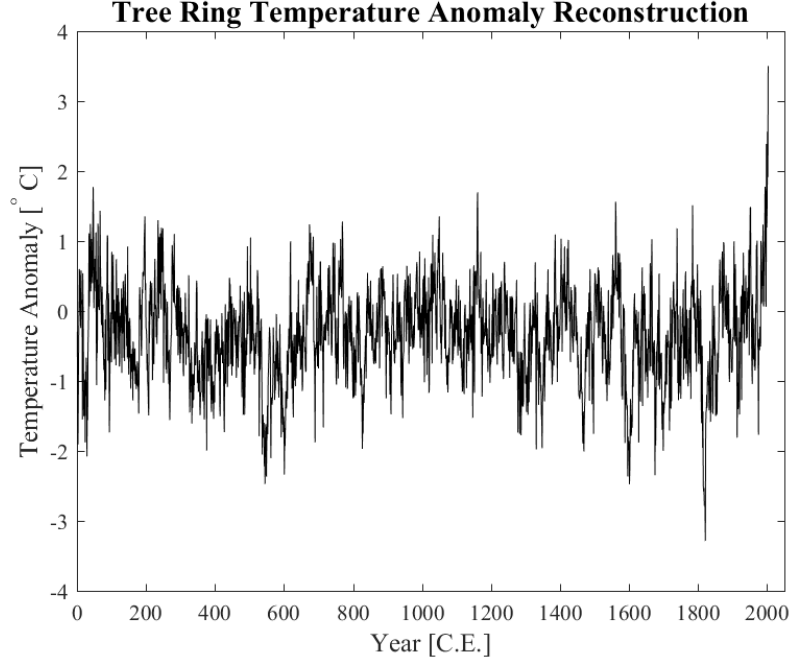


Figure 6: Raw data from scientific paleo proxies is collected and analyzed to create climate reconstructions. This 2000-year temperature anomaly reconstruction estimates annual temperature anomalies across Central Europe from tree ring data. This plot was produced from data collected by Büntgen et al. (2016).

et al., 2014; Büntgen et al., 2016) and the remaining four map precipitation anomalies (Griggs et al., 2007; Cooper et al., 2013; Wilson et al., 2013; Amann et al., 2015). Of these reconstructions, six are tree ring-derived (Griggs et al., 2007; Büntgen et al., 2013; Cooper et al., 2013; Wilson et al., 2013; Esper et al., 2014; Büntgen et al., 2016), three are lake core-derived (Larocque-Tobler et al., 2010; Trachsel et al., 2010; Amann et al., 2015), and two are speleothem-derived (Mangini et al., 2005; Martín-Chivelet et al., 2011). The eleven paleo proxy reconstructions and respective information pertaining to location, proxy type, reconstruction type, duration, and season captured are presented in Table 1.

For any paleo proxy reconstruction that was created from an array of

Reference	Location	Proxy Type	Reconstruction	Duration	Season
Mangini et al. (2005)	Spannagel Cave, Austria	Speleothem	Temperature	90 B.C.E. – 1935 C.E.	Annual
Griggs et al. (2007)	Northern Aegean	Tree Ring	Precipitation	1089 C.E. – 1989 C.E.	MJ
Larocque-Tobler et al. (2010)	Lake Silvaplana, Switzerland	Varved Lake Core	Temperature	1032 C.E. – 1975 C.E.	July
Trachsel et al. (2010)	Lake Silvaplana, Switzerland	Varved Lake Core	Temperature	1175 C.E. – 1949 C.E.	JJA
Martín-Chivelet et al. (2011)	N. Central Iberia	Speleothem	Temperature	1949 B.C.E. – 2000 C.E.	Annual
Büntgen et al. (2013)	Eastern Europe	Tree Ring	Temperature	1040 C.E. – 2011 C.E.	MJ
Cooper et al. (2013)	East Anglia, U.K.	Tree Ring	Precipitation	900 C.E. – 2009 C.E.	MAMJJ
Wilson et al. (2013)	S. Central England	Tree Ring	Precipitation	950 C.E. – 2009 C.E.	MAMJJ
Esper et al. (2014)	Northern Europe	Tree Ring	Temperature	17 B.C.E. – 2006 C.E.	JJA
Amann et al. (2015)	Lake Oeschien, Swiss Alps	Varved Lake Core	Precipitation	884 C.E. – 2008 C.E.	MJJA
Büntgen et al. (2016)	European Alps	Tree Ring	Temperature	1 C.E. – 2003 C.E.	JJA

Table 1: Medieval European temperature and precipitation paleo proxy reconstructions used in this analysis presented with proxy location and type, climate reconstruction type, reconstruction duration, and season captured.

proxies from different locations, I took the average latitude and longitude of the fleet of proxies and used this discrete location as the reference point for that reconstruction.

Calibration of Proxy Records with Instrumental Data

The first step in comparing documentary data with the paleo proxy reconstructions in a statistically robust manner is to determine the accuracy of the paleo proxy estimates. The best way to determine whether the reconstructions do in fact truthfully capture climate anomalies is to compare these reconstructions to “known” data, namely instrumental data from the past century.

It is worth mentioning the potential for inherent positive bias in the comparison of paleo proxy reconstructions with instrumental data, as raw data from the paleo proxies are often calibrated with modern instrumental data to produce the resulting reconstructions. A simplistic comparison of the reconstructions with the instrumental data, therefore, may be inclined toward positive outcomes. As a result, the methodology developed in this analysis is chosen specifically to avoid potential circularity when calibrating the reconstructions with documentary data.

Instrumental Data

The Climatic Research Unit (CRU) at the University of East Anglia seeks to monitor Earth’s climate system via a fleet of well-dispatched and numerous instruments and gauges. By compiling the discrete instrumental records from the various stations around the globe, CRU has created and continues to improve upon gridded instrumental records of climate phenomena across the

planet. As the relevant paleo proxies for this analysis reconstruct Medieval temperature and precipitation, I used CRU’s 5° by 5° temperature anomaly data set (Jones et al., 2012) and its 2.5° by 3.75° precipitation anomaly data set (Hulme, 1992, 1994; Hulme et al., 1998).

The temperature data set covers the period from 1850 until November of 2016 and the precipitation data set covers 1900-1998. Because all paleo proxy reconstructions continue forward in time to these contemporary periods, the correspondence between the observed anomalies and the estimated anomalies is relatively straightforward. Extracting the average anomaly for the growing season, estimated to be April through September, for each grid cell located within the reference space of continental Europe, defined here as 10° West to 40° East and 35° North to 70° North, allowed for a simple comparison of the time series of the instrumental data with the proxy reconstructions at both the location of the proxy and across all of Europe.

Methods of Record Comparison

A common statistical metric used to compare linear dependence between two data sets is the correlation coefficient, R . The correlation coefficient can inclusively take a value between ± 1 , where -1 is total negative linear correlation, $+1$ is total positive linear correlation, and 0 is no linear correlation. For more information on correlation, see Appendix A2.

The first, and potentially most important, statistical metric that can be gained from comparing the paleo proxy reconstructions with the instrumental data is a simple correlation over the instrumental reference periods, 1850-2016 for temperature and 1900-1998 for precipitation. The correlation between the

reconstruction and the instrumental data at the proxy location should tell us the relative strength of the proxy reconstruction, as reconstructions with high correspondence will have a higher correlation. Extending this across Europe, one would expect the highest correlation with the instrumental data at the proxy location and lower correlations as distance from the paleo proxy increases.

A second useful means of comparing and mapping the instrumental data with the paleo proxy reconstructions is to correlate the instrumental record from each grid-box with the instrumental record from the proxy location. Using the paleo proxy as an anchor point, with this metric we can see how similar the climate is across Europe to the climate at the proxy location. If there is a high correlation between a certain grid-cell and the anchor point, we would imagine that a climate event at this other location could potentially be captured by the paleo proxy. Conversely, if there is a low correlation, the climate at that location is statistically different enough from the proxy location that we would not expect to pick up the climate event in the paleo proxy reconstruction.

Finally, R , tends to emphasize low-frequency variation more than high frequency variation. Because of the nature of documentary data, which as a result of human observational limitations records anomalously extreme events rather than long-term trends, a separate statistical metric is also useful for a more accurate comparison of both data sets. This metric would be helpful in assessing whether the proxy reconstructions and instrumental data do not in fact correspond or whether there is a low correlation due to mismatched long-term variation. If the proxies and instrumental record match on peaks,

there is a relatively good chance that the extreme climate events reported in the documentary database would be captured by the proxies.

Taking guidance from Nick Patterson’s statistical appendix in McCormick et al. (2007), which determines whether the probability that the temporal correspondence of historical events and isotopic data is in fact significant, I sought to create a test which created a similar metric of statistical significance. First, by taking the rolling Z -score of the proxy data, as described in Appendix A1, we can normalize the reconstruction time series to observe relative anomalies. Then, using the five years in the instrumental record with the highest and lowest values as indices, the proxy record’s average Z -score for these years is calculated and is treated as the “true” value. Using a Monte Carlo analysis to shift the reconstruction time frame while maintaining the spectral integrity, we can determine whether the average Z -score of the index years in this new shifted configuration is greater or less than the “true” Z -score.

The p -values in this test are defined as the probability throughout this analysis that even after randomization the constructed Z -score has a larger magnitude than the “true” Z -score value. Here, we treat a p -value of less than 0.05 to be significant at the 95% confidence level, as this shows that even after randomization the “true” orientation of the data is stronger than subsequent permutations. Using this Monte Carlo analysis determines statistical significance and cleverly maintains the spectral shape of the proxy and instrumental data by reassigning the year that each data point is tied to. For a more in-depth look at this statistical exercise, see Appendix A3.

Using this contrived method of statistical comparison between paleo proxy reconstructions and instrumental records, we can determine the correspon-

dence between these two data sets. If we determine there is a low p -value between the proxy and its corresponding instrumental grid cell, we know that the proxy is a strong source of paleoclimate information and would be a strong candidate to capture historically reported events. Mapping the p -values across Europe allows for a spatial conceptualization of where these proxy reconstructions are strongest and weakest.

These three methods of comparison, correlation between proxies and instrumental data, correlation of instrumental data using the proxy location as an anchor point, and determining p -values between the proxy and instrumental record via Monte Carlo analysis, allow for a thorough investigation of the similarities and differences between the paleo proxy and instrumental data. Informed thus, we have a much better idea of the strengths and weaknesses of each proxy reconstruction and are well on our way to determining whether they could potentially capture climate events suggested by the documentary database.

Statistical Comparison of Documentary and Paleo Proxy Data

The ultimate goal in this analysis is to determine whether we can statistically relate the chosen paleo proxy reconstructions with the documentary climate reports. One means of completing this analysis is by optimizing the proxy reconstructions to detect a specific year, as suggested by the documentary database, and seeing whether that year in fact stands out in the proxy reconstructions.

To begin this comparison, we must first choose several years which stand

out in the documentary database as uniquely extreme. Grouping summer precipitation, flood, and storm events as “wet” climatic events and grouping summer heat and drought events as “hot” climatic events, I took the rolling Z -score of these two time series and defined the five years from each record with the largest Z -score as my case study years.

These five extreme “wet” years and five extreme “hot” years visibly and statistically stand out from the rest of the documentary time series and provide a good starting point for proxy comparison. The wet case study years are useful for comparison to highly positive anomalies in the precipitation reconstructions, whereas it is useful to compare the hot case study years to both the highly positive temperature anomalies and the highly negative precipitation anomalies (droughts).

Next, for every case study year, I developed a means of scoring each proxy. Using the results of the paleo proxy and instrumental time series correlation, every proxy which had a correlation above ± 0.2 was considered. Mapping these proxies with the documentary events from each case study year onto the proxy-anchored instrumental correlation maps not only shows the spatial distribution of historical climate reports in relation to the proxy, but also whether the location of each historical report experiences similar climatic conditions to the proxy location.

The location of each historical event is tied to a certain spatial correlation and the proxy’s score for each case study year was determined as the maximum spatial correlation value of all historical reports from that year. In this case, using the maximum correlation is a suitable method of scoring the proxy because it selects the historical report location where climate conditions are

most similar to the proxy location. Therefore, the historical event at this location is the best candidate to determine whether the proxy record capture this documentary-suggested climatic event.

With each proxy scored with a spatial correlation value for all case study years, we can use these scores to create fifteen distinct weighted average reconstruction time series- five for precipitation optimized toward the wet years, five for temperature optimized toward the hot years, and five for precipitation optimized toward the hot years. Each time series is a sum of the relevant proxy reconstructions weighted by the correlation and is optimized to capture the climate event from the case study year.

Finally, a simply performing a rolling Z -score on these fifteen time series provides the standard score for each year. That standard score is translated to a p -value to determine statistical significance (see Appendix A4 for the mechanism of translation).

Ideally, the p -value for the case study year that the time series is optimized to detect should be 0.05 or lower. These p -values and Z -scores statistically determine whether the optimized proxy reconstructions in fact capture the climate events that drove historical figures to record their observations many centuries ago.

Results

In this section I present pertinent results and statistics gained from this interdisciplinary study. The methodology outlined in the prior section was developed to robustly compare an historical documentary database of climate reports with scientific paleo proxy climate reconstructions. Though this methodology can be easily extended toward a different documentary database and any number of paleoclimate reconstructions, the results presented in this section specifically pertain to the Medieval climate reports, originally gathered by Pierre Alexandre and digitized by SoHP, and the eleven pertinent paleoclimate reconstructions of temperature and precipitation in Medieval Europe available through NOAA.

Not all maps and plots created throughout this analysis are presented in this section; rather, I present demonstrative examples for each step of the analysis. A more in-depth discussion of these results and their implications for future studies is considered in the Discussion section.

Comparison of Paleo Proxy and Instrumental Data

As outlined in the Methods section, I undertook three primary means of comparing the paleo proxy reconstructions with the instrumental data from the CRU over the relevant twentieth century reference period. I spatially correlated the reconstructions directly with instrumental data, spatially correlated instrumental data with the instrumental data co-located with the proxy, and used a rolling Z -score and Monte Carlo analysis to determine whether the average Z -score of the reconstruction, as indexed by extreme years in the

instrumental record, varied after randomization. See Appendix A1-A3 for a more in-depth look at these three methods

Direct Spatial Correlation of Proxy and Instrumental Data

The temperature and precipitation instrumental data from the CRU is available for the reference periods of 1850 - 2016 and 1900 - 1998, respectively. Each paleo proxy reconstruction presents annual values for either the entire instrumental reference period or some subset of that period. For every shared year, it is a simple exercise to correlate the paleo proxy predicted annual climate anomaly with the co-located average instrumental anomaly for the growing season (April through September). Table 2 presents the eleven paleo proxy reconstructions and their corresponding instrumental R values, reconstruction type, and range of compared years.

The R values presented in Table 2 correlate the paleo proxy climate reconstruction with the instrumental data of the co-located grid-box. In this table, we see that the R values are strong for certain reconstructions, but in other cases exceedingly weak. The values presented in Table 2 give a rough estimation for the accuracy of the paleo proxy reconstruction, if we are to consider instrumental data to be a true gauge for what is happening during the twentieth century. Of course, this also assumes that the accuracy of the paleo proxies has remained constant throughout time, meaning that the proxies are not more or less accurate in the twentieth century than during the Medieval era. Table 2 also presents the type of climate anomaly that each reconstruction aims to recreate, as temperature is generally easier to reconstruct and is indicative of larger spatial values.

Proxy Reconstruction	Correlation with Instrumental Data	Reconstruction Type	Years of Comparison
Esper et al. (2014)	0.5944	Temperature	1850-2006
Griggs et al. (2007)	0.5158	Precipitation	1900-1989
Büntgen et al. (2016)	0.5006	Temperature	1850-2003
Larocque-Tobler et al. (2010)	0.3829	Temperature	1850-1975
Cooper et al. (2012)	0.3176	Precipitation	1900-1998
Wilson et al. (2013)	0.3095	Precipitation	1900-1998
Trachsel et al. (2010)	0.2658	Temperature	1850-1949
Martin-Chivelet et al. (2011)	0.2300	Temperature	1850-2000 [†]
Mangini et al. (2005)	-0.2062	Temperature	1850-1935 [‡]
Büntgen et al. (2013)	0.1836	Temperature	1850-2011
Amann et al. (2015)	-0.0747	Precipitation	1900-1998

Table 2: The eleven paleo proxy reconstructions used in this analysis presented with correlation values from co-located instrumental data, reconstruction type, and range of years specifically compared. R values for certain reconstructions are strong, while others are extremely weak. The R values give a rough idea for the accuracy of the paleo proxy reconstruction.

[†]Martin-Chivelet et al. (2011) report discrete values for 59 years within this range.

[‡]Mangini et al. (2005) report discrete values for 49 years within this range.

Since CRU has instrumental data across most of Europe, we can also correlate the proxy reconstruction with each grid-box across the continent. We expect the strongest correlation at the proxy location with correlations gradually decreasing as distance from the proxy location increases. A good example of this falling off correlation is evident in Figure 7, where Esper et al. (2014)’s temperature anomaly reconstruction is correlated with instrumental data across Europe. In the case of a strong local correlation, such as in Figure 7, the spatial pattern of continental correlation generally makes sense.

Esper et al.’s reconstruction has the highest R value at the proxy location, and follows the trend that we expect. However, if we compare these results to those gathered when the same exercise is performed on Amann et al. (2015)’s

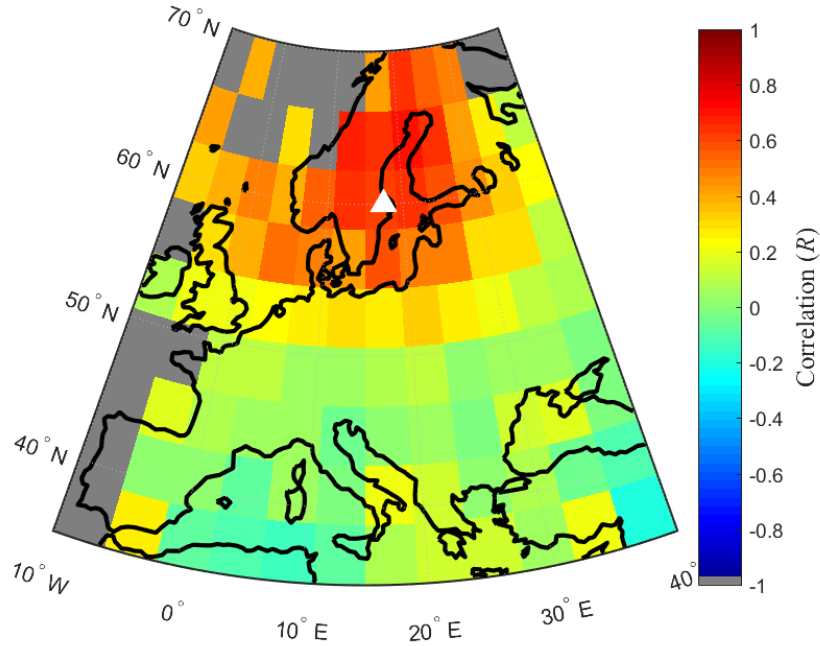


Figure 7: Mapping correlation values over the temporal reference period of 1850-2006 of Esper et al. (2014)’s temperature anomaly reconstruction with the CRU instrumental data. The correlation is highest around the proxy location (white triangle) and falls off as distance from the proxy increases. Esper et al. (2014)’s reconstruction has the highest correlation with instrumental data of all proxies considered in this study.

precipitation reconstruction, the reconstruction with the lowest R value at the proxy location, we see a very different picture. In Figure 8, we see that the correlation with instrumental data is weak at the proxy location and seemingly random throughout Europe. There are actually instrumental data far away from the proxy location which have stronger correlations to the reconstruction than local climate.

The R values gathered from comparing the paleo proxy reconstructions with instrumental data provide important insights into how well the reconstruction in question captures local and regional climate anomalies and inform our investigation as such. Regarding the potential for positive bias described

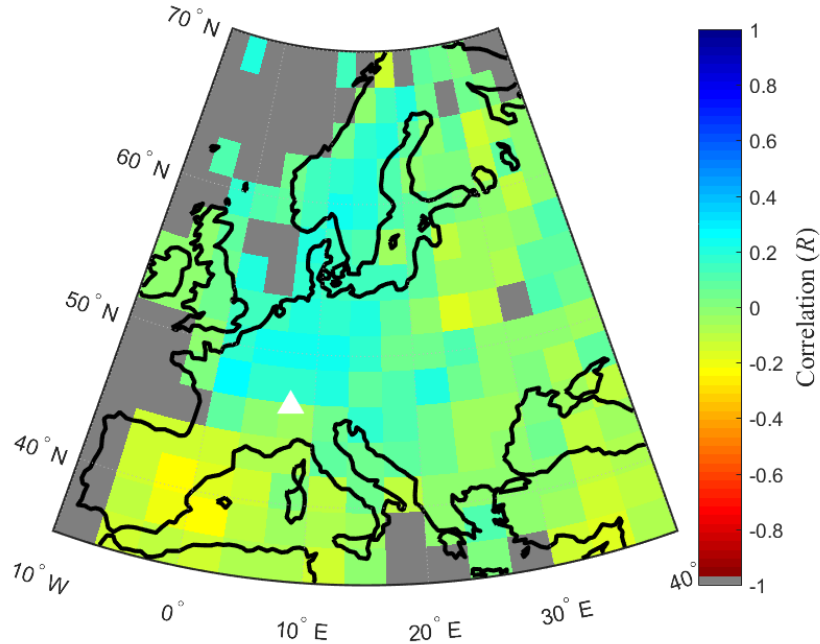


Figure 8: Mapping correlation values over the temporal reference period of 1900-1998 of Amann et al. (2015)'s precipitation anomaly reconstruction with the CRU instrumental data. The correlation is weak at the proxy location (white triangle) and stays seemingly random throughout Europe. Amann et al. (2015)'s reconstruction has the lowest correlation with instrumental data of all proxies considered in this study.

in the prior section, the lack of exceptionally strong R values and the variance of correlation from proxy to proxy suggest that although the raw proxy data are calibrated with modern instrumental records, the resulting reconstructions still vary enough that this method is useful to compare the relative strength of reconstructions. Paleo proxy reconstructions which do not pass this simple test of correlation to instrumental data are not the best candidates for comparison with documentary reports, a data source arguably more open to interpretation than instrumental records.

Of course, this is not to claim that producing accurate instrumental records is simple. Nevertheless, we rely on the work of CRU and take these data at

face value, as an analysis of these estimates of past temperature and precipitation, which are also sensitive to human errors (measurement timing, quality, protocol, data analysis, etc.), is beyond the scope of the present analysis.

Spatial Correlation of Instrumental Data with the Instrumental Data at the Proxy Location

The second important analysis to undertake while calibrating the eleven paleo proxy reconstructions is to correlate the instrumental data at the proxy location with the instrumental data across all of Europe. Through this analysis we are able to determine how similar the climatic conditions are across the continent to the climate conditions at the proxy location. This knowledge is important because if the climate in one grid cell does not correlate with the climate conditions at the proxy, we should not expect the proxy to record a climate event at this first location.

In this method, the correlation at the proxy location will clearly be equal to 1, and this correlation theoretically should, again, drop off with distance. Figures 9 and 10 show this analysis across Europe as performed on Büntgen et al. (2016)'s temperature reconstruction and Griggs et al. (2007)'s precipitation reconstruction.

In this proxy anchored instrumental-instrumental correlation mapping, the spatial pattern of continental correlation is clear and falls off with distance, implying a general correlation radius. We see strong correlations roughly within a radius of 7.5° latitude and longitude, or around 750 km, of the proxy location. Of course, there are also important regional differences in the European climate regime which may substantially change how spatial patterns

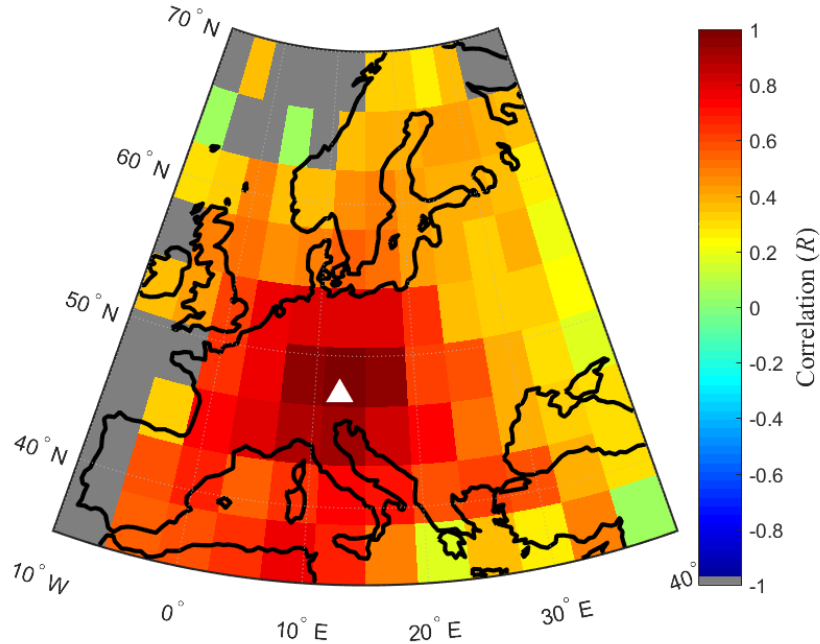


Figure 9: Correlating the CRU temperature instrumental data across Europe with the instrumental data co-located with Büntgen et al. (2016) (white triangle).

of correlation vary across the continent.

Inevitably, the presence of noise and finite-length records can lead to spurious correlations far from the proxy location, though there is also the possibility for teleconnections. A teleconnection refers to specific instances whereby climate anomalies at two geographically disparate locations are related. The most emblematic teleconnection is the Southern Oscillation, which links sea level pressures at Tahiti and Darwin, Australia. The Southern Oscillation was first described by Sir Gilbert Walker in the early twentieth century and was subsequently linked to El Niño (collectively referred to as ENSO) conditions in the Eastern Equatorial Pacific by Bjerknes (1969). Multiple studies have linked European climate conditions to ENSO through teleconnection (Wallace and Gutzler, 1981; Lloyd-Hughes and Saunders, 2002; Bell et al., 2009; Cagnazzo

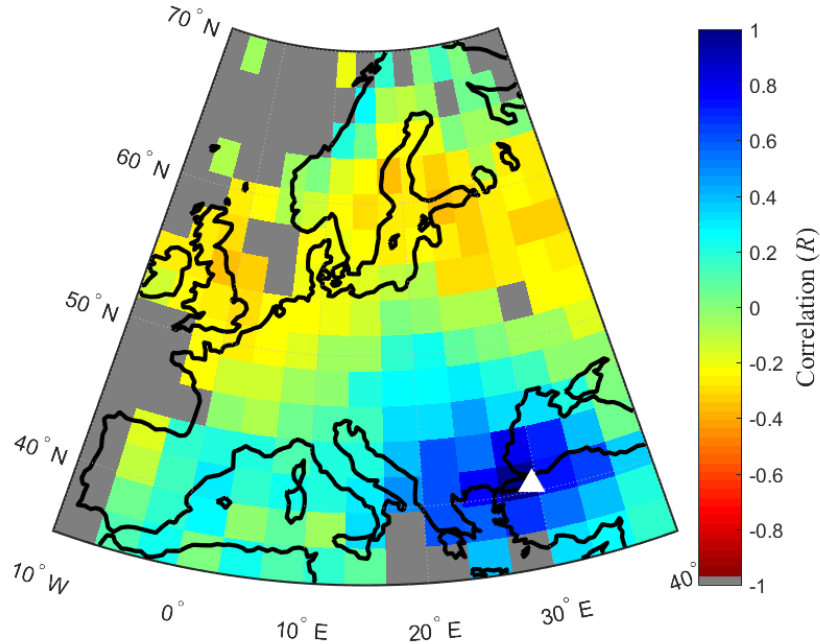


Figure 10: Correlating the CRU precipitation instrumental data across Europe with the instrumental data co-located with Griggs et al. (2007) (white triangle).

and Manzini, 2009; Ineson and Scaife, 2009), but other European teleconnections exist as well. In particular, the North Atlantic Oscillation (NAO), an index of a weather phenomenon in the North Atlantic Ocean resulting from variations in sea level pressure between the Icelandic low and Azores high, has several European teleconnections associated with it (Rogers, 1997; Wibig, 1999). Consideration of teleconnections may help to frame a discussion as to why certain spatial correlation patterns emerge in this analysis.

Of the three methods of comparing instrumental data with paleo proxy reconstructions, this exercise is most useful for our statistical analysis and for future studies. This endeavor allows us to determine how climate regimes tend to vary across Europe when compared to a specific anchor point and could be particularly useful for any study which seeks to spatially compare historical

climate reports. In this analysis the instrumental-instrumental correlation is anchored on the paleo proxy location, but this anchor point could easily be a report location as well.

Monte Carlo Analysis and p -Value Generation Method

The third and final method of calibrating the paleo proxy reconstructions with the CRU instrumental data over the relevant temporal reference period is described extensively in Appendix A3 and involves using a Monte Carlo analysis in order to generate a p -value. This p -value tells us the probability that after time series shifting, the magnitude of formulated average Z -scores are greater than the magnitude of the average Z -score of the unaltered proxy reconstruction indexed by the five most extreme instrumental years.

This analysis is useful for looking at years with extreme values in the instrumental record, whether they are extremely positive or extremely negative. In Figure 11, the five years in the instrumental record with the largest positive temperature anomalies are used as indices to look at Mangini et al. (2005)'s temperature anomaly reconstruction. Using the suite of instrumental data across Europe allows for the spatial comparison of p -values determined in this method. p -values of less than 0.05 are treated as significant at the 95% confidence level, and suggest that the proxy reconstruction is stronger in its published configuration than in shifted configurations created through the Monte Carlo analysis. The assumption here is that p -values at and around the proxy location would be significant, while p -values that are spatially dislocated would be insignificant.

While Figure 11 maps the p -values created from Mangini et al. (2005)'s

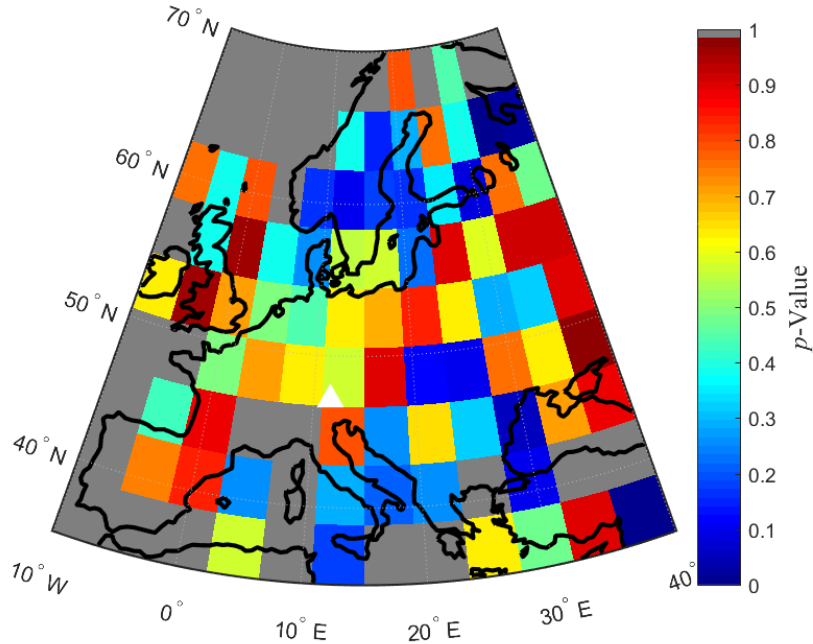


Figure 11: p -values across Europe created by comparing Mangini et al. (2005)’s temperature reconstruction (located at the white triangle) with the five most positively anomalous years from each grid cell’s instrumental data. For information on this analysis, see Appendix A3.

reconstruction and each cell’s five most positively anomalous temperature years from the CRU instrumental data, Figure 12 maps p -values based on the five most negatively anomalous temperature years from the instrumental grid cells. Both p -values are in theory useful here, as the positive temperature p -values suggest hot summers, while the negative temperature p -values suggest cool summers.

Perhaps the most eye-catching aspect of Figures 11 and 12 is how patchy the p -values are across Europe, as neighboring cells often show very different results. This Monte Carlo analysis and p -value generation method does not show the expected visual pattern seen in the prior two calibration mapping methods and suggests volatility within either the data or this specific method-

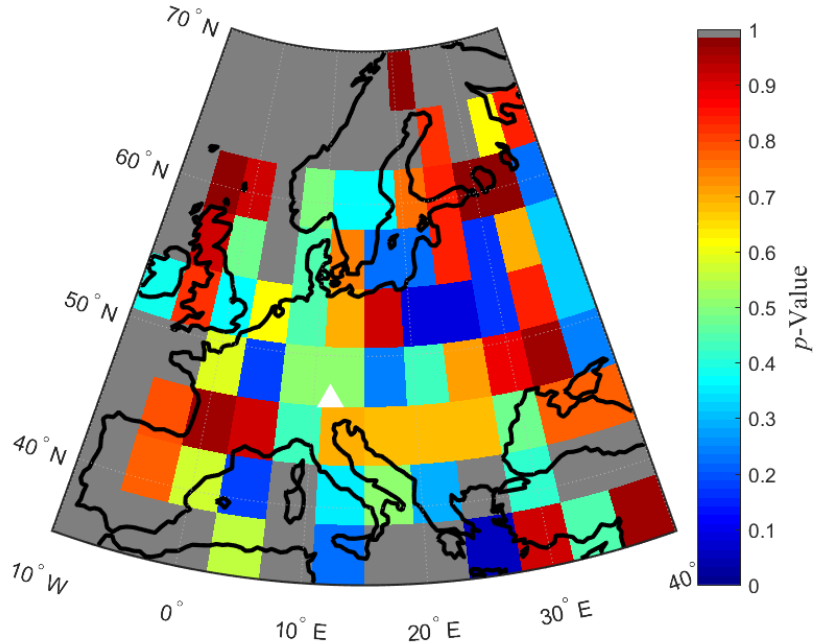


Figure 12: p -values across Europe created by comparing Mangini et al. (2005)’s temperature reconstruction (located at the white triangle) with the five more negatively anomalous years from each grid cell’s instrumental data. For information on this analysis, see Appendix A3.

ology. Therefore, the results from this method were only seriously considered at the location of the proxy and, even then, only for proxy reconstructions with relatively strong instrumental correlations as presented in Table 2.

The theoretical versatility of looking at the significance of both extreme positive and extreme negative years as we are able to in this calibration method is useful because it informs what type of documentary evidence each paleo proxy might be best suited to capture. For example, this analysis performed on Griggs et al. (2007)’s and Wilson et al. (2013)’s precipitation reconstructions, two reconstructions with relatively high R values from Table 2, and the five years in the co-located instrumental record with the most negative precipitation anomalies produced highly significant p -values of 0.000. In contrast, the

five years that were most positively anomalous were insignificant.

This result qualitatively informed subsequent data analysis because it suggested that precipitation reconstructions may track dry events better than wet events. Therefore it is just as important to consider historical records of heat and drought with precipitation reconstructions as it would be to consider records of precipitation and flooding. This conclusion fits with dendrochronological expectations because tree ring reconstructions depend primarily on growth limitation (Fritts, 1976). Thus, a signal of less rain, rather than more rain, might be expected to emerge more clearly.

Having undertaken these three distinct calibrations of the paleo proxy reconstructions with the CRU instrumental data, we learn several important things. We gain an appreciation for how the proxy reconstructions capture local and regional climate, how climate varies across Europe and how a certain location’s climate may be similar or dissimilar to another location, and which specific climate phenomena the paleo proxy reconstructions are best suited to capture.

Historical Case Study Selection

After calibrating the eleven paleo proxies and recognizing their strengths and weaknesses, we must select pertinent case study years from the historical documentary record. As described in the Methods section, the process for selecting the five “hot” and “wet” case study years involves taking the rolling Z -score of the respective time series of heat and drought events and precipitation, storm, and flooding events contained in the historical record. The years corresponding to the five maximum values of these rolling Z -score time series

are selected as the case study years. Figure 13 shows these two time series and marks the five case study years on each plot with an asterisk.

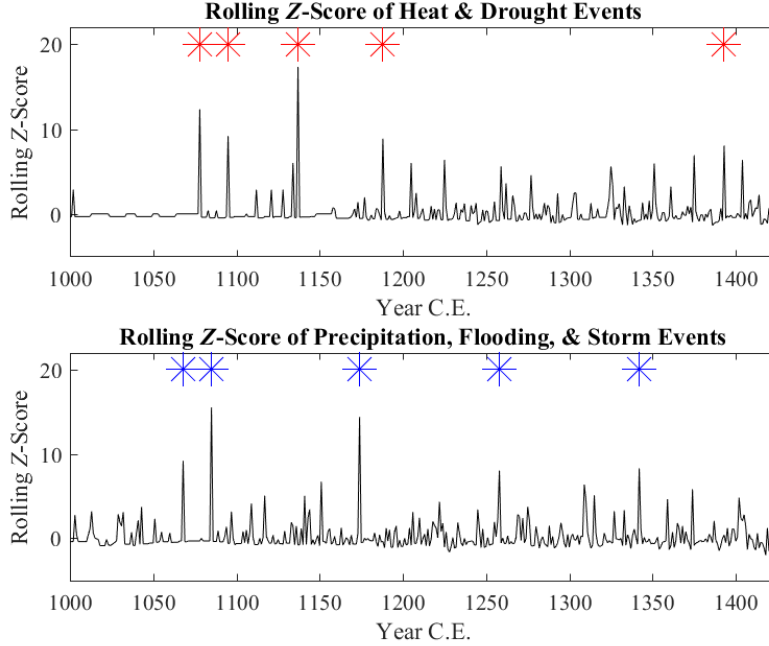


Figure 13: Rolling Z -scores of the documentary time series for “hot” and “wet” summer events. Case study years defined as the years with the five highest Z -score values and are marked above the time series. Red asterisks are hot and dry case study years and blue asterisks are wet case study years.

Figure 13 shows that the hot and wet case study years are generally spread throughout the entire era and not disproportionately weighted toward the early or later Medieval period. Additionally, Table 3 lists these case study years.

Hot & Dry Case Study Years	Wet Case Study Years
1078 C.E.	1068 C.E.
1095 C.E.	1085 C.E.
1137 C.E.	1174 C.E.
1188 C.E.	1258 C.E.
1393 C.E.	1342 C.E.

Table 3: Case study years as determined from taking a rolling Z -score of the documentary record of climate events.

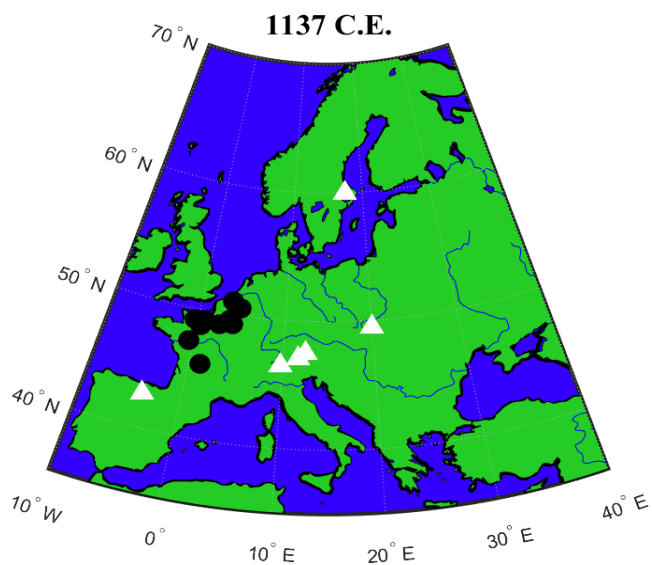


Figure 14: Map of historical heat and drought events (black circles) across Europe in 1137 C.E. Temperature paleo proxy locations are represented as white triangles.

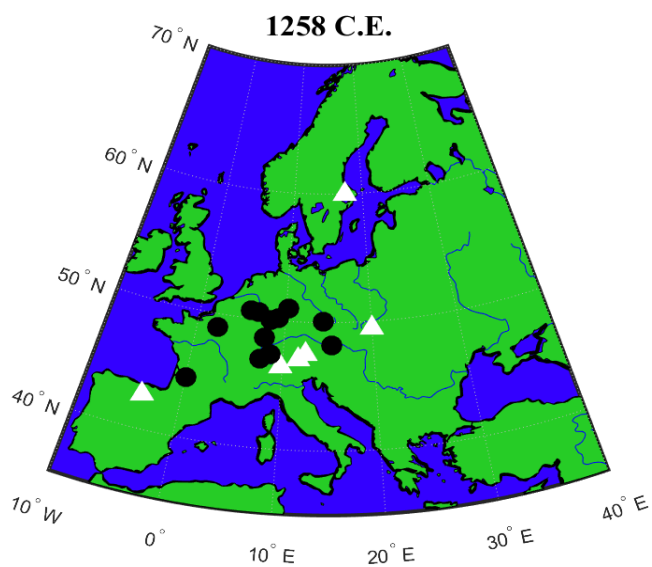


Figure 15: Map of historical heat and drought events (black circles) across Europe in 1258 C.E. Temperature paleo proxy locations are represented as white triangles.

These case study years stand out as visually and statistically extreme in the documentary record. Zooming in on these years, we can map where the reported climate events occurred across Europe, as exemplified in Figures 14 and 15. Examining the spatial distribution of reports allows us to determine whether or not the historically reported climate events were regional or local in origin. A comparison of Figures 14 and 15 shows that the location of reported heat events is strongly dependent on that year’s specific climate patterns. The 1137 C.E. climate reports, for instance, originate primarily from Northwestern France and the Low Countries, whereas the reports from 1258 C.E. originate throughout Western Europe.

Statistical Analysis of Paleo Proxy Reconstructions and Historical Documentary Reports

Having compared the paleo proxy reconstructions with instrumental data from the twentieth century and having singled out five years from the documentary records which seem to be good candidates as having been extremely hot and dry or extremely wet, we can apply the methodology described previously to statistically compare the scientific paleo proxy reconstructions and the written historical records.

Mapping the relevant historical events from each case study year onto the proxy-anchored instrumental-instrumental correlation maps allows us to determine which reports originated from grid cells that have a high correlation to the proxy location and likely experience similar climatic regimes. See Figures 16 and 17 for examples of this mapping.

From these maps, each paleo proxy reconstruction can be “scored” for

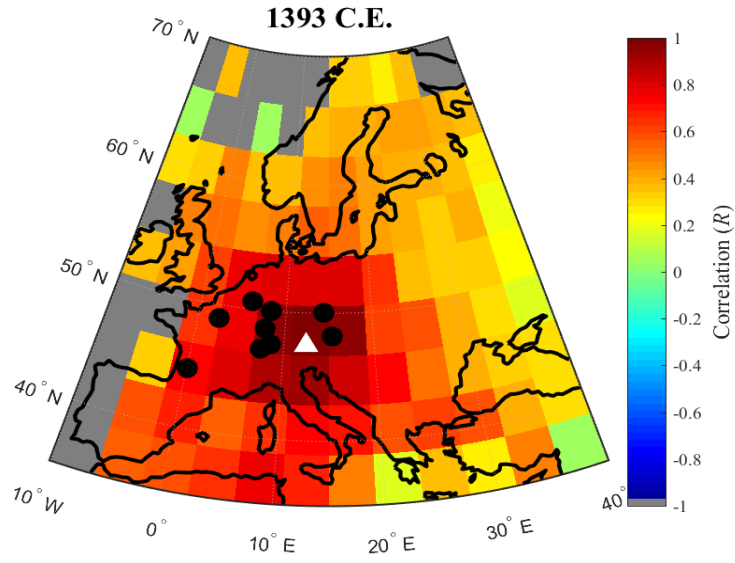


Figure 16: Heat and drought events (black circles) across Europe in 1393 C.E. mapped onto the instrumental-instrumental correlation map anchored on Büntgen et al. (2016) (white triangle).

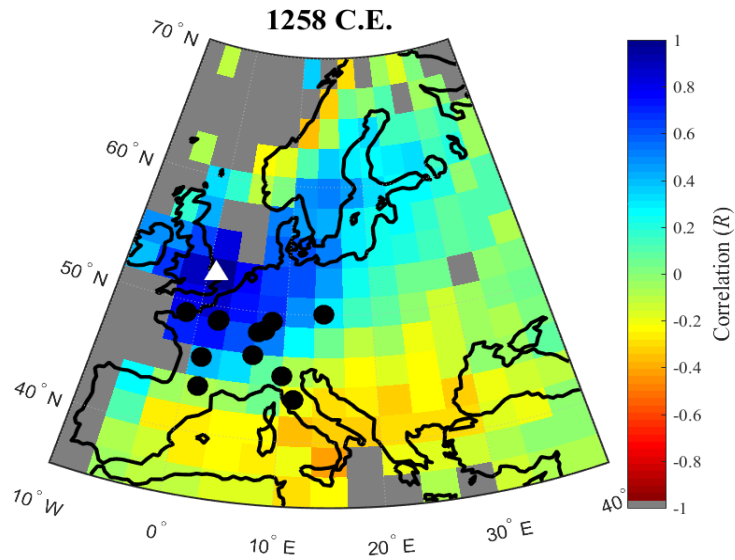


Figure 17: Precipitation, flood, and storm events (black circles) across Europe in 1258 C.E. mapped onto the instrumental-instrumental correlation map anchored on Cooper et al. (2013) (white triangle).

every case study year. The score of each proxy is defined as the maximum correlation value of all grid cells in which an historical event took place that year. Tables 4, 5, and 6 show these correlation scores for every proxy during the case study years. The seven temperature reconstructions were scored for each hot and dry case study year, while the four precipitation reconstructions were scored for both wet and hot and dry case study years as an attempt to capture both excessive rainfall and drought.

Reconstruction	1078 C.E.	1095 C.E.	1137 C.E.	1188 C.E.	1393 C.E.
Mangini et al. (2005)	0.76749	0.76749	0.76749	0.80385	1.00000
Larocque-Tobler et al. (2010)	0.87184	0.80974	0.80974	0.93107	0.93502
Trachsel et al. (2010)	0.87184	0.80974	0.87184	0.93107	0.93502
Martín-Chivelet et al. (2011)	0.85230	0.66074	0.85230	0.79680	0.85230
Büntgen et al. (2013)	0.32999	0.32999	0.32999	0.42334	0.70960
Esper et al. (2014)	0.40915	0.50429	0.65133	0.62099	0.65133
Büntgen et al. (2016)	0.76749	0.76749	0.76749	0.80385	1.00000

Table 4: Temperature proxy scoring for the five hot and dry case study years.

Reconstruction	1068 C.E.	1085 C.E.	1174 C.E.	1258 C.E.	1342 C.E.
Griggs et al. (2007)	-0.16083	-0.22769	-0.27830	-0.27830	-0.23145
Cooper et al. (2013)	0.67175	0.73783	0.84635	0.84635	0.75378
Wilson et al. (2013)	0.61349	0.67960	0.78085	0.85764	0.70277
Amann et al. (2015)	0.19463	1.00000	0.27095	1.00000	0.54427

Table 5: Precipitation proxy scoring for the five wet case study years.

Reconstruction	1078 C.E.	1095 C.E.	1137 C.E.	1188 C.E.	1393 C.E.
Griggs et al. (2007)	0.19842	-0.27830	-0.27830	-0.22404	-0.22769
Cooper et al. (2013)	0.72319	0.84635	0.84635	0.72319	0.73783
Wilson et al. (2013)	0.62097	0.78085	0.85764	0.73328	0.67960
Amann et al. (2015)	0.41828	0.27095	0.28256	0.53114	0.28256

Table 6: Precipitation proxy scoring for the five hot and dry case study years.

Multiplying each proxy reconstruction time series with the corresponding scores from Tables 4, 5, and 6, we can then separately add all temperature

proxies and all precipitation proxies together. Because the correlations of both Büntgen et al. (2013)’s and Amann et al. (2015)’s reconstructions with local instrumental data were less than ± 0.2 , these proxy reconstructions were excluded in the optimized reconstruction combinations. Taking the average of these summed reconstructions creates fifteen time series which correspond to and are optimized to detect a specific case study year. These optimizations based entirely on location and correlations during the instrumental reference period.

Of the fifteen time series, ten are conglomerated precipitation anomaly reconstructions, half of which are optimized to detect the wet years and half of which to detect the hot and dry years. The other five time series are conglomerated temperature anomaly reconstructions optimized to detect the hot and dry years. Through this practice, we retrospectively attempt to detect a climate event in the paleo proxy reconstructions from information gathered entirely from documentary and instrumental data.

The lower plot in Figure 18 shows an example of one of these conglomerated temperature time series, specifically optimized to detect the 1137 C.E. heat and drought event suggested by the documentary database.

Once we have an optimized time series, such as in Figure 18, we can take the rolling Z -score of this array and determine the Z -score of that year which the reconstruction combination was optimized to detect. The top plot in Figure 18 shows the optimized time series normalized via the rolling Z -score method.

Figure 19 presents another example of an optimized proxy reconstruction combination and its corresponding Z -score time series. In this case, the three precipitation reconstructions are combined to create a time series of precip-

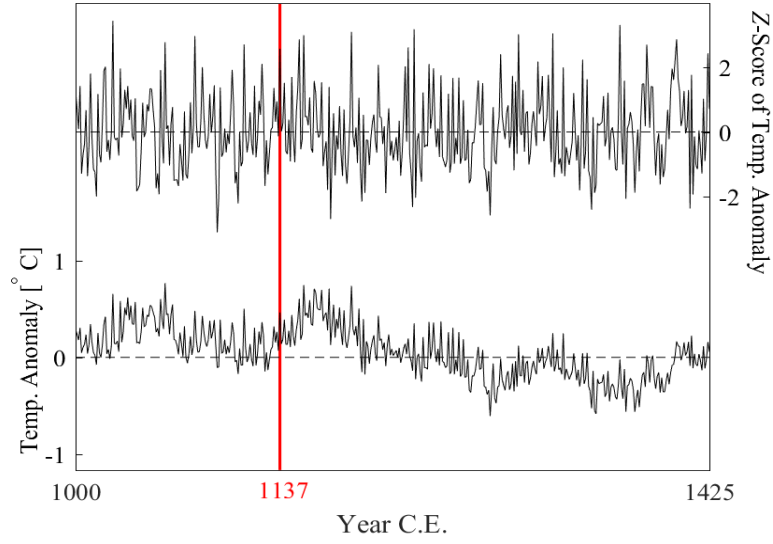


Figure 18: The bottom plot tracks the temperature anomaly time series, constructed from six proxy reconstructions, optimized to detect the 1137 C.E. heat and drought event suggested in Medieval documentary reports. The top plot tracks the rolling Z -Score of this optimized time series. The red vertical line is the reference case study year.

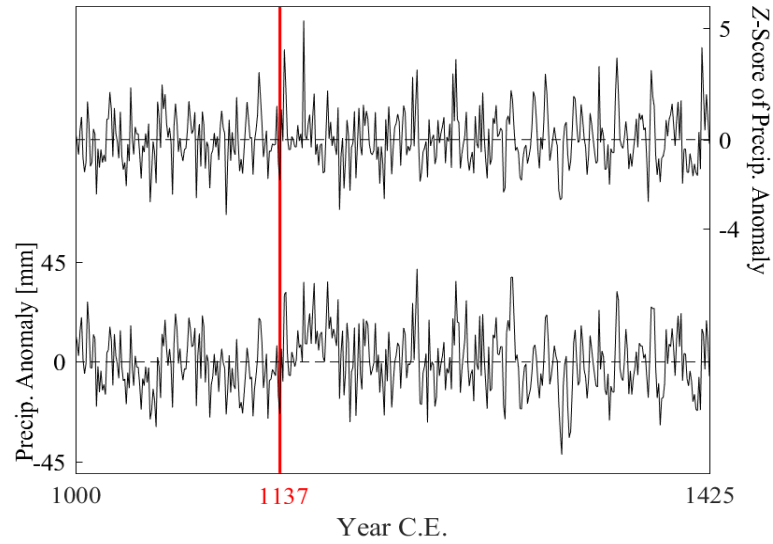


Figure 19: The bottom plot tracks the precipitation anomaly time series, constructed from three proxy reconstructions, optimized to detect the 1137 C.E. heat and drought event suggested in Medieval documentary reports. The top plot tracks the rolling Z -Score of this optimized time series. The red vertical line is the reference case study year.

itation anomalies optimized to detect the same 1137 C.E. heat and drought event that Figure 18 considers. For all time series of proxy reconstruction combinations and their Z -scores, see Appendix B.

A Z -score is easily translated to a p -value via the mechanism explained in Appendix A4. Thus we are able to determine whether the year that the reconstruction combination was optimized to detect is significantly different from other years in that time series. Table 7 lists the p -values associated with the case study year that each combined reconstruction was optimized to detect.

Hot & Dry Years	1078 C.E.	1095 C.E.	1137 C.E.	1188 C.E.	1393 C.E.
<i>Temperature Reconstructions</i>	0.7702	0.9948	0.0049	0.4617	0.5918
<i>Precipitation Reconstructions</i>	0.6361	0.5616	0.0342	0.0416	0.1993

Wet Years	1068 C.E.	1085 C.E.	1174 C.E.	1258 C.E.	1342 C.E.
<i>Precipitation Reconstructions</i>	0.2217	0.0979	0.6153	0.9030	0.6296

Table 7: p -Values from optimized climate anomaly reconstructions. Bolded values are significant at the 95% confidence level.

From Table 7, we see that while the majority of p -values produced in this analysis suggest a lack of statistical significance, there are certain years that are clearly captured in both the paleo proxy and documentary databases. Particularly promising is the 1137 C.E. heat and drought event which is captured in both the temperature reconstructions as anomalously hot and the precipitation reconstructions as anomalously dry. We can visually see these

two conclusions in the Z -score time series presented in Figures 18 and 19, where a peak is present in the normalized temperature reconstruction time series and a trough is present in the normalized precipitation reconstruction time series, respectively suggesting hot and dry conditions.

If this historical database of climate events and paleo proxy reconstructions are in fact comparable, as the hypothesis of this thesis hopes to determine, the climate event which we would most expect to capture in both data sources is this 1137 C.E. hot and dry event. As we saw in Figure 13, 1137 C.E. has the maximum Z -score value of the entire documentary heat and drought event time series.

In the following section, I describe the strengths and weaknesses of the statistical framework developed in this analysis to compare these two distinct data sources and undertake an exploration of why certain years show up as statistically significant and others do not.

Discussion

Major steps have recently been taken in the interdisciplinary field of climate history. Though scientists and historians had previously considered their paleoclimate evidence separately, a dynamic shift in thinking has popularized the notion that perhaps the discrete paleoclimate knowledge possessed by both scientists and historians should be considered in tandem for a more complete picture of the history of climate.

Prior to this study, work in this field has primarily taken the form of estimates originating from one database with qualitative corroboration from the other. Though several recent studies, such as McCormick et al. (2007) and Ludlow et al. (2013), suggest that the ability to compare historical and scientific climate records in certain specific instances is possible, a robust statistical framework for the general comparison of documentary records and scientific paleo proxy data has not been developed.

In this thesis, I sought to determine, first and foremost, whether or not historical documentary records of climate events could be compared to paleo proxy climate data in a statistically significant way. In answering this question, I hoped to create a robust methodology and statistical framework for this comparison and ascertain which climate events this interdisciplinary comparison is best suited for detecting. The creation of new statistical tools to compare scientific and historical data and the use of these tools on new data serves to bolster this growing field of climate history

The methodology developed and the results collected throughout this thesis emphatically suggest that historical records of certain climate phenomena and paleo proxy derived climate reconstructions are in fact comparable in

a statistically robust manner. In this section, I discuss the findings and results gathered from this analysis, specifically highlighting conclusions, both expected and unexpected, which suggest that the methodology presented in this thesis is sound and that the results are significant.

Comparison of Paleo Proxy Reconstructions with Instrumental Data

Perhaps one of the most striking results from this analysis is the generally low correlation values between the paleo proxy reconstructions and the co-located instrumental data, presented in Table 2. In this analysis, this metric is used merely as a means of determining the strength of the proxy and whether or not it should be used in the documentary comparison. However, further consideration of why these proxy reconstructions do not match instrumental observations as well as expected is worthwhile.

The most logical hypothesis for why these two data sources do not match is that the instrumental data gathered by all stations within a grid cell are averaged into a discrete time series for that cell. As a result, the CRU instrumental data gives the average temperature or precipitation for the entire grid cell and this spatial average may not match the specific climatic conditions occurring at the precise proxy location. Paleo proxies, as discussed previously, are generally located in settings where the peculiar conditions present succeed in preserving the climate signal. For example, the reconstructions of Larocque-Tobler et al. (2010), Trachsel et al. (2010), and Amann et al. (2015) are all created from data gathered in the Swiss Alps. The specific climate regime present in the Swiss Alps, at elevation, is undeniably different than the climate

regime experienced in the Alpine foothills, though both locations are contained within the same grid cell. Nevertheless, this instrumental averaging across large swathes of Europe must make do until greater granularity of instrumental observation is available.

Another potential explanation for the lack of correlation between proxy reconstructions and instrumental data could be how the “growing season” is defined. In order to maintain continuity throughout this analysis, I defined a growing season of April through September and the value of the “annual” instrumental anomaly was in fact the average of the monthly time series within this growing season. However, certain paleo proxy reconstructions only claimed to reconstruct specific portions of this growing season, with individual seasons reported in Table 1. Though this strict definition of the growing season necessarily disadvantages reconstructions which only report a fraction of the period, it is most important in this analysis to constrain the instrumental, paleo proxy, and documentary time series over the same season annually.

The paleo proxy and instrumental comparison which proved to be most useful for this analysis was the correlation of instrumental data across Europe with the instrumental data co-located with the proxy. This comparison is useful because it estimates how similar the climate across an entire continent is to a certain location. Future studies may find this exercise useful in approximating climatic conditions between two documentary report locations or in determining a general radius around a specified location in which strong instrumental correlations ought to exist. A particularly interesting finding from this portion of the analysis that merits further consideration is the instrumental precipitation correlation maps. Figure 20 shows the correlation

maps focused on the four precipitation paleo proxy reconstructions.

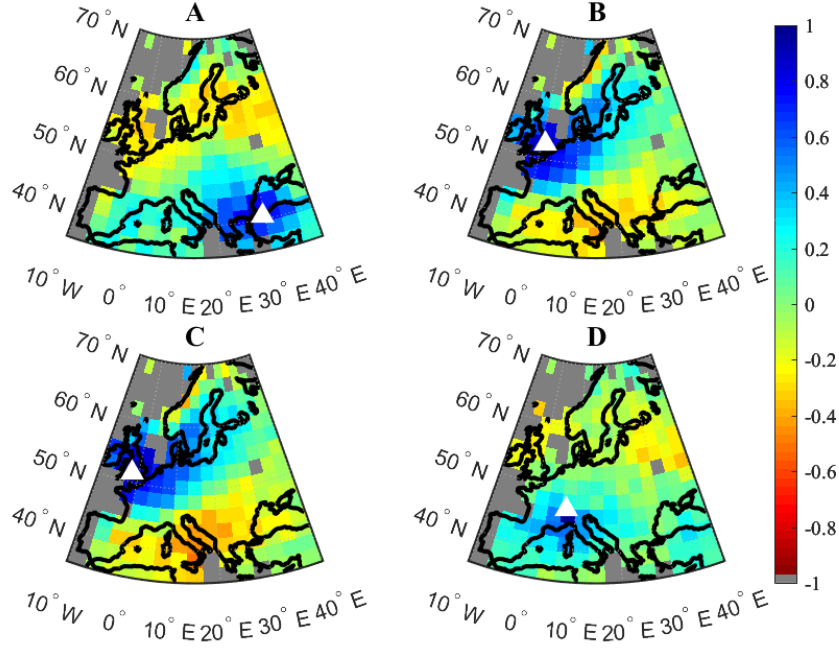


Figure 20: Correlation maps of CRU's precipitation data with the instrumental data from the proxy locations (white triangles) of (A) Griggs et al. (2007), (B) Cooper et al. (2013), (C) Wilson et al. (2013), and (D) Amann et al. (2015). Notice the large asymmetries in all four maps, suggesting that over the twentieth century Europe's precipitation patterns were bimodal in nature.

In Figure 20 we observe large asymmetries in all four precipitation correlation maps. These asymmetries suggest that over the twentieth century, during the months of April through September, there exist two rough climatic halves of Europe and these halves experienced vastly different precipitation patterns. From these plots, we know that if one half of Europe was dry, for instance, the other half of Europe would likely be wet and vice versa. Precipitation is clearly strongly influenced by geography.

This finding independently verifies the asymmetries in precipitation across Europe observed by Trigo et al. (2002). The authors of this 2002 study suggest that the variable and asymmetrical patterns are a result of the North Atlantic

Oscillation. The NAO has a potentially huge influence on European climate and atmospheric circulation patterns, even leading to certain teleconnection areas as reported by Rogers (1997) and Wibig (1999). This observation of asymmetrical precipitation patterns lends credence to Trigo et al. (2002)'s hypothesis and, in suggesting the presence of teleconnection areas, can potentially strengthen future studies on the NAO and how it might change in the face of a changing climate.

Statistical Significance of Case Study Years in Combined Paleo Proxy Reconstructions

Table 7 in the Results Section presents the p -values for the year that each combined paleo proxy time series was optimized to detect. Assuming a significance level of 95%, no precipitation reconstructions were able to detect a year suggested to be unusually wet in the documentary record, one temperature reconstruction was able to detect a hot and dry year, and two precipitation reconstructions were able to detect hot and dry years. In order to understand why certain years were captured by the paleo proxy reconstructions and others were not, it is useful to look at an example of a case study year where the methodology works and a year where it does not. This historical deep dive into the case study years can help to shed light onto when we can expect documentary and paleo proxy climate data to be easily comparable and when we cannot.

1137 C.E. & the “*Terre brûlée*”: A Significantly Hot & Dry Year Captured by Paleo Proxies

When looking at the Z -score of heat and drought events in the documentary record, 1137 C.E. clearly stands out as the year with the largest Z -score (see Figure 21.)

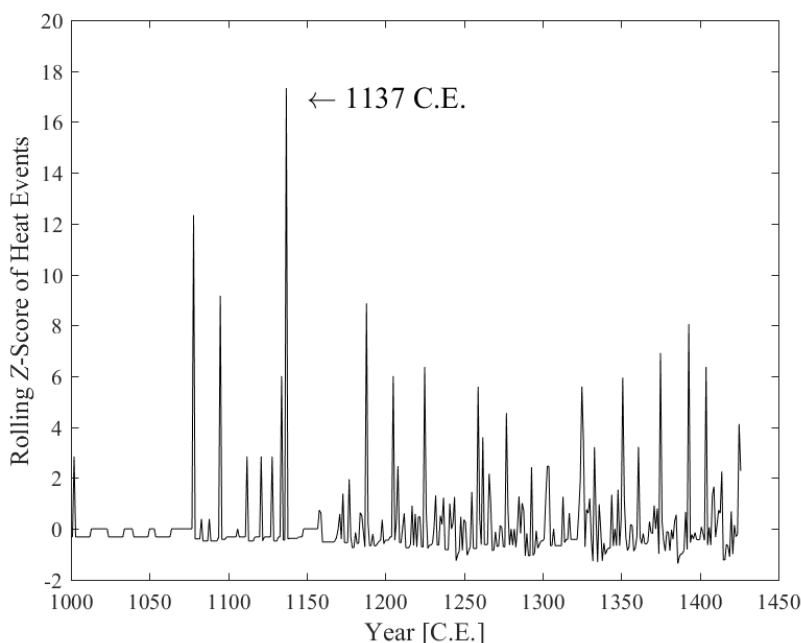


Figure 21: Normalized time series of heat and drought events from the documentary record throughout the Medieval era. 1137 C.E. stands out as the year with the largest Z -score and therefore most significantly different from the local norm.

Alexandre gathered many discrete reports of heat and drought originating from this year, primarily from Northern France and the Low Countries. The location of these heat events was mapped in Figure 14. The very fact that the most significant heat event in the documentary database occurs in the twelfth century underlines its significance. In a time when fewer people were literate, paper was less readily available, the population was lower, and preservation

techniques were worse than, for instance, in the fourteenth century, it must have taken a mighty climate shift to influence so many separate historical figures to document their observations.

Figure 22 lists the reports of heat and drought events from Alexandre (1987). We see reference to *grande chaleur* and *grande sécheresse*, or great heat and drought, multiple times in this list of 1137 C.E. climate events. Several descriptions particularly stand out. Alexandre notes that at Le Bec monastery there was “drying of ponds and streams, drying of plants, and a burned earth” (Alexandre, 1987). In Utrecht, the drought apparently lasted for six months; a corroborating record from Tours claims that the drought lasted from March through September (Alexandre, 1987).

These vivid descriptions of the heat and drought events that occurred throughout the spring and summer months of 1137 C.E. must arouse any historian’s interest upon reading them. The image of a *terre brûlée* is striking. However, we of course need to consider the human bias of the historical figures writing these climate reports- what may seem to be particularly hot in that historical figure’s frame of reference may not in fact be very hot in the scheme of many centuries. Thus, the statistical validation of 1137 C.E. as the most anomalous year in the heat and drought documentary record throughout the entire Medieval era allows us to be more confident in this year than if we only had extreme language to lean upon.

This suite of drought and heat reports is obviously particularly strong in the documentary database, but equally important is this year’s strength in the paleo proxy reconstructions. The data suggest that the strength and geographic spread of the temperature reconstructions, particularly the strong

1135		Bh.5	Prague	Cl.	Le mauvais temps commence en novembre 1134, et dure pendant toute l'année 1135.
1136		Mo.1	Olmütz	In.	Inondation du Danube en Autriche.
1137		W.27	Gembloux	Cl.	Sécheresse, assèchement des sources et des marais. (25)
1137	1136	W.31	Fosses	Cl.	Grande chaleur vers le solstice d'été (21/6); dessèchement des plantes.
1137	1136	W.40	Tournai	Cl. R	Grande sécheresse. Bonne récolte.
1137		Pc.7	Laon	Cl.	Grande sécheresse; assèchement des sources et de certains cours d'eau.
1137		Pc.11	Soissons	Cl.	Grande sécheresse.
1137		Ch.1	Reims	Cl.	Grande chaleur.
1137		Fl.11	Gand	Cl.	Grande sécheresse.
1137		N.10	Le Bec	Cl.	Sécheresse; assèchement des étangs et des cours d'eau, dessèchement des plantes, terre brûlée.
1137		N.15	S.Evrault	Cl.	Grande sécheresse; assèchement des sources et des étangs et de certains cours d'eau. Grande chaleur en été: en juillet, en août et jusqu'au 13/9(20/9).
1137		N.18	Caen	Cl.	Grande sécheresse; assèchement des sources et des cours d'eau.
1137		P.2	Tours	Cl.	Grande sécheresse de mars à septembre.
1137		P.9	Angers	Cl.	Grande sécheresse.
1137		H.6	Utrecht?	Cl.	Grande sécheresse pendant tout le printemps et l'été: grande chaleur.
1137		Ag.1	Limoges	Cl.	Grande sécheresse pendant six mois.
1138		S.25	Zwiefalt.	R	Bonne récolte.
1139		V.19	Vérone	In.	Inondation de l'Adige le 30/8(6/9).
1141		W. 7	Liège	Cl.	Temps serein dans la région de Bouillon du 1/9(8/9) au 18/9(25/9); tempête le 18/9.

Figure 22: Reports of 1137 C.E. heat and drought event as compiled by Pierre Alexandre in 1987.

reconstructions of Esper et al. (2014) and Büntgen et al. (2016), for instance, allow 1137 C.E. to be captured as anomalous by the temperature paleo proxy records. Additionally, as stated previously, temperature is generally easier to reconstruct from paleo proxies and is indicative of larger spatial values. As noted by the documentary records, this heat and drought event was clearly long lasting and wide-spread, so it is to be expected that the paleo proxies would be stressed enough to record this phenomena.

However, what really makes 1137 C.E. significant is that the precipitation paleo proxy records also capture this year as anomalously low. After dropping Amann et al. (2015) from the analysis for its weak correlation value, the remaining three precipitation proxies were all tree ring-derived. Because dendrochronology depends on growth limitation (Fritts, 1976), tree ring reconstructions are expected to be more sensitive to less rain than to more rain. If 1137 C.E. is truly as hot and dry a year as the documentary records seem to suggest, it follows that these three tree ring-derived precipitation proxies would capture this extremely dry year acutely.

The verification of 1137 C.E. as anomalous in two completely independent measures of paleoclimate reconstructions strengthens the conviction that this year is significant and stands as a shining example of the value of the statistical methodology developed throughout this thesis.

1342 C.E. & the “*Pluies abondantes et continuelles*”: A Significantly Wet Year Not Captured by Paleo Proxies

Though this methodology was able to capture certain hot and dry years in the paleo proxy combinations, no wet year was found to be anomalously

high in the paleo proxy precipitation reconstructions. Of the five wet case study years, as determined by precipitation, storm, and flooding events in the documentary record, 1342 C.E. is as good of a candidate as any to consider why the methodology failed here. It also has the added advantage of being later in the Medieval era, and, as a result of increased literacy and paper availability, better preservation conditions, and population and institutional growth, more reports are present for this year than for case study years from earlier in the Medieval period.

In Alexandre's compilation of climate reports from 1342 C.E., as seen in Figures 23, 24 and 25, the author makes note of many instances of *inondations*, or floods, that occur during late July on many of the major rivers across continental Europe. Flooding is reported on the Rhine, the Rhone, the Main, the Waal, the Meuse, the Weser, and the Danube, among others (Alexandre, 1987).

The majority of the reports from 1342 C.E. consist of floods, though there are also several mentions of *pluies abondantes*, or heavy rains. These heavy rains seem to be tied to the flooding events in a causal fashion as they are generally stated as having occurred in the same time period of late July. In Munster it is reported that the rains were "heavy and continuous from July 25th through November 1st" (Alexandre, 1987). This one mention of the temporal duration of the heavy rains is the only clue in the documentary database which suggests that perhaps the 1342 C.E. event may have been more than a cloudburst that caused widespread and massive, but temporary, flooding.

In general, flood events are highly localized and often last for only a short amount of time. Temporally transient and geographically isolated climate

1342		R.17	Cologne	In.	Inondations en été à Cologne.
1342		R.23	Trèves	In.	Inondation du Main et du Rhin le 24/7(1/8).
1342		R.30	Mayence	Cl. In. H-R	Pluies abondantes. Inondations pendant plusieurs semaines à partir du 24/6(2/7); inondations des cours d'eau, notamment du Main et du Rhin; inondations à Cologne, à Mayence et à Francfort. Récoltes de foin et de céréales détruites par l'inondation des cours d'eau.
1342	1344	R.31	Mayence	In.	Inondations le 21/7(29/7).
1342		Be.II	Chartres	In. R	Inondations à Chartres. Mauvaise récolte.
1342		Be.9	Vendôme	In.	Inondation (du Loir) à Vendôme, notamment à l'abbaye de la Trinité, pendant la semaine du 10/2 au 17/2 (18-25/2).
1342		N.3	Rouen	In.	Inondation de la Seine à Rouen vers le 22/2.
1342		N.5	Rouen	In.	Inondations du 6/2(14/2) au 24/2 (4/3); inondations à Rouen, notamment au prieuré de Notre-Dame du Parc.
1342		H.8	Tiel	In.	Inondation du Rhin, du Waal et de la Meuse les 24 et 25/7(1-2/8) dans la Betuwe inférieure et supérieure, notamment dans la région de Tiel.
1342	1341	Sa.6	Minden	In. R	Inondation des cours d'eau; inondation du Weser à Minden vers le 22/7. Récoltes dévastées par l'inondation des cours d'eau.
1342		Sa.11	Munster	Cl. In. R	Pluies abondantes et continuelles du 25/7(2/8) au 1/11(9/11). Inondations vers le 25/7. Mauvaise récolte, due aux pluies.
1342		Sa.17	Brunswick	In.	Inondation des cours d'eau le 21/7 (29/7).
1342		Sa.23	Magdebourg	In.	Inondations.
1342		Th.8	Erfurt	In.	Inondation (de la Gera) à Erfurt le 21/7(29/7); inondation (de l'Unstrut) à Wetzendorf. Inondation (du Main) à Wurtzbourg; inondations (du Danube) à Ratisbonne; inondations à Dresde, à Francfort, à Bamberg.

Figure 23: Reports of 1342 C.E. precipitation event as compiled by Pierre Alexandre in 1987. Part 1 of 3, considered along with Figures 24 and 25.

1342		F.3	Cassel	In.	Inondation de la Fulda dans la "Neustadt" à Cassel.
1342	1344	F.4	Limburg	In.	Inondation de la Lahn à Limburg vers le 25/7(2/8).
1342		F.8	Francfort	In.	Inondation du Main à Francfort et à Sachsenhausen du 20/7 au 22/7(28-30/7).
1342		F.9	Francfort	In.	Inondation du Main à Francfort le 21/7(29/7).
1342		F.13	Wurtzbourg	In.	Inondation du Main à Wurtzbourg le 21/7(29/7).
1342		F.1	Wurtzbourg	In.	Inondations.
1342		F.20	Bamberg	In.	Inondation(de la Regnitz) à Bamberg le 21/7(29/7).
1342		F.21	Nuremberg	In.	Inondation à Nuremberg le 19/7(27/7).
1342		B.3	Ensdorf	In. Fr.	Pluies abondantes. Récoltes dévastées par les pluies vers le 21/7.
1342?	1344	B.10	Ratisbonne?	In.	Inondations en hiver et en été; inondation du Danube, de l'Inn et du Rhin.
1342		B.11	Straubing	In.	Inondation (du Danube) à Straubing.
1342		B.19	Eichstätt	In.	Inondations en juillet.
1342		S.9	Lindau	Cl. Cl-In.	Orage au début du mois de mai dans les régions de Leutkirch en Souabe. Pluies abondantes en été. Orages en Lombardie avant le 11/11. Inondation du Danube, due à la fonte des neiges, vers le 2/2. Inondation des cours d'eau en été, due aux pluies; inondation (du Main) à Francfort et (du Neckar) à Esslingen; ces inondations d'été ne touchent pas la Lombardie. Inondations en Lombardie, notamment dans la région de Padoue, avant le 11/11(19/11), à la suite de pluies abondantes.
1342		S.10	Constance	R Cl.	Mauvaise récolte, due aux pluies. Gel du 10/2(18/2) à la mi-mars.
1342		S.30	Ellwangen?	In.	Inondations.
1342		PV.2	Avignon	In.	Inondations à Avignon.

Figure 24: Reports of 1342 C.E. precipitation event as compiled by Pierre Alexandre in 1987. Part 2 of 3, considered along with Figures 23 and 25.

1342		PvIV	Avignon	Cl-In.	Inondation du Rhône et de la Durance à Avignon, à la suite de pluies abondantes.
1342		Lg.1	Vintimille	Cl.	Neige abondante le 18/1(26/1).
1342		V.32	Padoue	In.	Inondations à Padoue.
1342		Em.9	Plaisance	In.	Inondation du Pô à Plaisance le 6/10(14/10).
1342		Em.29	Bologne	Cl.	Neige abondante les 25 et 26/2 (5-6/3).
1342		T.6	Pise	Cl.	Neige abondante (au début de l'année). Mauvais temps pendant l'année.
1342		T.1	Pistoia	Ph.	Vendanges à partir du 1/10(9/10).
1342		T.11	Florence	Pr.	Cherté du vin à Florence (à la fin de l'année).
1342		Om.9	L'Aquila	Cl.	Gel en hiver.
1342		La.5	Meissen?	In.	Inondation de l'Elbe à Meissen.
1342		La.6	Dresde?	In.	Inondation de l'Elbe à Dresde.
1342		La.7	Altzelle	In.	Inondation (de l'Elbe) à Dresde et (de la Moldau) à Prague peu après le 9/2(17/2).
1342		Bh.7	Prague	Cl.	Hiver rude : grand gel en Bohême jusqu'au 1/2(9/2); vent chaud du Sud, pluie "printanière" et dégel le 1/2(9/2).
				In.	Inondation (de la Moldau) à Prague le 1/2(9/2), due à la fonte des glaces et des neiges. (212)
1342		Bh.9	Prague	In.	Inondation (de la Moldau) à Prague le 2/2(10/2).
1342		C.2	Neuberg	In.	Inondations.
1342		C.8	Viktring	Cl-In.	Inondation des cours d'eau dans toute l'Europe. Inondation des cours d'eau, due à la fonte des neiges. Inondation du Danube, du Rhin et du Main. (211)
1343	1342(A)	R.23	Trèves	Cl.	Orage et grêle le 23/1(1343)(31/1). (165)
1343?	1344	B.10	Ratisbonne?	R	Grêle détruisant les récoltes. Mauvaise récolte en Bavière.
1343		B.19	Eichstätt	In.	Nouvelles inondations, à la même époque de l'année qu'en 1342.
1343		B.35	Mattsee	R	Mauvaise récolte, notamment dans la région de Mattsee.

Figure 25: Reports of 1342 C.E. precipitation event as compiled by Pierre Alexandre in 1987. Part 3 of 3, considered along with Figures 23 and 24.

events have perhaps the lowest potential to be captured by paleo proxies- a tree is much more likely to notice a season of pronounced rainfall than an afternoon of pronounced rainfall. Conversely, simply as a result of human observational limitations, historical figures are much more likely to make note of a cloudburst which caused severe flooding for several days than make note of a season which seemed slightly more rainy than usual. This disconnect between the type of precipitation events historical figures would most likely report and what events paleo proxies would most likely capture is almost certainly a major reason for the failure of the statistical methodology with the precipitation reconstructions and the wet case study years.

Another potential problem with the comparison of precipitation reconstructions and precipitation documentary events is the suite of precipitation paleo proxies available for Medieval Europe. Of the four precipitation reconstructions available from NOAA's paleoclimate website, Amann et al. (2015) was dropped from the final analysis for its weak correlation to local instrumental data. The remaining three precipitation reconstructions were geographically dislocated from many of the 1342 C.E. precipitation reports, but also more generally from many of the precipitation reports contained throughout Alexandre (1987). The paleo proxies for Cooper et al. (2013) and Wilson et al. (2013) are both in the southern United Kingdom, whereas Griggs et al. (2007)'s proxies are located in Northern Aegean. Though in theory the instrumental-instrumental correlation maps with proxy anchoring should account for these geographic differences, the absence of a strong precipitation reconstruction close to the documentary reports may play a role in the statistical insignificance of 1342 C.E. and the wet case study years in general. Additionally, the climate

in the British Isles or in the Aegean may be so different from Western Europe that the comparison of climate patterns shows no association at all.

Interpretations and Suggestions for Future Studies

Through this analysis we see that documentary reports of climate and paleo proxy reconstructions are indeed comparable in a statistical framework. Determining that certain years, as suggested by the documentary record to be statistically anomalous, are also significantly anomalous in the paleo proxy reconstructions is a major step forward in the interdisciplinary study of paleoclimate. The methodologies and statistical explorations developed in this analysis provide a wealth of knowledge regarding both scientific and historical records of paleoclimate that will be useful for future studies in this field of consilience.

The methodology introduced throughout this thesis is robust enough to detect certain climate events between records, but of course future studies could improve upon it. The first and most important improvement would be to use more climate anomaly reconstructions than what are currently publically available on NOAA's paleoclimate website.

The precipitation reconstructions available through NOAA may have been either too uncorrelated to the instrumental record or too geographically distant to give an accurate measure of climate in Western Continental Europe, where most of the reports originated from. In contrast, the temperature reconstructions available were generally well-correlated to the instrumental records and relatively closer to the report locations. Until this analysis uses at least as many precipitation reconstructions as temperature reconstructions,

we cannot be sure whether the methodology completely misses precipitation events because of the temporally short nature of oft-reported flood events or if the reconstructions currently used are merely too weak. Ideally, additional precipitation reconstructions would report regional precipitation trends rather than continental trends; for instance, a potential addition might be the three regional precipitation reconstructions reported by Büntgen et al. (2011b). Though regional precipitation reconstructions are preferred to geographically widespread averages for comparison to localized written reports, adding any robust paleo proxy reconstructions could do nothing besides improve this analysis.

Another way that future studies could expand upon this study would be to improve how the weights of the individual proxies that comprise the averaged reconstructions are determined. In this analysis, the score was defined as the highest correlation value of all historical events from the case study year mapped onto the proxy-anchored instrumental correlation map. This means of scoring was deemed acceptable in this analysis because we were comparing extreme peaks and troughs between datasets. For future studies, which may not deal in extremes, a more robust means of scoring could be accomplished by creating a covariance matrix corresponding to all historical event locations. Using this covariance matrix would allow us to better weight and score the proxies so that proxies that are geographically proximate do not unduly influence the reconstruction combinations.

A final means of strengthening this methodology, which may or may not be possible, would be to gain more data in the historical database. A major inconsistency in the documentary data was that some reports had months

attached to them and others did not. Through my event classifying procedure, reports which occurred in the same month, in the same location, and with the same climate event codes were categorized as one event. However, if two similar reports had no months listed and occur in the same location, I chose to take a conservative approach and list these reports as two separate events.

My reasoning for choosing a more conservative approach was that if there are two reports of a flood event in the same city in one year, we cannot be certain that one report was not a flood as a result of snowmelt in late spring and the other a result of a massive deluge at some other point in the season. Grouping both reports as one event merely because of their year and location and without any other evidence that they are indeed the same event, seemed to compress the data too much. Plus, it seemed to be out of step with the reality that I observe in everyday life, as Boston certainly could experience the same climatic event several times in a week, let alone a year. In fact, in Figures 23, 24, and 25, Alexandre lists many reports of 1342 C.E. flooding. Some of these floods happen in the same location, and yet they occur at very different times of the year. In this case we have the month data, but in other situations, particularly the early Medieval era, this discrepancy would be collapsed and ignored unless a conservative approach to event grouping is used.

Conclusion

The interdisciplinary field of climate history is a burgeoning field that will provide valuable insight into future paleoclimate investigation. The goal of this thesis was to determine whether scientific paleo proxy data could be compared to historical documentary data in a statistically significant way. Prior to the work completed in this study, there had been no major attempt to compare documentary and scientific paleoclimate data in a statistical framework. The vast majority of purported relationships between historical and scientific data that have been reported in the literature are qualitative in nature. The few-and-far-between statistics that are reported in the literature are individualized to specific data and not easily translated to new data and new time periods.

In this thesis, I have developed a statistically robust methodology that compares an historical documentary database of climate reports from Medieval Europe with paleo proxy climate reconstructions from the same temporal reference period. Using twentieth century instrumental data to calibrate these reconstructions, three discrete and independent data sets have been successfully integrated into a system that seeks to retrospectively predict whether a certain year will be anomalous in the reconstructions based solely on information contained within the documentary and instrumental data.

The most important result contained within this thesis is that the year in the documentary record which is most statistically anomalous (highest Z -score) in regards to heat and drought events is also statistically anomalous in multiple temperature and precipitation paleo proxy reconstructions. Additionally, another anomalously hot year within the documentary time series was significant in the precipitation reconstructions. These two positive results

suggest that the methodology developed in this thesis is definitely applicable to historical heat and drought events and temperature and precipitation paleo proxy reconstructions.

Though this methodology did not preempt any anomalously wet years in the precipitation reconstructions, there is reason to believe that better data may in fact remedy this issue. However, if this methodology, even after adding precipitation reconstructions that are better correlated to instrumental data and closer to source reports, still does not produce significant results, a different, but equally interesting, conclusion begins to take shape. Assuming that precipitation events are not comparable in the documentary and scientific data sets introduces a potential dissonance between what paleo proxies and historical figures are likely to record. If the former only capture long-term, subtle trends and ignore flash flood and deluge events, while the latter focus only on these short, but intense, precipitation events, the question of whether we can and should continue comparing historical and scientific records of precipitation necessarily arises.

In reaching these results and conclusions, several solutions were engineered for problems common to the field of climate history. For instance, the rolling Z -score, described at length in Appendix A1, handily solves the problem created by the increasing number of reports generated through the course of the Medieval era. Through this method, the relative number of reports, rather than the total number of reports, is emphasized. Another problem common to this field is how to best consider both the spatial and temporal dimensions of the data, as climate varies not only yearly but also geographically. The instrumental calibration and case study year approach resolves the issue of

temporality and locality.

Though this analysis was focused on Medieval Europe, in theory the methods described within are applicable to any time period and geographic location where historical reports of climate events and paleo proxies coexist spatially and temporally. Hundreds of paleo proxies exist across the globe and many manuscripts from past global civilizations have been recovered; the possibilities for application of this methodology are vast.

Ultimately, an increased understanding of how the climate behaved throughout history is useful for several reasons. First of all, we can better understand what modern climate system behavior should be considered normal or abnormal through knowledge of how the climate behaved in the past. Secondly, knowledge of past climate can help provide explanations to mysteries which otherwise lack satisfactory answers. For example, without understanding changes in sea level throughout human history, many patterns of human migration and evolution make little sense. Finally, and perhaps most importantly for our future in the face of rapid, anthropogenic climate change, understanding how climate changed in the past allows us to put the responses of historical societies into context and perspective.

Climate is widely considered to have been a fickle beast for many historical civilizations. A mighty civilization could be brought to its knees by a series of overly dry or wet years. Though in the twenty-first century we are less acutely affected by climate than our ancestors were millennia ago, there is no doubt that climate continues to play a major role in food production, migration patterns, and economic prosperity.

As the climate changes in new and unpredictable ways, modern humanity

must adapt in order to persist. To ignore the lessons learned from our forebears on the best and worst ways to respond to climatic changes would be foolish. Adopting statistically robust methods to accurately describe paleoclimatic conditions allows modern humanity to precisely contextualize historical climate trends and, with this knowledge, formulate successful strategies to combat anthropogenic climate change and mitigate its societal impacts. As the dire consequences of climate change increase in magnitude and frequency, it is more important than ever to bridge disciplines and consider all sources of data that may help to tackle this gargantuan problem.

Appendix A: Statistical Metrics and Formulae

A1: Rolling Z -Score

A Z -score, or standard score, is the number of standard deviations (σ) a data point is above the mean (μ). The variation of a rolling Z -score used in this analysis takes the Z -score of each point i in an array, using the mean and standard deviation of the proceeding n points before i . Throughout the time series analyses contained in this thesis, we define $n = 10$ to correspond to the decade preceding year i .

$$Z_{rolling} = \frac{X_i - \mu_j}{\sigma_j}$$

Where:

$$\mu_j = \frac{X_{i-n} + \dots + X_{i-2} + X_{i-1}}{n}$$

&

$$\sigma_j = \sqrt{\frac{1}{N} \sum_{k=i-n}^{i-1} (X_k - \mu_j)^2}$$

A2: Correlation Coefficient

The correlation coefficient, R_{XY} , is a measure of the strength of the linear relationship between two variables X and Y . R_{XY} takes on values inclusively ranging between ± 1 .

$$R_{XY} = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{(n-1)s_X s_Y}$$

Here, $\bar{X}$ and $\bar{Y}$ are the sample means of X and Y and s_X and s_Y are the sample standard deviations of X and Y .

A3: Monte Carlo Analysis Method

Let *ProxySeries* be defined as the proxy reconstruction corresponding to the instrumental reference period & *InstSeries* be defined as the instrumental record corresponding to the instrumental reference period.

After taking the rolling Z -score of the *ProxySeries* to standardize the time series, we define *HeadYrs* as the five years with the highest values in *InstSeries* and *TailYrs* as the five years with the lowest values in this same series. If we take the arithmetic mean of the years in the normalized *ProxySeries* which correspond to the years given in *HeadYrs* and *TailYrs*, we have the average standard score for the years in *ProxySeries* with the five highest and five lowest values in *InstSeries*. We treat these as the “true” values.

Next, we perform a Monte Carlo analysis by iterating n times, where n is the length of *ProxySeries*, and shifting the years forward n spots in the series and placing the displaced ending years at the front of the time series during each iteration. For instance, if $n = 5$ in a time series of 1950-2000, 1950-1995 would be shifted forward five spots and 1996-2000 would be placed at the front of the time series. For each iteration, we continue to use the indexing years of *HeadYrs* and *TailYrs*, and, as the spectral integrity of the standardized

ProxySeries is maintained, each of these indexing years now corresponds to a different value in *ProxySeries*. Taking the average Z -score of the values that now correspond to *HeadYrs* and *TailYrs* creates a constructed value.

Finally, with two arrays of average Z -score values from *ProxySeries* for the years that correspond to the years in *HeadYrs* and *TailYrs*, we can see how many times an artificially constructed value is higher than the “true” value. We define the p -value as:

$$p = 1 - \left(\frac{1 - m}{n} \right)$$

Where m is equal to the number of times that the constructed value is higher than the “true” value if we are using *HeadYrs* or the number of times that the constructed value is lower than the “true” value if considering *TailYrs*. A p -value of less than 0.05 is treated as significant at the 95% confidence level.

A4: Converting Z -scores to p -values

Determining the p -value given the Z -score is a relatively straightforward process of integrating the normal distribution from $-\infty$ to the Z -score.

$$p(Z \leq z) = \int_{-\infty}^z \frac{1}{\sqrt{2\pi}} e^{\frac{-u^2}{2}} du$$

Appendix B: Optimized Paleo Proxy Reconstructions and Z -Score Time Series

In the Results section, I presented combinations of paleo proxy climate reconstructions which were optimized via historical report location and instrumental correlation maps to detect certain case study years suggested in the documentary record as particularly anomalous. Taking the Z -score of these optimized time series normalizes these arrays. Figures 18 and 19 present two such pairs of optimized time series and corresponding Z -score time series. Beginning on the next page, Appendix B presents all fifteen pairs of optimized time series and Z -score time series, breaking these fifteen pairs into three groups of five.

Appendix B1 presents temperature anomaly reconstructions optimized to detect hot and dry events, Appendix B2 presents precipitation anomaly reconstructions optimized to detect hot and dry events, and Appendix B3 presents precipitation anomaly reconstructions optimized to detect precipitation, flooding, and storm events.

B1: Temperature Anomaly Reconstruction Combinations Optimized to Detect Heat and Drought Events

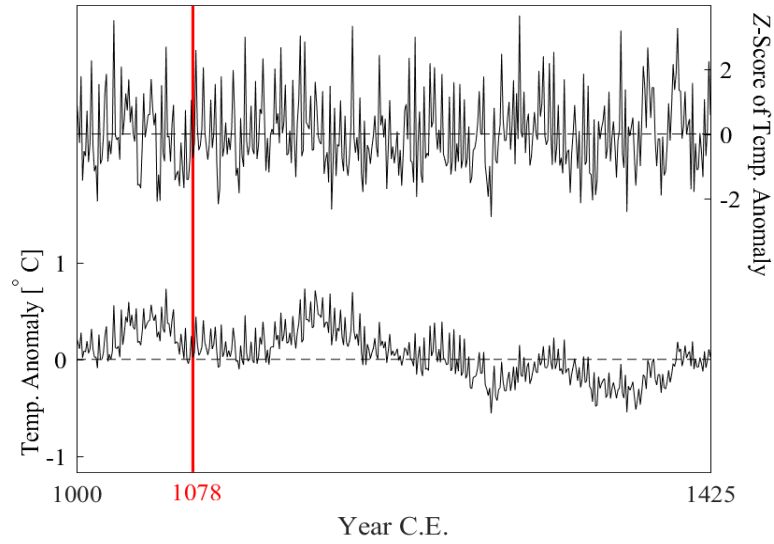


Figure 26: The bottom plot tracks the temperature anomaly time series, constructed from six proxy reconstructions, optimized to detect the 1078 C.E. heat and drought event suggested in Medieval documentary reports. The top plot tracks the rolling Z -Score of this optimized time series. The red vertical line is the reference case study year.

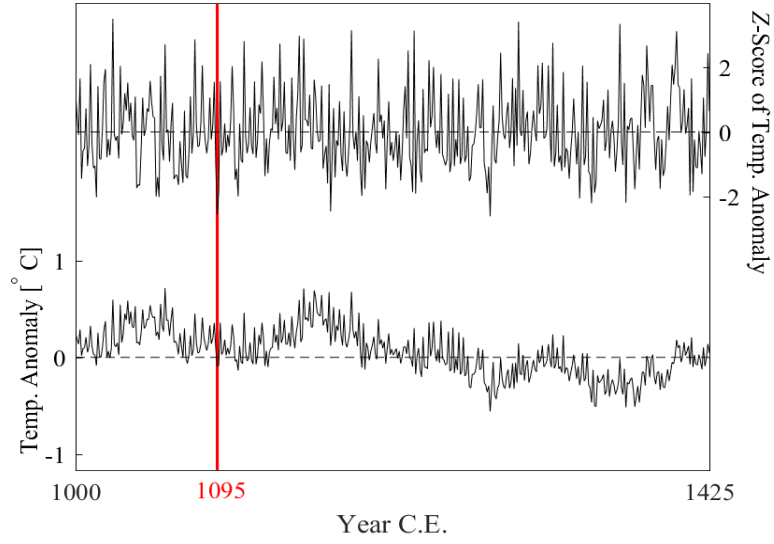


Figure 27: The bottom plot tracks the temperature anomaly time series, constructed from six proxy reconstructions, optimized to detect the 1095 C.E. heat and drought event suggested in Medieval documentary reports. The top plot tracks the rolling Z -Score of this optimized time series. The red vertical line is the reference case study year.

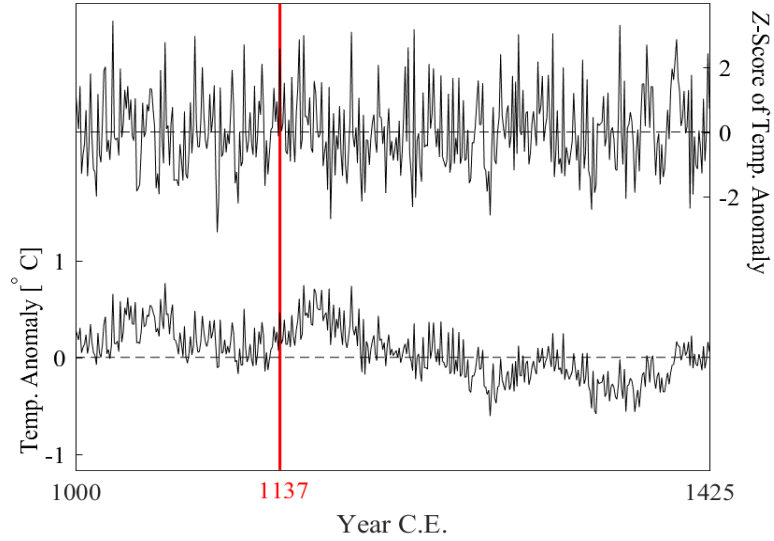


Figure 28: The bottom plot tracks the temperature anomaly time series, constructed from six proxy reconstructions, optimized to detect the 1137 C.E. heat and drought event suggested in Medieval documentary reports. The top plot tracks the rolling Z -Score of this optimized time series. The red vertical line is the reference case study year.

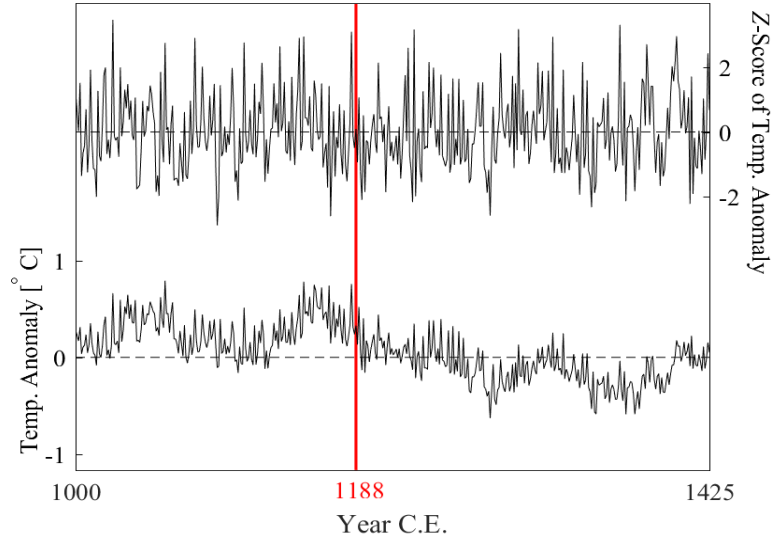


Figure 29: The bottom plot tracks the temperature anomaly time series, constructed from six proxy reconstructions, optimized to detect the 1188 C.E. heat and drought event suggested in Medieval documentary reports. The top plot tracks the rolling Z -Score of this optimized time series. The red vertical line is the reference case study year.

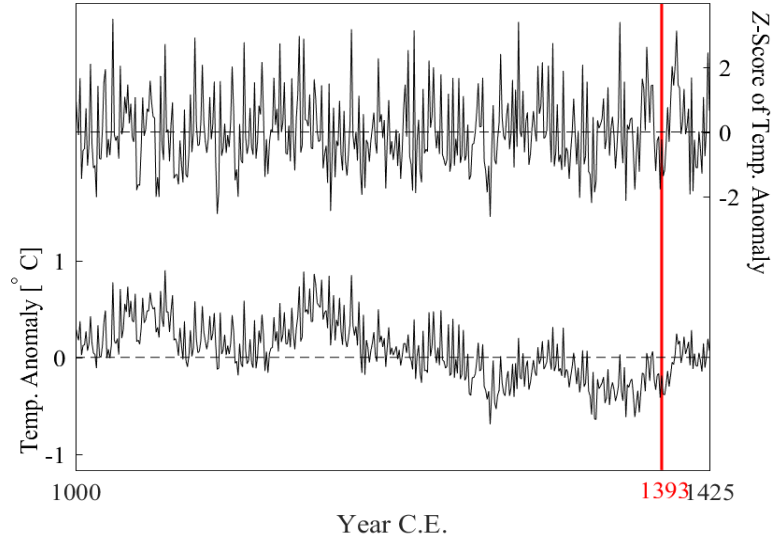


Figure 30: The bottom plot tracks the temperature anomaly time series, constructed from six proxy reconstructions, optimized to detect the 1393 C.E. heat and drought event suggested in Medieval documentary reports. The top plot tracks the rolling Z -Score of this optimized time series. The red vertical line is the reference case study year.

B2: Precipitation Anomaly Reconstruction Combinations Optimized to Detect Heat and Drought Events

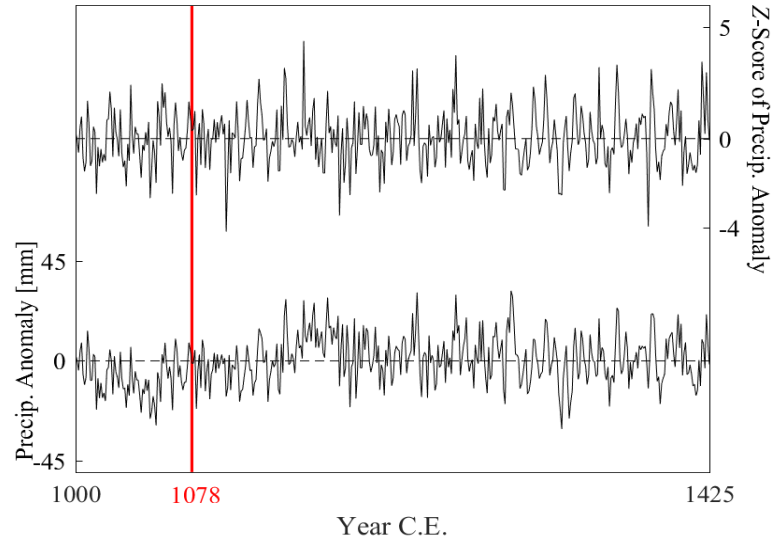


Figure 31: The bottom plot tracks the precipitation anomaly time series, constructed from three proxy reconstructions, optimized to detect the 1078 C.E. heat and drought event suggested in Medieval documentary reports. The top plot tracks the rolling Z -Score of this optimized time series. The red vertical line is the reference case study year.

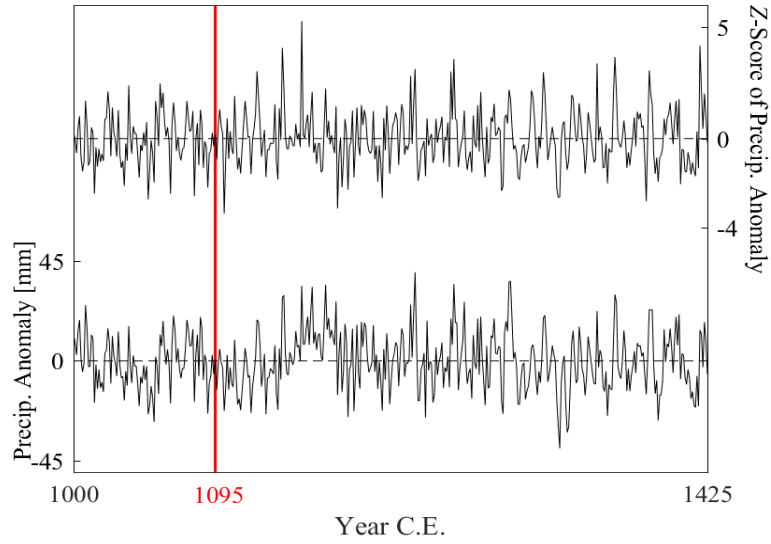


Figure 32: The bottom plot tracks the precipitation anomaly time series, constructed from three proxy reconstructions, optimized to detect the 1095 C.E. heat and drought event suggested in Medieval documentary reports. The top plot tracks the rolling Z-Score of this optimized time series. The red vertical line is the reference case study year.

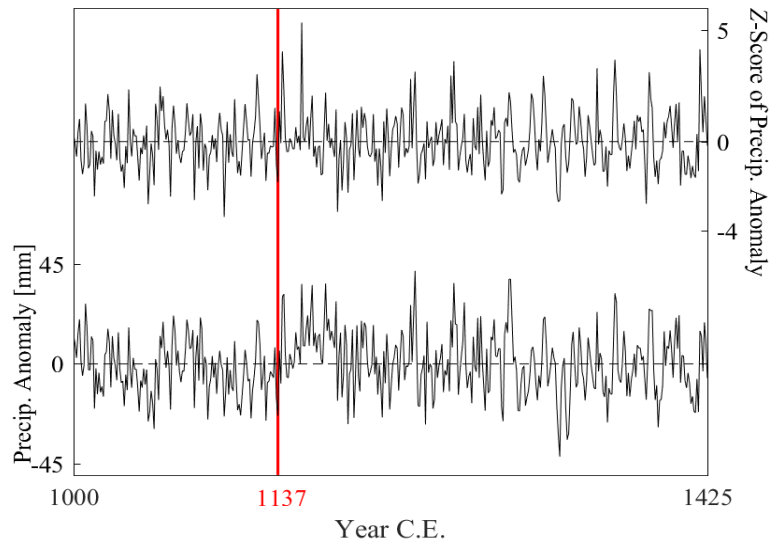


Figure 33: The bottom plot tracks the precipitation anomaly time series, constructed from three proxy reconstructions, optimized to detect the 1137 C.E. heat and drought event suggested in Medieval documentary reports. The top plot tracks the rolling Z-Score of this optimized time series. The red vertical line is the reference case study year.

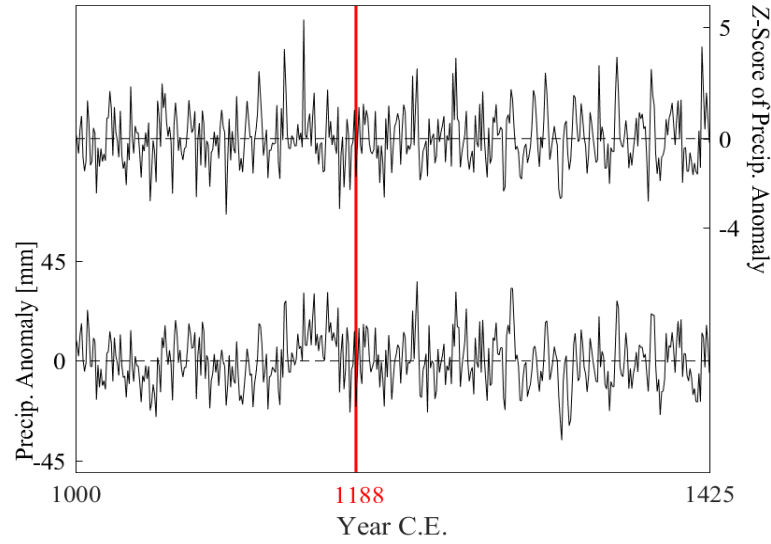


Figure 34: The bottom plot tracks the precipitation anomaly time series, constructed from three proxy reconstructions, optimized to detect the 1188 C.E. heat and drought event suggested in Medieval documentary reports. The top plot tracks the rolling Z-Score of this optimized time series. The red vertical line is the reference case study year.

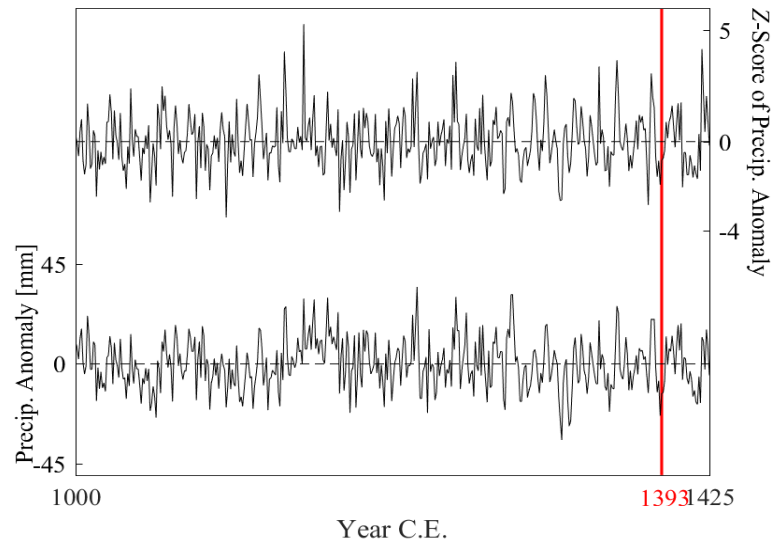


Figure 35: The bottom plot tracks the precipitation anomaly time series, constructed from three proxy reconstructions, optimized to detect the 1393 C.E. heat and drought event suggested in Medieval documentary reports. The top plot tracks the rolling Z-Score of this optimized time series. The red vertical line is the reference case study year.

B3: Precipitation Anomaly Reconstruction Combinations Optimized to Detect Precipitation, Storm, and Flooding Events

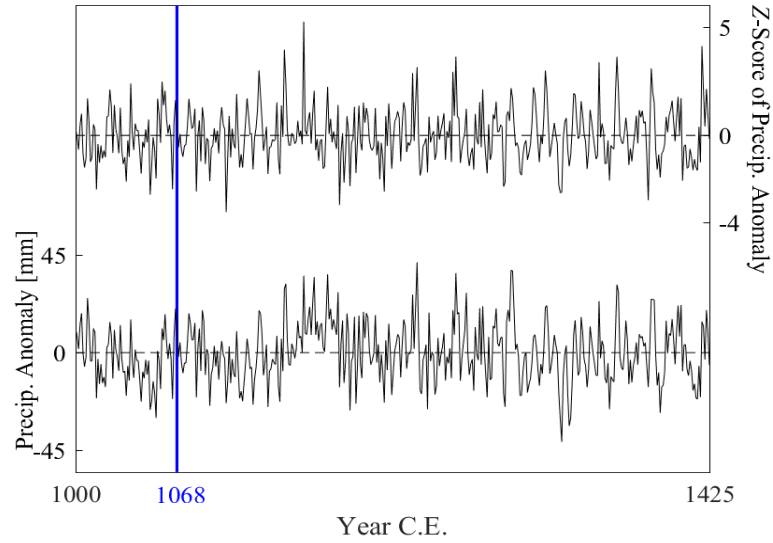


Figure 36: The bottom plot tracks the precipitation anomaly time series, constructed from three proxy reconstructions, optimized to detect the 1068 C.E. precipitation, storm, and flooding event suggested in Medieval documentary reports. The top plot tracks the rolling Z-Score of this optimized time series. The blue vertical line is the reference case study year.

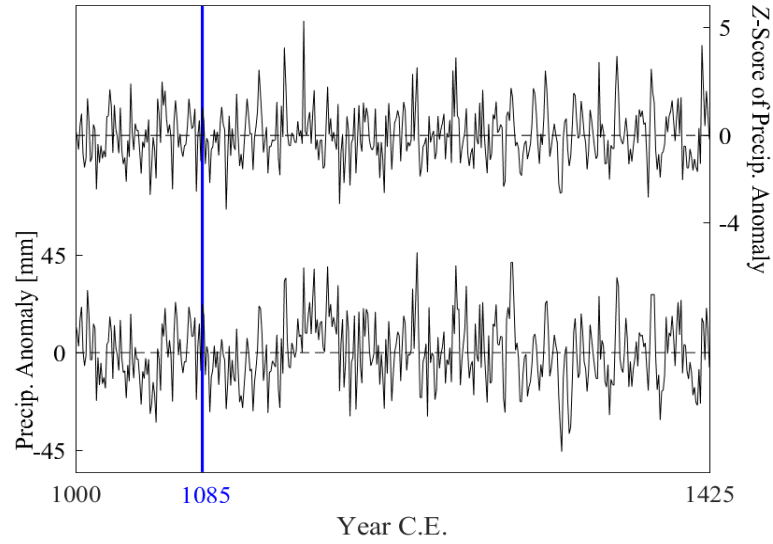


Figure 37: The bottom plot tracks the precipitation anomaly time series, constructed from three proxy reconstructions, optimized to detect the 1085 C.E. precipitation, storm, and flooding event suggested in Medieval documentary reports. The top plot tracks the rolling Z-Score of this optimized time series. The blue vertical line is the reference case study year.

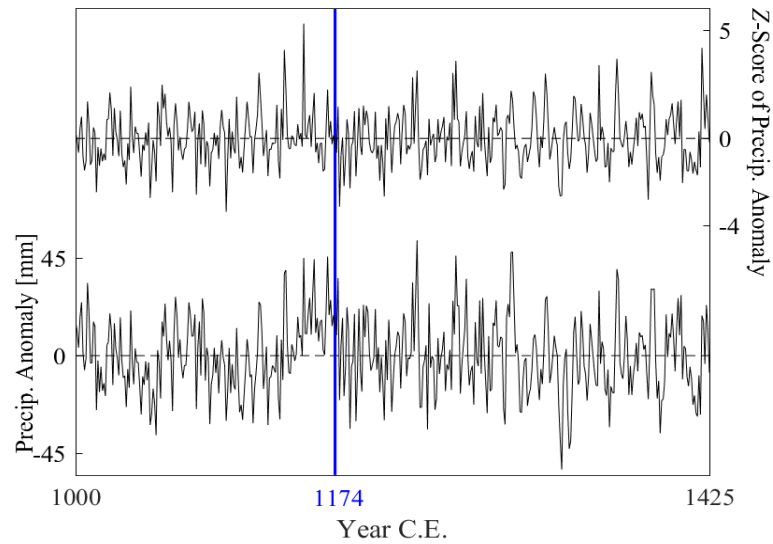


Figure 38: The bottom plot tracks the precipitation anomaly time series, constructed from three proxy reconstructions, optimized to detect the 1174 C.E. precipitation, storm, and flooding event suggested in Medieval documentary reports. The top plot tracks the rolling Z-Score of this optimized time series. The blue vertical line is the reference case study year.

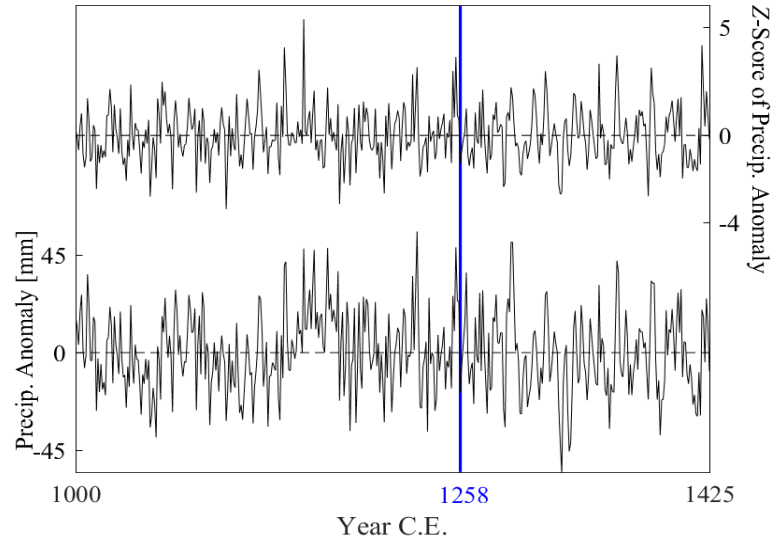


Figure 39: The bottom plot tracks the precipitation anomaly time series, constructed from three proxy reconstructions, optimized to detect the 1258 C.E. precipitation, storm, and flooding event suggested in Medieval documentary reports. The top plot tracks the rolling Z-Score of this optimized time series. The blue vertical line is the reference case study year.

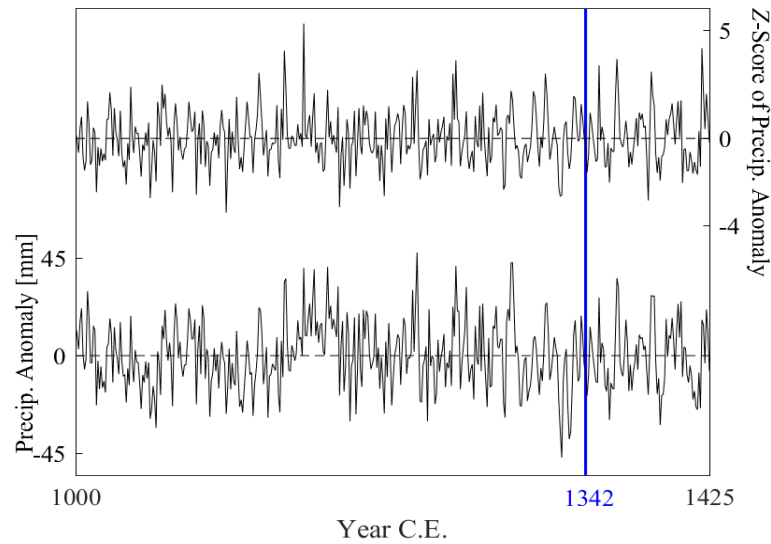


Figure 40: The bottom plot tracks the precipitation anomaly time series, constructed from three proxy reconstructions, optimized to detect the 1342 C.E. precipitation, storm, and flooding event suggested in Medieval documentary reports. The top plot tracks the rolling Z-Score of this optimized time series. The blue vertical line is the reference case study year.

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