Four centuries of summer temperature changes in Tierra del Fuego: atmospheric drivers and tree-ring reconstruction from the southernmost forests of the world

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Abstract

Proxy climate records, such as those derived from tree rings, are necessary to extend relatively short instrumental meteorological observations into the past. Tierra del Fuego is the most austral territory with forests in the world, situated close to the Antarctic Peninsula, which makes this region especially interesting for paleoclimatic research. However, high-quality, high-resolution summer temperature reconstruction are lacking in the region. In this study we used 63 tree-ring width chronologies of \textit{Nothofagus pumilio} and \textit{Nothofagus betuloides} and partial least squares regression (PLSR) to produce annually resolved December-to-February temperature reconstruction since AD 1600 which explains up to 65\% of instrumental temperature variability. We also found that observed summer temperature variability in Tierra del Fuego is primarily driven by the fluctuations of atmospheric pressure systems both in the South Atlantic and South Pacific, while it is insignificantly correlated to major hemispheric modes: ENSO and SAM. This fact makes our reconstruction important for climate modelling experiments, as it represents specific regional variability. Our reconstruction can be used for direct comparison with model outputs to better understand model limitations or to tune a model or contribute to larger scale reconstructions based on paleoclimatic data assimilation. Moreover, we showed that PLSR has improved performance over principal component regression (PCR) in the case of multiple tree-ring predictors. According to these results, PLSR may be a preferable method over PCR for the use in automated tree-ring based reconstruction approaches, akin widely used point-by-point regression.
Keywords: Southern hemisphere, Nothofagus pumilio, Nothofagus betuloides, dendroclimatology, large-scale atmospheric patterns, Southern Atlantic

1 Introduction

Long-term, robust climate proxy records provide a baseline against which recent climate variability can be compared, and climate models evaluated to refine their predictive skill. To identify accurately the spatial patterns of climate change, an extensive land proxy network is required, but this is problematic for the Southern Hemisphere given the paucity of sites surveyed at present in various continental sectors. For the last decades, there are indications that many areas of South America have experienced climatic and ecological changes driven by regional, but also global and hemispheric-scale, ocean-atmosphere processes (Parmesan 2006; Moy et al. 2009), and that these changes are projected to have greater intensity in the future (Marengo et al. 2009).

The archipelago of Tierra del Fuego (hereafter TdF), at the southern tip of South America, has a privileged position to carry out paleoclimatological studies (Boninsegna et al. 2009; Roig et al. 1996). TdF is the most extensive and austral territory with forests in the World, situated close to the Antarctic Peninsula. Climate of the most of Patagonia is significantly affected by subtropical anticyclones over the Atlantic and Pacific oceans, whereas the thermal regime in TdF during the whole year is influenced by the Circum-Polar Current and subpolar westerly winds (Jacques-Coper and Bronnimann 2014; Garreaud et al. 2009, 2013). The climate of TdF is of the subpolar oceanic type according to Köppen classification, with cold summer (average temperature (T) around 9°C) and mild winter (average T around 0°C). The southern islands of the archipelago have tundra climate with the mean annual T about 3°C, winter T below 0°C and annual amplitude of about 5°C (Paruelo et al. 1998). The amount of precipitation reaches a maximum on the south-west coast (above 1000 mm/year) due to the orographic enhancement by the Andes and reduces to 500-700 mm/year in the south-eastern part and to 300 mm/year in the northern part of the island (Garreaud et al. 2013). Precipitation in TdF falls almost uniformly throughout the year.

Since TdF climate is strongly influenced by large-scale atmospheric circulation systems, we should expect the significant connection of air temperature with the main Southern Hemispheric atmospheric and ocean-atmospheric modes: The Southern Annual Mode (SAM, also known as the Antarctic Oscillation, AAO) and the El Niño-Southern Oscillation (ENSO). Nevertheless, several studies revealed that the linear correlation of summer T anomalies with the main atmospheric circulation indices does not confirm this connection. Jacques-Coper and Bronnimann (2014) showed that the correlation coefficients of interannual summer T anomalies in Southern South America with ENSO 3.4 and SAM indices for 1907-2001 strongly depend on the time period. In particular, the positive significant correlation was found for several periods in the middle of the XX century, but the negative correlation with ENSO 3.4 (-0.23) and almost zero with SAM (0.09) for 1980-2001 years. According to Marshall et al.
(2006) the correlation of summer T at Punta Arenas with SAM index was equal to 0.16. It should be noted that atmospheric circulation indices in most cases are simple proxies of the large-scale circulation patterns and they may be not representative for a certain region due to regional variability.

Beside its unique location, TdF has vast opportunities for paleoclimate studies, as many proxy archives are represented in the region, including peat bogs, lakes, glaciers and trees (Rabassa et al. 1989; Roig et al. 1996). The most detailed (i.e. high resolution) information about the climatic and environmental changes of the last millennia can be obtained from tree-ring records. Still, dendrochronological studies from TdF are quite few and many questions remain open. These questions include: are the trees growing in TdF sensitive enough to be used for climate reconstructions? Which climatic parameters can be reconstructed from tree-ring data, including relevant large-scale and regional ocean-atmosphere processes, and which processes, regional or hemispheric, are more important? Robust tree-ring reconstructions of TdF climate may provide information on pre-industrial climate variability, as well as on the processes behind those. This information is crucial for the advancement of Southern Hemisphere paleoclimatology, including paleoclimate modelling.

In this study we address these questions. With this aim in mind, we compiled a set of tree-ring chronologies from TdF, including 44 lenga (Nothofagus pumilio) and 19 coihue de Magallanes (N. betuloides) chronologies (Boninsegna et al. 1989; Massaccesi et al. 2008; Roig et al. 2010; Llancabure 2011; Soto-Rogel, Aravena 2017; Matskovsky et al. 2019; Fuentes et al. 2019). Using this data set, we compared the usefulness of partial least squares regression (PLSR) and principal components regression (PCR) methods in tree-ring based reconstructions with multiple chronologies. We showed that PLSR may be a preferable method for the use in settings with multiple chronologies, especially in automated settings akin point-by-point regression (PPR). We further used the compiled data set of 63 chronologies to develop the longest summer (December through February, DJF) mean temperature reconstruction to date representing the region starting in CE 1600. To better understand regional summer temperature drivers, and to put our reconstruction in a palaeoclimatic context, we analyzed pressure patterns that are responsible for summer temperature variations in the region. Finally, we discussed the new reconstruction, its possible advantages and its usefulness for the palaeoclimate community.

2 Materials and Methods

2.1 Climate data sets

Climatic data from CRU TS 4.01 archive (Harris et al. 2020; 0.5° resolution) was extracted and averaged for 49 non-empty grid points that cover the study area (73.75° – 66.75° W, 53.75° – 55.75° S), defined as to include locations of the available chronologies. Monthly values of mean temperature for the whole period 1901-2016 were used, however the longest meteorological record that is situated inside the selected region starts in 1931 (Ushuaia weather station). Punta Arenas and Punta Dúngenes stations, which both cover the whole period, are situated to the north of this
region. However, they contribute to the extracted CRU data due to the interpolation methods used to create the archive based on sparse station locations.

We used geopotential height and wind speed data for 1000 mb, 850 mb, and 500 mb levels from the twentieth Century Reanalysis V3 (Slivinski et al. 2019; 1.0° resolution). Summer (DJF) averages of the SAM were acquired from the reconstruction of Viesbeck (2009), and monthly values, based on the methodology of Marshall (2003), were acquired from the British Antarctic Survey (https://legacy.bas.ac.uk/met/gjma/sam.html).

Monthly values of the Niño 3.4 index (Trenberth and Stepaniak 2001) for the period 1870-2020 based on HadISST (Rayner et al., 2003), represented ENSO and were acquired from the National Oceanic and Atmospheric Administration (NOAA): https://psl.noaa.gov/geos_wgsp/Timeseries/Data/nino34.long.data.

2.2 Tree-ring data and chronology development

The present study is based on 63 tree-ring width chronologies derived from *Nothofagus pumilio* and *N. betuloides* forests, mainly distributed in the Argentinean sector of Tierra del Fuego, except seven *N. betuloides* chronologies from the Chilean sector. The chronologies of the Argentine sector are the result of several contributions during the last 30 years (Boninsegna et al. 1989; Roig et al. 1996; Roig and Villalba 2008; Massaccesi et al. 2008; Matskovsky et al. 2019). Of these, 44 chronologies of *N. pumilio* were used by Matskovsky et al. (2019) to analyse non-climatically induced seven-year cycles, and to remove these cycles for enhancement of climatic signal recorded in tree-ring widths. Six chronologies of *N. betuloides* from Chile were described in Fuentes et al. (2019). The longest *N. betuloides* chronology (LRB, 1492-2002, see Table S1) has been described in Llancabure (2011) and Soto-Rogel and Aravena (2017). The remaining 12 *N. betuloides* chronologies from Argentina were described in Boninsegna et al. (1989) and Roig et al. (2010). Basic statistics on all the chronologies used in the study are shown in Table S1. A kml file with coordinates of all the chronologies is provided for the possibility of rigorous investigation of their locations. All ring-width measurements were quality checked using the COFECHA program (Holmes 1983; Grissino-Mayer 2001). Tree-ring chronologies were computed using the ARSTAN program (Cook 1985; Cook et al. 2017) through the visually controlled application of multiple detrending functions: Hugershof function, negative exponential, negative or zero-slope straight lines. Indices were computed as the ratios between the original measurements and the fitted curves. Then, for each calendar year, a mean value was computed using a bi-weight robust estimate. No variance stabilization was used. The expressed population signal (EPS), computed in a 30-year moving window with a 29-year overlap, was used to assess how well a finite-sample chronology compares with the theoretical population chronology based on an infinite number of trees (Wigley et al. 1984). For the reconstruction purposes, the commonly used EPS value of 0.85 was used as a threshold to cut the earlier, poorly replicated part of the chronologies.
2.3 Reconstruction method

2.3.1 Partial least squares regression and principal component regression

We compared PLSR and PCR when reconstructing climatic parameters (dependent variables) from multiple tree-ring chronologies (independent variables). Although the physical logic of the process is reversed (the growth of trees depends on the climate parameter, and not vice versa), the problem statement for solving it using data-driven methods uses exactly this formulation – from data to process (Reichstein et al. 2019). PCR is commonly used in dendroclimatology, so we will not describe it in detail, but it is the base of the Point-by-Point Regression method (PPR, Cook et al. 1999), which is widely used for spatial drought reconstructions based on tree-ring data (Cook et al. 2015, 2020; Morales et al. 2020). PLSR originated from social sciences but found its broad application mainly in chemometrics (Abdi, 2010). It has also been used in some dendroclimatological studies (e.g. Kalela-Brundin 1999; Timilsena and Piechota 2008; Bauwe et al. 2016), but has not received wide recognition.

Both methods help to deal with the problems connected to multicollinearity, which is inevitable in case of highly correlated tree-ring datasets. Both methods use latent variables, i.e. variables that are inferred from the observed variables through a mathematical model, in our case a linear model. A principal difference between PLSR and PCR is that when constructing latent variables (which in the case of PCR are called principal components, PCs) from the initial predictors, the latter method maximizes the explained variance in the set of the predictors, while the former method maximizes the explained variance in the dependent variable. In other words, PCR decomposes $X$ in order to obtain components which best explains $X$. By contrast, PLS regression finds components from $X$ that best predict $Y$, where $X$ and $Y$ are the matrices of independent and dependent variables correspondingly. For a detailed mathematical description of PLSR please refer to Abdi (2010) and references therein.

We explored PLSR and PCR to select the most suitable reconstruction method for our data. We tested how the performance of the methods changes depending on the number of predictors and latent variables. We used $R^2$ to evaluate the methods’ performance. We used cross-validations to overcome possible overfitting. The cross-validation workflow consisted of multiple iterations where k-fold cross-validation with k running from 2 to 6 was repeated 10 times each. The data withheld from calibration were used for calculation of $R^2$. To address the performance of the methods with different number of predictors and different number of latent variables, we randomly selected specified number of predictors from the full dataset and calculated $R^2$ for different numbers of latent variables from 1 to the number of selected predictors. To reduce dependence of the results from specific sets of good or bad predictors, for each number of predictors and each number of selected latent variables we made 50 repetitions with random subsets of predictors. The workflow is described in detail in the Appendix.

When using methods which utilize latent variables, such as PCR and PLSR, a question of selection of the appropriate number of latent variables emerges. In contrast to PCR, in PLSR latent variables are sorted in the order of decreasing explained variance of the dependent variable, and we can stop adding new latent variables in a certain point, that finally explain the cumulative sum of variance for them. In PLSR this cumulative
explained variance will increase steadily, while in PCR it will increase irregularly with big steps when adding the next principal component (PC) which explains a significant amount of variance of the dependent variable. At the same time, when using PLSR it is especially important to use cross-validation, as it is strongly subjected to overfitting due to its ability to adjust to the target variable (Geladi and Kowalski 1986; Abdi 2010). In our study we used cross-validation to select the appropriate number of latent variables. This experiment may be considered as a theoretical example of one step of point-by-point regression (PPR), tested with real data for TdF archipelago.

2.3.2 Nested reconstruction approach

To get advantages of both the number of chronologies and the lengths of some of these, we used a nested reconstruction approach (Meko 1997). In this approach, we provide one reconstruction for the whole period covered with the appropriate data, but parts of the reconstruction are produced using different sets of chronologies. Thus, each part of the reconstruction has different calibration-validation statistics, with the quality usually decreasing back in time. In this way we, on the one hand, provide the maximum reasonable length of the reconstruction, and on the other hand provide the maximum reconstruction skill for each period. Statistics $r$, $R^2$, RE and CE on cross-validation were used to describe the skill of each part of the reconstruction (see Appendix for details).

To select the target variable for the reconstruction we were guided by a set of considerations. First, it was previously demonstrated, that air temperature for different summer months is the main driver of tree growth in the region, with higher correlations in December for $N.\ pumilio$ chronologies and in January for $N.\ betuloides$ chronologies (Massacessi et al. 2008; Matskovsky et al. 2019; Fuentes et al. 2019). Second, DJF temperatures has been widely used in multiple climatological and paleoclimatological studies, including modelling. Hence, this target variable was preferred for compatibility with other studies. Third, in our experiments with different target variables we found that mean DJF temperature was one of the best performing targets for our dataset.

To select the predictors, different sets of tree-ring chronologies were tested. We used a manual analogue of stepwise regression, adding and removing predictors in an attempt to find the best set. The earliest part of the reconstruction, which was based on the longest chronology, was derived by the scaling method. The chronology was adjusted to have the same mean and standard deviation as the instrumental data for their common period.
3 Results

3.1 Observed summer temperature variations in Tierra del Fuego and its drivers

Although climate in southern South America is strongly influenced by large-scale atmospheric systems in the Southern Hemisphere (Garreaud et al. 2009, 2013), we found that observed summer temperature in TdF was weakly connected to major Southern Hemisphere indices. There were no significant correlations with either summer SAM (r=-0.10, p=0.3, 1901-200; r=0.01, p=0.94 1957-2016), nor with summer ENSO 3.4 (r=0.08, p=0.39, 1901-2016). Hence, we expected regional variability of atmospheric circulation to be responsible for summer temperature oscillations in TdF.

Circulation pattern for positive temperature anomalies larger than 1 °C (Fig. 1a,b, red isolines) shows dominance of an active low-pressure centre to the west of Antarctic Peninsula (mostly pronounced in December) and a high-pressure ridge near the east coast of Patagonia (which is stretched to Antarctic Peninsula in February). This system enhances the meridional circulation and promotes the advection of warm northern air masses into TdF. For the years with negative summer temperature anomalies with absolute values greater than 1 °C (Fig. 1a,b, blue isolines), the atmospheric circulation pattern shows dominance of a cyclonic activity near the Weddell Sea, which probably strengthens the westerlies and produces the southwest cold air advection into TdF. These two patterns of pressure systems for positive and negative summer temperatures in Southern South America were also discussed in Alessandro (2008).

According to the average wind speed data for the 1901-2015 period, during summer (DJF) climate in TdF is affected by the westerly winds (Fig. 1a-c). However, there is a difference in geopotential heights between years with positive and negative temperature anomalies (Fig. 1c). These anomalies represent an anticyclone in the Southern Atlantic with the centre between Malvinas and South Georgia Island. Another anomaly forms a cyclone in the Southern Pacific with the centre migrating from north to south at the longitude of approximately 100°W.

These processes are not actual synoptic processes but rather an average of pressure anomalies for many years. However, this atmospheric dipole explains rather well the variability of summer temperatures in TdF. Correlations of regional monthly temperatures with 850 mb geopotential heights reach r=0.73 (p<0.001) in the centre of this anticyclone and have significant negative values (up to r=-0.4, p<0.001) in the cyclone (Fig. 2c). Wind vectors show that during warm temperature anomalies the intensity and frequency of northern winds in TdF increase (Fig. 2a,c). The described dipole system was found to be more intensive in December and February, than in January, and there is a difference in the positions of negative pressure anomalies (Fig. 2).
The geopotential height and wind anomaly composite fields for temperature anomalies greater than 1°C at TdF (Fig. 2a) confirm that in December and January, the pressure centre that drives positive temperature anomalies is a part of a quasi-stationary wave train with a quasi-barotropic structure, extending from Australia across the South Pacific, and ending with a cyclonic circulation centre in the South Atlantic Convergence Zone (SACZ). In February, the wave train appears to extend less westward, spreading over the adjacencies of southern South America and the Antarctic Peninsula. Conversely, negative temperature anomalies in TdF are associated with a circulation scheme with anomalies of inverse sign to those of the positive temperature anomalies (Fig. 2b). An anomalous low-pressure centre is located over the South Atlantic affecting the TdF region with enhanced southern circulation. This centre is also part of a wave train that extends along the Pacific ending in the SACZ, in this case in a more zonal form, and extended towards the Indian Ocean for all months.

Based on these results, we argue that regional oscillations of large-scale pressure systems forming on the way of Southern Hemisphere subpolar westerly winds affect summer temperature variability in TdF. The sign and intensity of summer temperature anomalies depend on the existence and intensity of the atmospheric dipole and the storm tracks in the South Atlantic and South Pacific.

### 3.2 Comparison of PLSR and PCR

We first made a series of experiments to address the methods’ performance with increasing number of predictors and variable number of latent variables (Fig. 3). For the PCR method, the maximum $R^2$ on cross-validation was steadily increasing with the number of predictors used. It was also increasing with the number of PCs, reaching maximum values with 10 to 25 PCs (Fig. 3a). The number of PCs for the best $R^2$ may be hard to define, e.g. when using more than 50 predictors we got comparable values of $R^2$ for 15 to 25 PCs. For the PLSR method the maximum $R^2$ on cross-validation was also steadily increasing with the number of predictors used. In contrast to PCR, it consistently reaches maximum $R^2$ values with much fewer (3-5) latent variables. Larger numbers of latent variables did not give an improvement of $R^2$. On the contrary, the prediction skill drops rapidly, especially when the number of predictors is big. This may be explained by an ability of PLSR to concentrate the signal in the first latent variables, while the noise is left in the remaining ones. Figure 3c is a cross-section of the results presented in Figures 3a and 3b for the maximum number of predictors (N=63). Here we can make several additional observations. First, the PCR method shows negative $R^2$ for the first several PCs. It reaffirms that the main modes of the common variability in our tree-ring dataset are insufficient for an adequate representation of the target variable, and that the additional lower-order components that contain valuable information are required. Second, the PCR method shows similar explained variance for the number of PCs from 15 to 25, while the spread of the $R^2$ values acquired for various experiments with randomized samples is increasing with the increased number of PCs. Lower spread points to an advantage of a reduced number of selected PCs. Finally, PLSR
consistently outperforms PCR in our experiment (Figure 3d). The maximum average $R^2$ was higher for the PLSR method for each number of predictors.

Although Figure 3 shows that the more predictors we have, the higher values of $R^2$ we get, it does not mean that we cannot get better performance with fewer predictors. Our experiments showed that rigorous selection of predictors by a step-by-step procedure akin stepwise regression helps to improve the results. In Figure 4 we show the results for 10 best predictors which were finally used for the most skilful part of the reconstruction (AD 1803-2002). In contrast to PLSR, where we observe that a large portion of target variance was explained by the first five latent variables, for PCR we observe that the 3rd, 6th and 10th PCs added more information than the others. This is another confirmation that the important information about the climate variability may be hidden in the principal components of lower order (those that explain less common variance of the dataset of predictors). In this case, both PCR and PLSR reached equal performance with the maximum number of latent variables.

### 3.3 Summer temperature reconstruction in Tierra del Fuego since CE 1600

The final reconstruction (Fig. 5) was derived for the target variable of summer (DJF) air temperatures using PLSR and a nested reconstruction approach. In Figure 6, all individual reconstructions (nests) are shown, and their performances are described in Table 1. With a reduced number of available and well-replicated chronologies, the skill of the reconstruction is reduced back in time. Having almost 65% of explained variance for the best-replicated part (1889-2002), and 17.5% of the variance is explained by the nest (chronology) representing the oldest part of the reconstruction (1600-1750). Nevertheless, even this early part of the reconstruction evidence positive skill, providing valuable information about summer temperature variations in the past.

The best part of the reconstruction agrees with the instrumental data very well, including high- and low-frequency variations (Fig. 5a,b). The most prominent agreement is seen for the first half of the 20th century, while in the second half we see a divergence, including the cold peak of 1970-71 which is not adequately reproduced by the reconstruction. This divergence is in line with the finding of decreased temperature signal in tree-ring widths of *N. pumilio* in TdF since 1970s (Matskovsky et al. 2019). However, in general the reconstruction follows the instrumental data very well, with all the warm peaks represented and having comparable values. The reconstruction indicates extended warm periods centred around 1625 and 1700, as well as more than a century-long warm period between 1760 and 1905, with short cold interruptions in 1810s, 1850s and 1880s. The colder periods also include the intervals 1640-1670, 1715-1745 and 1930-1975.

Figure 6 gives an opportunity to explore the similarities and differences of the individual reconstructions (nests). Even those parts that include chronologies with EPS values lower than 0.85, and therefore were excluded from the final reconstruction, are in a good agreement, especially throughout the 19th century. This fact increases our confidence in the reconstruction for this period. The spread among the reconstructions is higher
during the transition from the 18th to 19th century, with the reconstructions of higher explained variance demonstrating lower reconstructed values. However, these parts are of less confidence because of lower sample replication. At the same time, the longest individual reconstruction (and the less skilful one) shows rather good agreement with the other reconstructions for the period 1700-1980, especially at lower frequencies. Altogether, the intercomparison of the individual reconstructions reaffirms credibility of the nested reconstruction approach used in this study.
Table 1. Description of the reconstruction nests. Bold text shows the chronology and the year which limit the reconstruction for each sub-period based on EPS>0.85 criterium.

| Period    | Chronologies used (number) | Correlation with the target variable | $R^2$ | $R^2$ on cross-validation | MIN EPS>0.85            | Period in the final reconstruction |
|-----------|----------------------------|--------------------------------------|------|--------------------------|------------------------|----------------------------------|
| 1803-2002 | CUC, GUA, KRS, KR4, **KR8**, MBR, PAR, PG, VAH, LRB (10) | 0.806 | 0.649 | 0.567                   | 1776, 1796, 1760, 1839, **1889**, 1759, 1854, 1766, 1844, 1600 | 1889-2002 |
| 1782-2002 | CUC, GUA, KRS, KR4, MBR, **PAR**, PG, VAH, LRB (9) | 0.779 | 0.607 | 0.500                   | 1776, 1796, 1760, 1839, 1759, **1854**, 1766, 1844, 1600 | 1854-1888 |
| 1723-1985 | BRI, **ESJ**, OBS, VAL, LRB, DP, DF2 (7) | 0.709 | 0.503 | 0.377                   | 1727, **1765**, 1716, 1751, 1600, 1754, 1755 | 1765-1853 |
| 1675-1984 | BRI, **MIC**, VAL, LRB, DP, DF2 (6) | 0.634 | 0.402 | 0.264                   | 1727, **1761**, 1751, 1600, 1754, 1755 | 1761-1764 |
| 1594-1984 | **VAL**, LRB, LE (3) | 0.506 | 0.256 | 0.182                   | **1751**, 1600, 1704 | 1751-1760 |
| 1489-1994 | **LRB** (1) | 0.418 | 0.175 | 0.142                   | **1600** | 1600-1750 |
4 Discussion

4.1 Local vs hemispheric drivers of summer temperature variations in Tierra del Fuego

According to our results, the effects of large-scale atmospheric patterns (SAM and ENSO) are limited in the summer temperatures of TdF. These results are in agreement with previous works (Soto-Rogel and Aravena 2017; Fuentes et al. 2019), and highlight the importance of mesoscale and synoptic scale atmospheric processes. It is unclear at this stage whether concomitant effects of ENSO and SAM (Fogt and Bromwich 2006) in the study area can be detected for surface summer temperatures within longer time scales as pointed out by Dätwyler et al. (2020). It is known that geopotential hight at centres of action such as the area of the Ross and Bellingshausen seas and the Weddell sea are of importance to the modulation of the advection over Southern South America.

On the other hand, other type of large-scale influences is detected in the results presented here: related to the possible regime shifts of the long-term trends that may imply significant changes in temperature and moisture regimes. In this regard, several works (Jacques-Coper and Bronnimann 2014; Jacques-Coper and Garreaud 2015) disclosed the shift in South American climate since the end of 1970s, when the intensification of the Atlantic subtropical anticyclone occurred, and the westerlies zone moved south. These processes probably caused divergent trends in winter and summer temperatures in Southern Patagonia after the year 1980, which are clear in the observed data (Fig. 7a,b). Negative temperature trend in TdF summer temperature since early 1980s also diverges from positive trend in South America and South Hemisphere summer temperature throughout the same period. Our reconstruction shows two long-period spectral peaks with cycles of 67 and 101 years long (Fourier analysis, significant at p<0.05 against red-noise spectrum), which are evident from the smoothed reconstruction (Fig. 5a). This cyclicity persists for the whole period of the reconstruction and is responsible for the observed summer temperature decline since 1970s. Hence, the recent climatic shift in the region may be a recurrent feature which persists throughout at least four centuries.

Jacques-Coper et al. (2016) have indicated that summer heatwaves in Patagonia (46-52°S, 201 cases were analyzed) usually form when an anticyclone exists in the Atlantic Ocean near the east coast of Patagonia, which causes the northern warm advection. The authors showed that this anticyclone begins to form near the west coast of TdF and moves further to the north-east. It was investigated (from 500 mb geopotential heights composites fields) that this high-pressure centre forms within the large-scale baroclinic wave system over the South Pacific. This process begins from the formation of a low-pressure anomaly near the south-east coast of Australia and develops over a period of 21 days throughout the South Pacific. Here we showed that the pressure dipole that is associated with summer temperature anomalies in TdF (Fig. 1c) is a part of the same large-scale pressure wave pattern (Fig. 2a,b).
Garreaud et al. (2013) highlighted that the stronger westerlies cause cooler summers at the southern part of South America. Besides, Alessandro (2008) showed that cold summer T anomalies occur in TdF when the trough at 500 mb level is situated over the Antarctic Peninsula or moves to the east and is centred over the Weddell Sea, producing the south-western cold advection. Thus, the positive summer T anomalies in TdF apparently are consequences of high-pressure anomaly to the east of Patagonia, which corresponds to a ridge in the region at high altitudes. As T anomalies in TdF are connected with the variations in storm tracks in South Pacific and South Atlantic, hence negative T anomalies occur when the storm track moves to the north, enhancing the cyclonic activity to the south-east from TdF.

4.2 PLSR as a substitute to PCR in tree-ring-based climate reconstructions

In our dataset we used chronologies derived from two tree species (*N. pumilio* and *N. betuloides*), growing in sites with different conditions, including altitude, exposition, soils, etc. According to previous studies (Massaccesi et al. 2008; Matskovsky et al. 2019; Fuentes et al. 2019) there are different patterns of climatic response of the two studied species: *N. pumilio* in the region has temperature response shifted to the end of spring and the beginning of summer (November, December), while the temperature response of *N. betuloides* is shifted towards the end of summer and autumn months (January, February, March). The best results we acquired for the sets of predictors that included both species, hence pointing on the potential ability of the reconstruction method to extract information about different periods of the summer season from the chronologies of different species.

Stability of climate-to-proxy relationships is another concern when reconstructing past climates, and especially when complex dependencies including many predictors are considered. In our case, similarity of different reconstructions based on different sets of chronologies (Fig. 6), including low-frequency variability, is an indirect confirmation of the stability of discovered relationships. Another confirmation is that all the reconstructions passed cross-validation tests and showed positive $R^2$ values on independent data (Table 1).

Concerning the methods for the extraction of climatic information from tree rings, here we considered two of them - PCR and PLSR. The difference between PLSR and PCR is that the former method constructs components to maximize the explained variance in the target variable, while the latter maximizes it in the matrix of predictors. Such a modeling approach implemented in PLSR seems reasonable in case of dendroclimatic reconstructions based on multiple chronologies, since we try to extract information related to the target climatic variable from every chronology, and not to extract common signal first, as is happens when using the PCR method. That is why it usually needs less latent variables to reach the same amount of explained variance. Less latent variables are better for interpretation, but we can also consider this method as a better filter that separates the signal from the noise. For the PLSR, the signal is left in the first few latent variables, and the noise is omitted with the others, which is confirmed by higher cross-validation statistics in comparison with PCR. For PLSR, the signal here is not considered as common variance of the tree-ring chronologies (which is the case when we use PCR), but as the target climate variable in the calibration period.
As we have seen in the results (Section 3.2), when using PCR, some important information may be contained not in the first principal components. Conversely, for PLSR explained variance increases rapidly for the first components, and then the increase decelerates. Such a property of PLSR makes it easy to fix the necessary number of components to cut, which is especially important for automated working with large datasets, as commonly happens for spatial reconstructions using the PPR method. Our results show perspective for substitution of PCR for PLSR in an automated setting like PPR, because PLSR showed higher cross-validation statistics and also made it easier to define the number of latent variables \textit{a priori}. However, our experiments were performed for a specific region and dataset, and additional tests are required to confirm this finding. Moreover, it may be difficult to define \textit{a priori} the chronologies which contain important information for the final model, as they might not correlate strongly with the target variable. That is why different screening procedures aimed at excluding some of the chronologies may lead to the loss of important climatic signal. In an automated setting, when rigorous selection of the chronologies is impossible, PLSR may show improvement over PCR, using less latent variables at the same time.

In our case PLSR better than PCR achieves the aim of extracting as much useful information as possible from a set of tree-ring predictors. It might be that some of the trees growing in specific conditions provide some useful information that is different from the information from other locations. That is why PCR which extracts common information from tree-ring predictors may leave this important information in the components of lower order, consequently losing it when those components are omitted.

4.3 Comparison with other regional temperature reconstructions

In this work we updated and incorporated some of the existing tree-ring chronologies in the area. Thus, some similarities among the datasets are unavoidable. We compared however our summer temperature reconstruction for TdF with other temperature reconstructions for TdF and Southern Patagonia. Such a comparison is necessary to place the new reconstruction into the paleoclimatic context in the region and to define its most reliable periods and time-scales. The reconstructions used for the comparison include a NDJF reconstruction of Ushuaia temperature (Boninsegna et al. 1989), a DJF temperature reconstruction for Southern Patagonia (Neukom et al. 2011), a mean annual temperature reconstruction for the southern sector of the southern Andes (Villalba et al. 2003), and a reconstruction of minimum annual temperature of Punta Arenas (Aravena et al. 2002), hereafter referred to as B89, N11, V03 and A02 respectively (Fig. 7, Table 2). All but N11 are based on tree-ring data, while N11 is a multi-proxy reconstruction. All reconstructions except B89 are produced for different regions, while B89 tree-ring data are acquired from the same region as our reconstruction, and many sites are the same. All reconstructions except N11 have different target seasons compared to our reconstruction. To explore the differences in target variables, the different temperature targets for different regions are plotted during the instrumental period (Fig. 7). Some of the differences between the reconstructions may be due to different target seasons or regions, however certain similarities of the reconstructions are also obvious. These similarities indicate the most prominent and reliable paleoclimatic
shifts in the region. One of the most obvious similarities is the pronounced cold period lasting almost a decade in the 1850s. Other common features include relatively warm periods in 1760s-90s (except B89), 1820s-30s, and 1910s.
Table 2. Correlation coefficients of various temperature reconstructions for Tierra del Fuego and Southern Patagonia. Coefficients were calculated for the common period AD 1830-1983.

|                      | This study, TdF DJF Temp | B89, Ushuaia NDJF Temp | N11 South Patagonia DJF Temp | V03 Southern sector of Southern Andes, mean annual Temp | A02 Punta Arenas minimum winter Temp | V03, detrended | A02, detrended |
|----------------------|--------------------------|-------------------------|----------------------------|--------------------------------------------------------|-------------------------------------|----------------|----------------|
| This study           | 1                        | 0.33                    | 0.10                       | 0.21                                                   | 0.38                                | 0.41           | 0.56           |
| B89                  |                          | 1                       | 0.12                       | 0.21                                                   | 0.21                                | 0.18           | 0.18           |
| N11                  |                          |                         | 1                          | 0.49                                                   | 0.47                                | 0.30           | 0.31           |
| V03                  |                          |                         |                            | 1                                                      | 0.52                                | 0.80           | 0.26           |
| A02                  |                          |                         |                            |                                                        | 1                                   | 0.27           | 0.86           |
| V03 detrended        |                          |                         |                            |                                                        | 1                                   | 0.32           |               |
| A02 detrended        |                          |                         |                            |                                                        |                                     |                | 1              |

To assess quantitative measure of similarity for the compared reconstructions, we calculated correlation coefficients between these reconstructions for the common period 1830-1983 (Table 2). Our reconstruction has the strongest correlation with A02 ($r = 0.38$). To compare the reconstructions at higher frequencies and to eliminate the effect of long-term trends, which may arise from data treatment, we also considered detrended (subtracted linear trend) reconstructions A02 and V03. Correlations with detrended reconstructions increase, reaching $r = 0.56$ and $r = 0.41$ respectively. We consider detrended data because some reconstructions based on tree-ring data may have spurious trends connected to detrending procedures and sampling biases (Briffa and Melvin 2011). For example, V03 reconstruction may contain a trend arising from ‘Modern-sample’ bias (Briffa and Melvin 2011, look at their Fig. 5.6) due to application of the Regional Curve Standardization (RCS) method to a sample consisting of living trees without inclusion of any subfossil trees. However, the question of actual low-frequency temperature variations, including trends for the last 350-400 years, remains open, as our reconstruction is limited in its ability to reproduce climatic trends on the timescales approaching the mean age of the trees due to the segment length curse (Cook et al. 1995) and the individual detrending approach we used to standardize the tree-ring series. At the same time, reconstructed temperature variations at periods up to 150-200 years long should be reliable due to mean length of tree-ring series used for the reconstruction.
The reconstructions N11, V03 and A02 showed high values of pairwise correlation coefficients (ranging from 0.47 to 0.52, Table 2) first due to common trends (correlation coefficients for detrended reconstructions are lower, ranging from 0.27 to 0.31) and second because of the presence of common predictors, since N11 includes data used for V03 and A02.

The differences between our and the other reconstructions (N11 and V03) are especially evident for the earlier part, particularly for the period between 1750 and 1850. Our reconstruction showed opposite medium-frequency variations (Fig. 8), and also negative or zero correlations ($r = -0.22$ and $r = 0.02$ for N11 and V03 respectively). Exceptionally high reconstructed values that are represented in our reconstruction in the 1770s and 1791 are not present in the other considered reconstructions. These discrepancies might be due to regional differences, as N11 and V03 represent continental part of the Southern Patagonia. Hence, our new reconstruction provides new paleoclimatic evidence for TdF which was not previously available from other reconstructions.

The change in variance of our reconstruction that is evident before the year 1765 is the direct consequence of the regression-based methods and difference of the variance explained in the instrumental period (Table 1). The latter part (after 1765) is much better in terms of the variance explained. The earliest part (before 1750) is based on only one chronology of *N. betuloides* (LRB) with more than a double drop of explained variance compared to the reconstruction segment after 1765. Still the earlier part has some skill, and we retain it, keeping in mind its difference from the latter part. For the consistency of different parts of the reconstruction in terms of variance, for the earliest part before 1750 we used the rescaling method. This technique is usually used to inflate variance that is partially lost due to application of regression-based methods (Lee et al. 2008). The reconstruction derived in this way looks more uniform and hence may be interpreted as a whole. However, caution should be kept when applying our results from the earliest part of the reconstruction.

### 5 Conclusions

- We developed a new summer temperature reconstruction for Tierra del Fuego covering the period 1600-2002 and explaining up to 65% of instrumental temperature variability. The reconstruction provides a new paleoclimatic record for the region with sparse high-resolution temperature archives. It has a remarkably high reconstruction skill, considering generally moderate climatic signal in tree-ring width in the region.

- Summer temperature variability in Tierra del Fuego is primarily driven by the fluctuations of atmospheric pressure systems both in the South Atlantic and South Pacific near the coast of Tierra del Fuego, while it is insignificantly correlated to major hemispheric modes such as ENSO and SAM. This fact makes our reconstruction important for climate modelling experiments, as it is more relevant for specific
regional variability. Our reconstruction can be used for direct comparison with model outputs to better understand model limitations or to tune a model or contribute to larger scale reconstructions based on paleoclimatic data assimilation. At the same time, the pressure system that drives summer temperature variability in TdF is a part of quasi-stationary wave train with a quasi-barotropic structure extending across the South Pacific.

- PLSR showed improved performance over PCR in the case of multiple tree-ring predictors without pre-screening. According to these results, PLSR may be a preferable method over PCR for the use in automated tree-ring based reconstruction approaches, e.g. widely used point-by-point regression. However, this conclusion should be additionally tested on multiple datasets from other environments.
- Due to its location in a remote and poorly studied region, extended length, widespread target variable, high explained variance, and described relationship of the target variable with the regional atmospheric processes, the new reconstruction is a unique and especially valuable source for the paleoclimatic community, including climate modellers.

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Declarations

The authors have no conflicts of interest to declare that are relevant to the content of this article.

Data availability

The datasets analysed during the current study are available from the corresponding author on reasonable request after consultation with the other authors who were responsible for the generation of the datasets.
Appendix. Cross-validation design

We used the following design of cross-validation to achieve a trade-off between the sample size used for model training and the size of the sample used for an independent validation.

To calculate the results for the Figure 3 the following loops were used:

- for the `number_of_predictors` from 1 to 63:
  - for the `number_of_latent_variables` from 1 to 35:
    - for the `predictors_permutations` from 1 to 50:
      - randomly permute predictors and select `number_of_predictors` from all the predictors
      - for `k` from 2 to 6:
        - for `validation_repetition` from 1 to 10:
          - randomly split the sample for calibration and validation into k equal parts
          - use k-1 parts of the sample for calibration and 1 for validation
          - calculate $R^2$ for the validation sample
  - For each number of predictors and each number of latent variables $R^2$ values for all the experiments were averaged.
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Figure 1: Meteorological processes affecting summer temperature in Tierra del Fuego for the period of 1901-2015. a. Average circulation patterns for positive (reddish colour) and negative (bluish colour) summer temperature anomalies in Tierra del Fuego for the period between 1901 and 2015 (from 20th Century Reanalysis V3). Contour lines show geopotential height at 1000 mb level. Arrows show wind speed at 1000 mb level. b. are the a panels zoomed in. c. Grey contour lines show average geopotential height at 1000 mb level. Coloured contour lines show geopotential differences for the years with positive and negative temperature anomalies. Blue arrows show wind speed at 1000 mb level.
Figure 2: a. Composite fields of geopotential height and wind anomalies for years with temperature anomalies $>1^\circ$C in Tierra del Fuego, corresponding to December (top), January (centre) and February (bottom), at the 500 hPa level. The shaded areas correspond to significant anomaly values at (p<0.1) (light) and (p<0.05) (dark) levels (positive in red, negative in blue). Only wind vectors when at least one component, u or v, is significant at the (p<0.05) level are plotted. b. Idem a., but for temperature anomalies $<-1^\circ$C in Tierra del Fuego. c. Correlation coefficients between temperature in Tierra del Fuego and geopotential height at 850 mb level. Only significant values are shown (p<0.05). Blue arrows show wind speed differences at 850 mb level for the years with positive and negative temperature anomalies.
Figure 3: Dependence of cross-validation $R^2$ from the number of predictors and the number of latent variables. 

- a. Results for PCR,
- b. results for PLSR,
- c. A cross-section of the panels a. and b. for the maximum number of predictors (N=63) for PCR (red) and PLSR (blue). Thin lines show individual cross-validation experiments, thick lines show an average value for all the experiments.
- d. The maximum values of the explained variance from the panels a. and b. are shown.
**Figure 4:** An example of cross-validation $R^2$ depending on the number of latent variables for PCR (red) and PLSR (blue) for 10 predictors. Thin lines show individual cross-validation experiments, thick lines show an average value for all the experiments. Here one set of 10 “good” predictors is used.
Figure 5: Comparison of the instrumental (red) and reconstructed (blue) DJF temperatures in Tierra del Fuego. a. Full period. b. Instrumental period. Series smoothed with 50-yr spline are shown with thick lines.
**Figure 6:** Individual reconstructions that were joined to produce the final nested reconstruction. The instrumental data is shown in black. Each reconstruction is shown with the color corresponding to the explained variance of the instrumental data (see colorbar). Reconstructions are shown for the full length, without cutting them on the base of EPS values.
Figure 7: Comparison of instrumental temperature records for Tierra del Fuego and Southern Patagonia. Mean November-February (NDJF), December-February (DJF), June-August (JJA) and annual temperature for Tierra del Fuego (TdF), annual mean of monthly minimum temperatures (Tmin) for TdF, and DJF temperature for South Patagonia (south to 45°S). a. Actual values b. z-scores. Thin lines are annual values, thick lines are 20-yr smoothing splines.
Figure 8: Comparison of various temperature reconstructions for Tierra del Fuego and Southern Patagonia. All the reconstructions are standardized to have the same mean and standard deviation for the period AD 1901-1983. Thin lines are annual values, thick lines are 50-yr smoothing splines.