UB

What trees tell us.

Dendrochronological and statistical analysis of the data.

Student: Liudmila Liutsko
Tutor: Dr. Antonio Monleón

with collaboration of ecology department:
Dr. Emilia Gutiérrez

BARCELONA, JUNE, 2008

Department of Statistics
Biology Faculty
University of Barcelona

TABLE OF CONTENT

List of Figures, Tables and Pictures

Figures:

Tables:

Pictures:

Glossary

ACF – Autocorrelation Function

ARSTAN – Autoregressive Standardization

CRU – Climate Research Unit

I – Index

MA – Moving Average

NA – Not Available

PACF – Partial Autocorrelation Function

PT – Power Transformation

RCS – Regional Curve Standardization

TRW – Tree Ring Width

UB - University of Barcelona

UK – United Kingdom

Acknowledgements

I would like to express my deepest acknowledgements to the Department of Statistics members (Dr. Jordi Ocaña, Dr. M. Ríos, Dr. J. Sánchez and all professors that directly or otherwise have participated in my statistical formation during 1st and 2nd years of PhD study).

My special thanks to my tutor Dr. Antonio Monleón for his help and profound recommendations done during statistical analysis of data and writing this paper.

Finally, I would like to express my sincerest gratitude to Dr. Emilia Gutiérrez for given to me the opportunity to study and work in the dendrochronology field and to thank as well the forestry staff of the Department of Ecology Elena Muntán, Isabel Dorado and Dr. Laia Andreu for their help in sampling and explanations done related with the part dendro.

Chapter 1. Dendrochronological study

1.1. Introduction

Dendrochronology, from the Greek, “chronology”= time and “dendro” = trees or tree-ring dating is the method of scientific dating based on the analysis of tree-ring growth patterns. This technique was developed during the first half of the 20th century originally by the astronomer A. E. Douglass (Douglass, 1940), the founder of the Laboratory of Tree-Ring Research at the University of Arizona. Douglass sought to better understand cycles of sunspot activity and reasoned (correctly) that changes in solar activity would affect climate patterns on earth which would subsequently be recorded by tree-ring growth patterns. Since the majority of trees have annual growth increment, which is a proper tree ring; the information related to its formation (and factors that influence it) can be represented by the specific characteristics of each ring: width, density and other visual or analytical parameters than can differ one ring from others (Schweingruber, 1988).

1.2. Dendrochronology and its applications

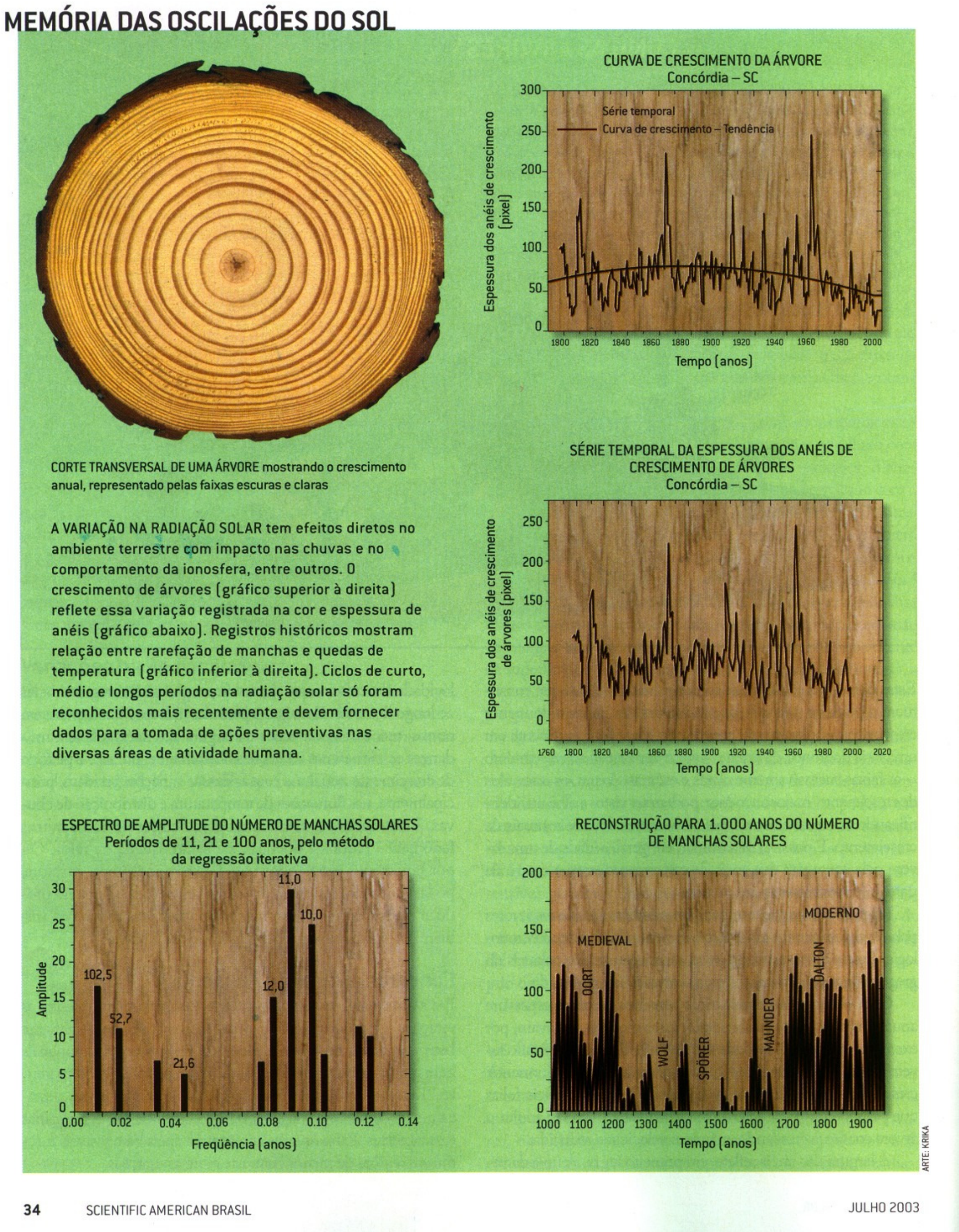
Dendrochronology is used in different spheres such as archaeology and history (Cook et al., 1995; Baillllie, 1982), art and criminology, forestry and ecology. Nowadays the use of dendrochronology is very popular in environmental sciences (Schweingruber, 1988; Jeffrey et al. (Eds), 1994), particularly with issues related to the climate change (Cook and Kairiukstis (Eds), 1990; Wigley, Briffa and Jones, 1984; Stahl et al., 1998).

The climate of our planet is expected to change significantly within the next century due to the increasing greenhouse effect. Our expectations are mainly based on model calculations, but also possible to reconstruct the response of the global climate system to certain disturbances by investigating past global changes. Tree-rings are excellent archives of such changes. The analysis of tree-rings not only allows for reconstructing the local temperature, the annual precipitation rate or other regional environmental parameters but also the composition of the atmosphere in the past.

Climate change is a one of the most current environmental problems that attract different branches of science, economy and politics to put their forces together to avoid the possible future “crisis”. In order to justify the claim that there really is a significant climate change, many scientists work on it, and the increment of about 0.5ºC of temperature per century is observed from various studies or just increasing tendency in general (Broecker, 2006; McCarthy et al. (Eds), 2001). In addition, studies of other climatic parameters are carried out as well since they are correlated in some manner, such as precipitation (Summer et al., 2003; Romero et al., 1998; Rodó, Baert and Comin, 1997; Norrant and Douguédroit, 2006; Martin-Vide and Lopez-Bustins, 2006; Llasat and Quintas, 2004), water stress (Macias et al., 2006), solar spots, wave and tornado activities, for example.

Tree rings width (TRW) growth is normally influenced directly by of climate parameters (generally changes in temperature and moisture or precipitation), and in some “sensitive” sites (where there is some strong limiting factor – temperature and/or precipitation), this link is quite strong, i.e. climate changes are “written” in the tree “archives”, their annual rings (Fritts and Swetnam, 1989). In areas where the climate is reasonably predictable, trees develop annual rings of different properties depending on weather, rain, temperature, etc., in different years. These variations may be used to infer past climate variations.

Since there are no very long records of the month or annual climatic data due to the technological and information revolution of the 20th century and very poor historical data about it, the tree ring widths can be used in some cases as a “tool” of decoding of climatic data at least as much as trees (or their fossils) for these periods can be found (Schweingruber, 1988). A good example of the inference of the climate variations is the research of Strumia (2005) about the temperature variations of the last 700 years reconstructed from a tree-ring chronology of the central Alps.



Source: Nordemann, D et al., 2003. (Picture taken from the Internet free presentation on-line).

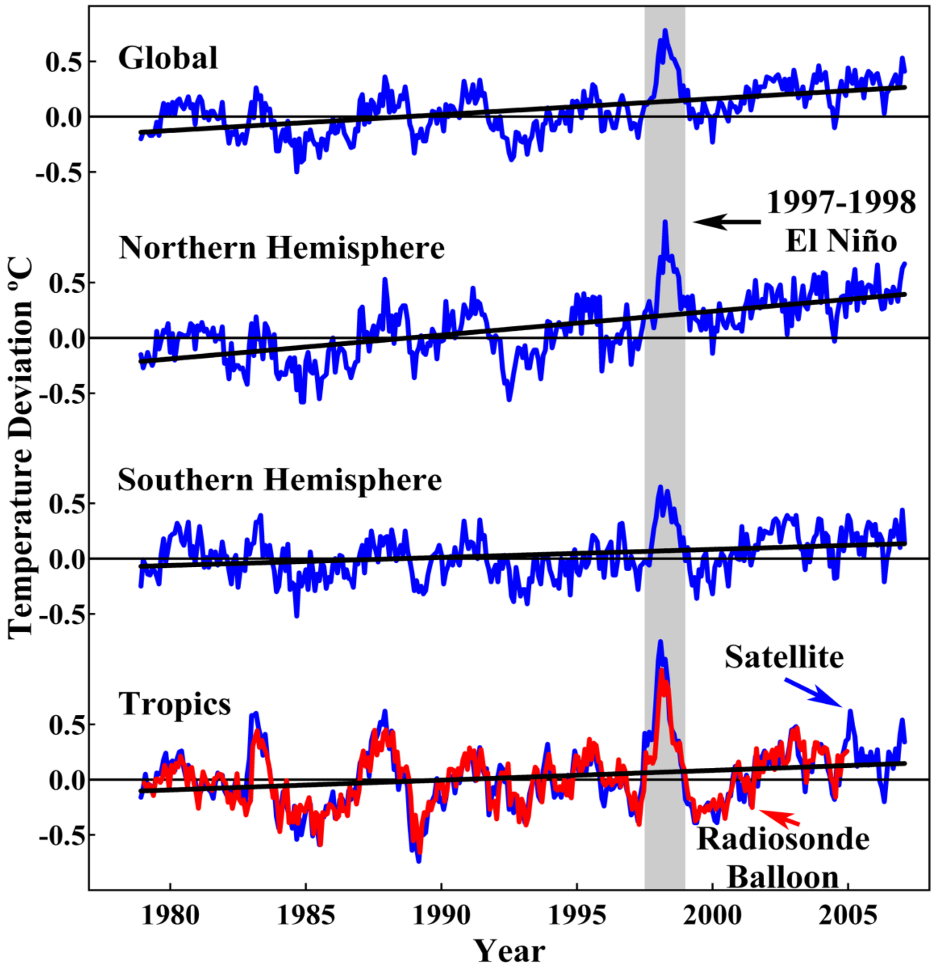
Figure 1. Millennium solar spot number reconstruction on a dendrochronological basis (TRW Series in Brazil)[1].

---

[1] *The following pictures are included in the Figure 1:*

- *Spectrum of solar spot numbers in the periods of 11, 21 and 100 years (x-axis: frequency (years) and y-axis: amplitude)*
- *Tree growth curve of the Concordia tree (x-axis: time (years) and y-axis: tree ring growth (pixels)*
- *Time series of the Concordia tree ring growth(x-axis: time (years) and y-axis: TRW (pixels)*
- *Solar spot number reconstruction for 1000 years (amplitude versa time in years).*

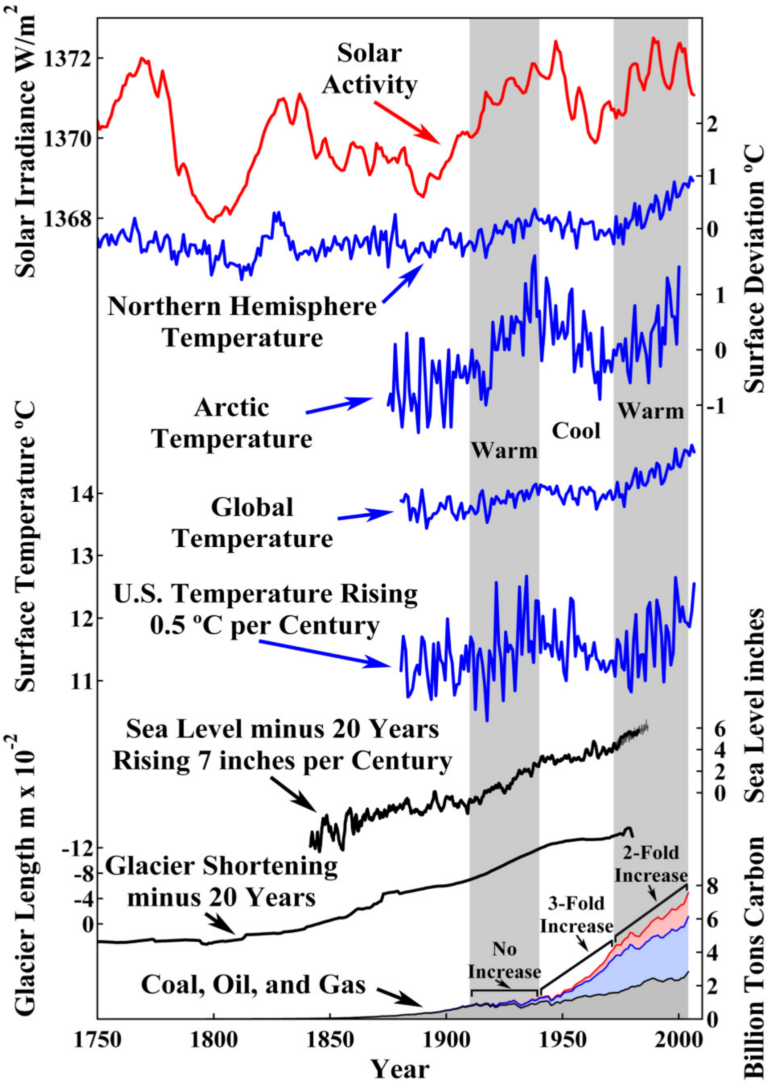
An example of the solar spot activity reconstruction is represented in Figure 1, where the solar spot number is reconstructed on a basis of Tree Ring Width Series for the last millennium by Brazilian scientists (Nordemann, D et al., 2003). The changes and annual temperature values for global, Northern and Southern Hemispheres and in the Tropics during years 1980-2005 with a tendency of little increase can be observed in Figure 2.



Source: Internet: http://www.oism.org/pproject/Slides/Presentation.ppt, seen on-line 23rd of March, 2008.

Figure 2. Changes and annual temperature value (global, Northern and Southern Hemispheres and in Tropics) during years 1980-2005.

From the Figure 3 we can observe that hydrocarbon use is uncorrelated with temperature since the temperature rose for a century before significant hydrocarbon use (temperature rose between 1910 and 1940, while hydrocarbon use was almost unchanged).



Source: Internet presentation: http://www.oism.org/pproject/Slides/Presentation.ppt, seen on-line 23rd of March, 2008).

Figure 3. Seven independent records solar activity, Northern Hemisphere, Arctic, global, and U.S. annual surface air temperatures; sea level; and glacier length all qualitatively confirm each other by exhibiting three intermediate trends warmer, cooler, and warmer.

1.3. Objectives

The objective of this research is an attempt of such kind of “decoding” information saved by live trees (*Pinus nigra*) in the Mediterranean Pre-Pyrenees region (Pentina forest, Pallars) for possible future applications. Thus, the main purpose of this research is to take out the climatic signal from the tree-ring annual increment data series using dendrological and statistical analytical methods in order to compare and discuss the existence of cross-correlations with available climatic data (temperature and precipitation) for the location.

Chapter 2. Material and methods

2.1. General description of the samples: site, climate conditions, sample size.

2.1.1. Tree rings width data

The samples of the current dendrochronological analysis, the cores of *Pinus nigra* were sampled in the Catalonian prePirineous (1.2" of longitude and 42.5" of latitude, Pallars region) at the altitude of about 1050-1600 m where the subalpinian climate predominate. The cores were taken by the increment bore of 5 mm at the breast height approximately (80-130 cm) in different directions. In total there are 38 cores represented 15 trees (2-3 cores per tree) thought for the strict 30 cores should be selected (2 per each tree).

Picture 1. *Pinus nigra* (*Source: Internet: Wikipedia*)

Picture 2. Sampled and prepared for further analysis cores (photo by author).

2.1.2. Climate data

There were used two types of climate data (provided Spanish meteorological stations and CRU – Climate Research Unit, UK) in this research.

Spanish meteorological data were obtained from the local observatories and though they are interesting because of their daily records and of the meteorological observatory location (very near to the sampling site), but in total time they cover quite "short" period (only the last 10 years), Vielha, Bonaigua and Seu d'Urgell stations.

Another data for the very close locality (Vielha) were used (with interpolations for longer period of time back to 1957) from the phD thesis data used by Josep Mª Riba (PhD thesis: "Bio-ecologia de los Scolytidae (Coleptera) que nidifican en los Abetales del Valle de Aran (Pirineos Orientales)", Barcelona, 1994).

Finally, the 3rd type of Spanish archives for temperature and precipitation of the Pallars region (were the present samples were taken) were given by Emilia Gutierrez (ecology department of UB) that were collected for using in different national and international research programs.

Upon the request of the climate data archives, the CRU (England) (CRU means Climate Research Unit) kindly sent available data for using in the frame of this research only, for the localities not much approximated but that can be still valid (Perpignan, Pyrenees, France and Leida, Spain), both for precipitation and annual/month temperatures with some periods with NA (not available data).

2. 2. Dendrochronological analysis

2.2.1. Main stages of the dendrochronological analysis

There are different stages of the dendrochronological analysis that start with an appropriate site and trees selection. It is crucial where we sample since can interfere in the results obtains depending on the purpose we are looking for. For example, in order to obtain the better climatic signal, it is recommended to chose the open site (no competency and alterations in the tree growth) from one side, with no anthropological activities nearby that can affect the tree growth as well from the other side, and, finally, the site with the most limiting factors related to climate (very dry site for example). All these 3 factors were taken into consideration in carrying out the investigation.

Generally, the main stages of the dendrochronological analysis are (Fritts, 1989; Schweingruber, 1988):

1. Sampling (using the increment borer, and normally 2 cores are taken per tree);
2. Mounting and sanding (the cores are prepared for the further observation with microscope)
3. Individual dating and cross-dating (it is a very important and delicate procedure in order to date carefully all tree rings since many times there are difficulties aroused of missing rings)
4. Measuring of the tree ring width (TRW) with microscope using special software for it; the results are given in the format of .CAT files.
5. Transformation of the .CAT files into .RW and .RWL files using the program CORING for further statistical analysis by the program COFECHA and ARSTAN (Cook and Holmes, 1986) with use of the last it is possible to obtained treated indexes of the raw data, detrended and standardized.
6. Statistical analysis of the data using various DENDROCLIM programs or any statistical software (Biondi, F and Waikul, K, 2002).

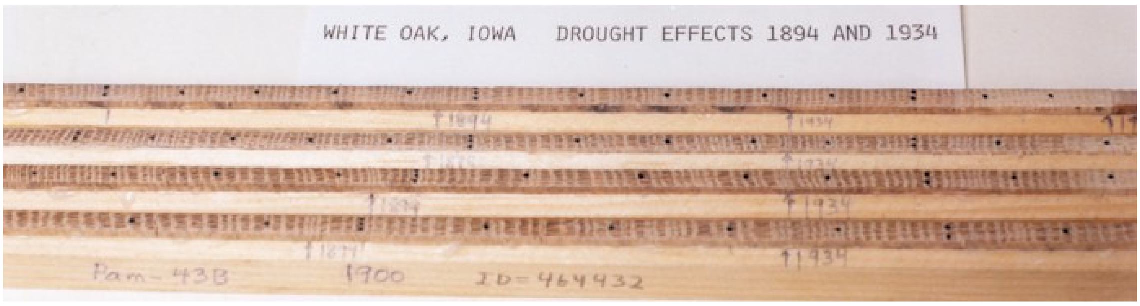
Sampling of the cores is normally carried out with use of the increment borer of 5 mm, taking at least 2 samples of each tree (in opposite directions) at the height of about breast (100-130 cm from the soil) if it is possible (see Picture 3).

After the samples were taken, they are dried naturally some days and mounted on the special rails for them with glue fixation in the manner that the wood tracheas can be seen under the loop. Later on, the surface of each core is sanded using different graduation of the sanding paper (starting for the sharpest one, Nº 0 for example, and then consequently substituted by the thinner ones: Nº 200, 400 and 500 or more) (see Picture 2).

Next stages, dating and cross-dating should be carried out very carefully to avoid further errors in the data analysis. Here the sequences are compared between them to see the common “marker” years and by this verifying the initial dating, resulting in the "skeleton"-plot for the series (Yamaguchi, 1990) that can be represented graphically or symbolically (see the symbolic "skeleton"-plot of the series used in research in the Annex 3). The problem is that the samples are taken from the trees that are growing in the extreme or limiting conditions, and dating can be complicated by missing or false (double) rings or other complicities to do simply count back from the taken date.

Source: on-line: http://web.utk.edu/~grissino/gallery.htm

Picture 3. Sampling the *Pinus caribbea*. (photo©H.D. Grissino-Mayer, used with permission).



Source: on-line: http://web.utk.edu/~grissino/gallery.htm

Picture 4. White oak trees cores (*Quercus alba*) growing in Iowa (photo © T.J. Blasing, used with permission of Grissino-Mayer from his web-page).

On the picture 4 is show dating and verification by cross-dating since there were presented "markers" years of two major drought events (one in 1894 and the other in 1934), reflecting on the thing width of the rings of the corresponded years (or the next ones).

Final stages prior to statistical analysis are measurement of the tree ring width (TRW) using a special computerized machine connecting to the loop (see Picture 5) and converting of the output files onto the formats that can be used by other general programs.

Picture 5. Cross-dating and measuring of the TRW with a special machine (photo by author).

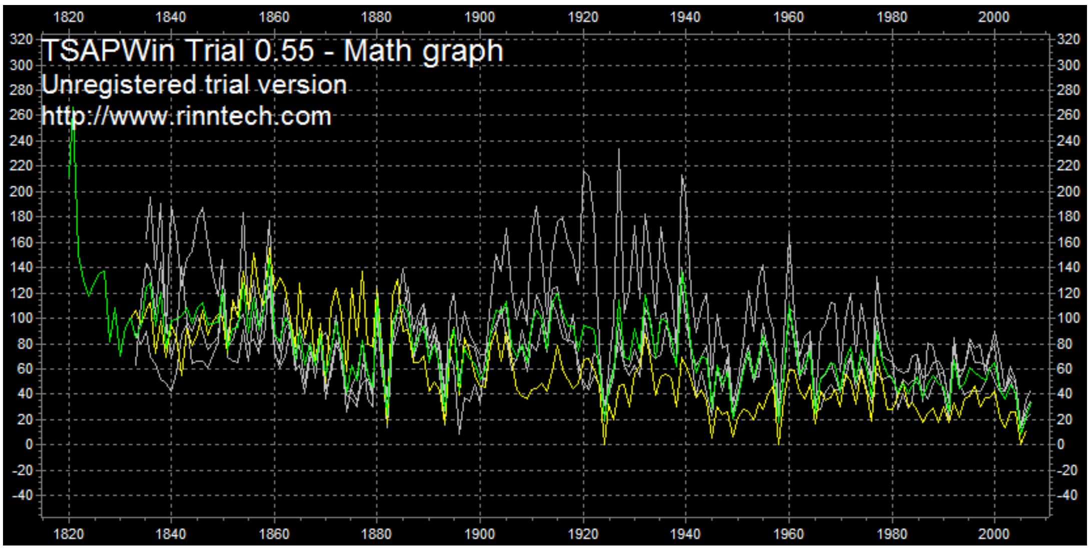


Figure 4. The time series of the first 5 sampled cores[2] (x-axis: time (calendar year) and y-axis: TRW measured values in mm*100).

If in the past all measurement procedures were done manual on the millimeter gridded papers, currently the modern automatic machine with high resolution are used

[2] *There were taken only 5 sampled cores in order to represent TRW growth values visually more clear and separated if there were taken altogether.*

with special computer programs elaborated for it, such as TSAP, for example (see Figure 4 for the graphical presentation of the sampled time series).

Since trees can grow and react differently to environmental changes due to their own properties (or endogenous factors) analysis of their common "behavior" should be carried both graphically and statistically. First impression can be taken from the graphical presentation, as we can see some agreement in the behavior of the tree growth shown at Figure 5; nevertheless it is important to see the correlation between them as well. A good comparative method for it, which is used in dendrochronological investigations, is the correlation of each core with the Master series that was constructed for this site (or previously or at the same time as a mean series of the representative samples) that is given as an output of COFECHA program. For example the average segment correlations (segments of 50 years with 25 years of overlap) for the samples series oscillate between 0.71 and 0.82 (that is quite high correlation), having m for more range of dispersion in values for each sample (the whole correlation table of sample and average, please, see in the Annex 4).

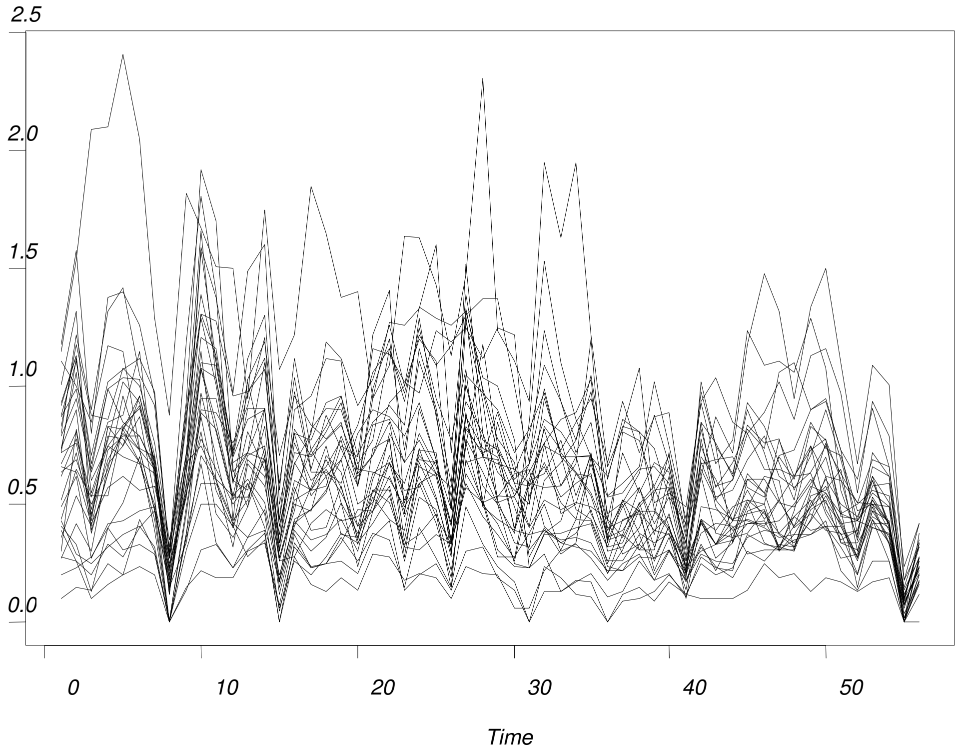


Figure 5. TRW time series plots of all cores from 1951 to 2006 time period[3] (x-axis: time in years and y-axis: TRW raw values in mm*100).

[3] *This period was chosen due to the common representation of the sampled cores and without age growth tendency (since first years are not included) for comparative similarity of the TRW growth behavior of all samples.*

At the plot of TRW series mean we can see min-max peaks in the tree rings with a general declining tendency due to physiological-geometrical growth limitation with time (see Figure 6).

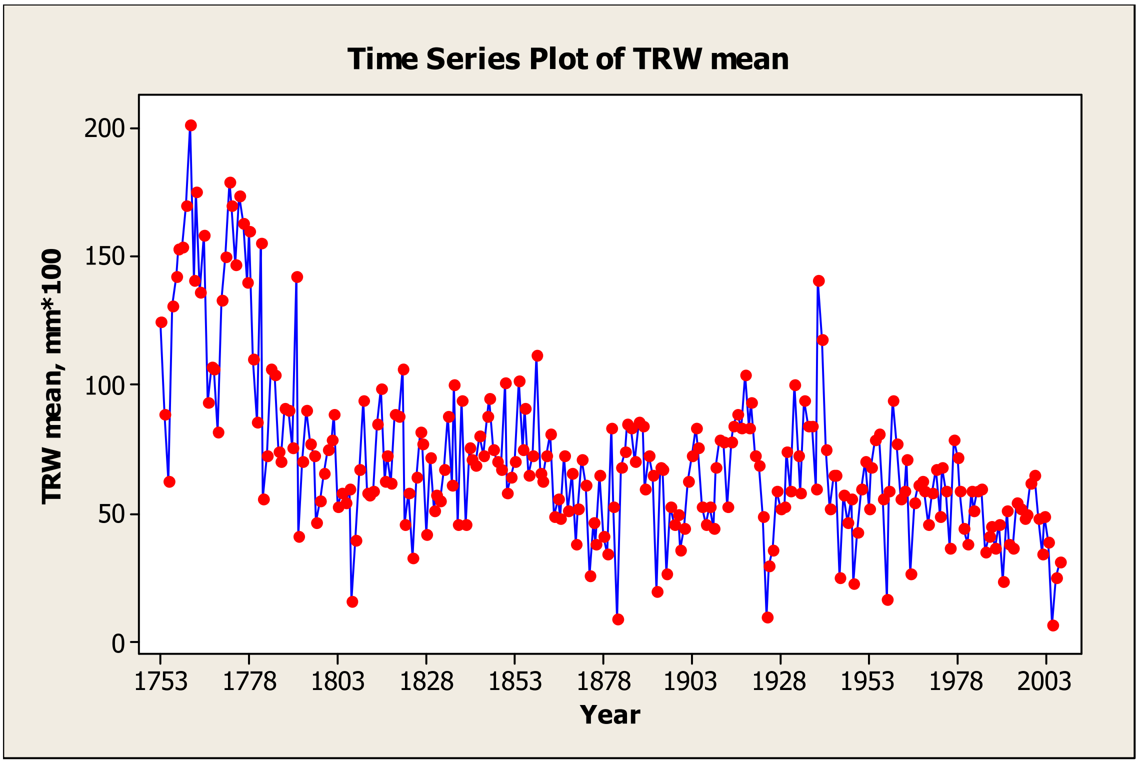


Figure 6. Time series plot of the mean value of the sampling data, TRW (in mm*100) for each year.

2.2.2. Reliability of data

Reliability of data depends on several factors and accuracy during the process of their obtaining. One of the limiting factors is a sample size representation (physiological or sampling factor) since not all trees are of the same age and it is quite difficult to meet many old trees within the same site. Thus from the total spine time covered by sampled cores from 1753 to 2007 (see the individual time spines of each sample in the Annex 2) the period starting from 1828 is approximately reliable since there the sample size is increased up to about 20 (see Figure 7).

Another important factor is very careful cross-dating and final dating since at this stage it is easy to confuse and make erroneous conclusion about the correct dating. Fortunately, in spite of complicity with many missing rings in the samples cores (only 4 cores of 2 trees have all rings, and other samples have missing rings even up to 14 absent ones in the core PEPN08U1, for example, see Appendix 1), there were some very clear "marker" years or better the entire sequences that were presented in almost all samples that gave the change to verify the dating. "Marker" years or sequences are those visually detected special rings that are repeated in the majority of samples (can be especially narrow or wide rings, or other properties of late or early wood of the ring such as shape (proportion to the early wood), density (reflecting on the dark or clear color a part of the wide or other sings).

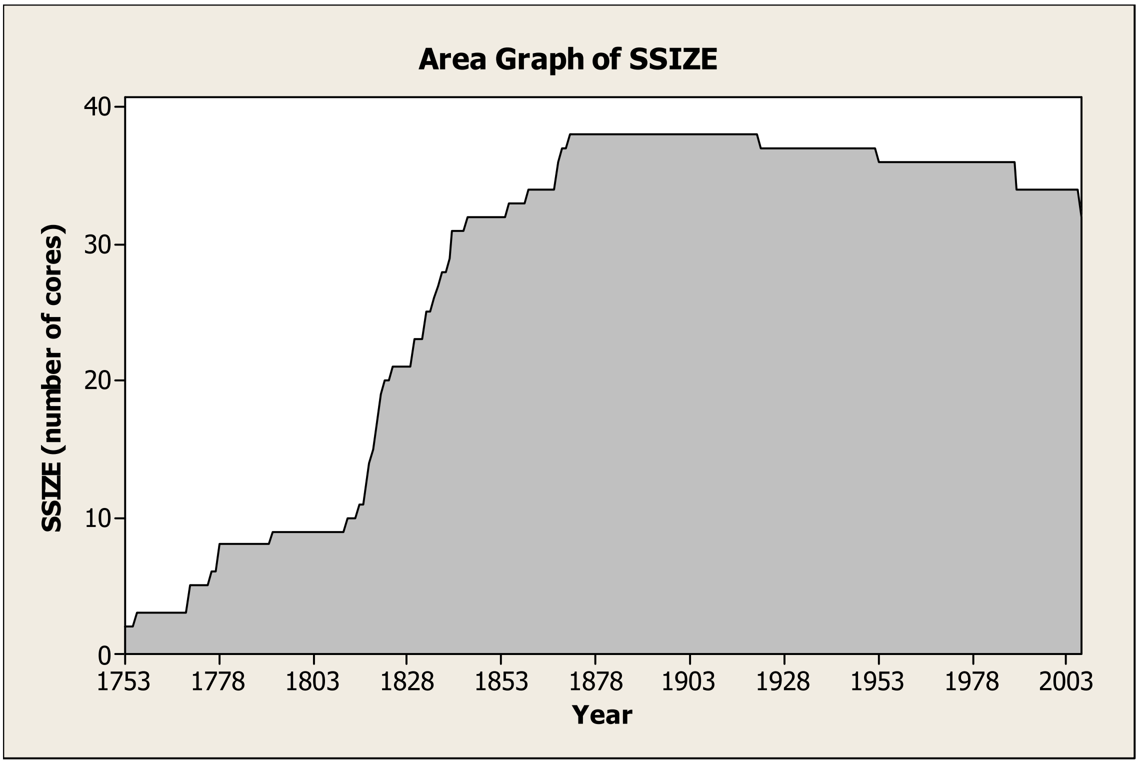


Figure 7. Sample size of the tree cores presented in the current research[4].

A part of visual cross-dating via comparative analysis of "marker" years or with a skeleton-plot, COFECHA is used as well for to verify how accurate the cross-dating was done since one of its outputs is the correlation between samples and problems occurring that are given by the determinate lags (Cook and Kairiuksis (Eds), 1990). If the correlation exists between samples that confirm both the suggestion that the trees correspond to the local and/or global environmental changes in their growth simultaneously

$$EPS = \frac{common\ variance}{total\ variance} = \frac{signal}{signal+noise}, \quad (1)$$

or can be defined via correlations between chronologies as

[4] *The time-span of sampled cores by lags is graphically represented in Annex 2 as well.*

$$EPS = \bar{r} / (\bar{r} + (1 - \bar{r})/N) \qquad (2)$$

where $\bar{r}$ is a mean value between all individual chronological correlations of each tree, and N is the number of trees.

The chronology is considered to be reliable if EPS≥0.85 (85%) (Wigley, Briffa and Jones, 1984). As we can see from Table 1, our data are reliable starting from the year 1800 that can be correlated with the sample size as well.

Table. 1 Lags correlation between samples and EPS means.

lags	1750-1799	1800-1849	1825-1874	1850-1899	1875-1924	1900-1949	1925-1974	1950-1999	1975-2007
cor(Mbt)	0,71	0,77	0,74	0,78	0,75	0,78	0,84	0,78	0,8
EPS	83,0%	87,0%	85,1%	85,7%	87,6%	85,7%	91,3%	87,6%	88,9%

2.2.3. General aggregative model

Growth of the tree rings width (TRW) can be described by a simplified general aggregative model as

$$\mathbf{R}_t = \mathbf{G}_t + \mathbf{C}_t + \delta\mathbf{D}_{1t} + \delta\mathbf{D}_{2t} + \varepsilon_t\,, \qquad (3)$$

where

- Rt – annual increment ring measurement (TRW)
- Gt – the age –related growth trend
- Ct – growth variations due to climate common signal in the year *t*
- D_{1t} – the occurrence of disturbance factors *within* the forest stand
- D_{2t} – the occurrence of disturbance factors *outside* the forest stand
- δ – indicates either a “0” for absence or “1” for presence
- ε_t - random variance (see Cook and Kairiuksis (Eds.), 1990a)
- *t* – index related to a common year.

The more complete model includes a pollution variable but in this case it is disregarded due to sampling in the site far away from human activities and for this reason is not included.

As per Golabek, E. and Tukiendorf, A. (Golabek and Tukiendorf, 2004), following the procedure relied on the Bayesian statistical modeling of their time series data for TRW, succeeded in the approximation of the linear perturbation model for each year to the normal distribution as

y_i ~Normal (μ_i, τ) (4)

y_i = d1 + d2t_i + d3cos(d4t_i) + d5sin(d4t_i) (5)

where

y_i - TRW (tree ring width)

μ_i and τ – distribution parameters (i.e. expected values and their variance component respectively)

d1…d5 – unknown regression coefficient (to be estimated).

The proposed method by Polish scientists can be interesting when applied to TRW data analysis, however, it has its limitations since, as was found by Shiatov and Mazepa (Cook and Kairiuksis, 1990a), after testing their TRW data for each year, that in some cases the distribution of data per year was a mixture of Normal distributions that would complicate the proposed model.

2.2.4. Standardization of TRW data

2.2.4.1. Removal of age dependence in the tree ring width data

Removal of age dependence is one of the major problems since apart from detection of the adequate growth model for the samples and application of a special "filter" to remove this dependence, how to preserve the climate signal (part of which can be removed as well)? There are different types of growth models that are normally used in dendrochronological study (Schweingruber, 1988), starting from the simplest ones like lineal or negative exponential function and finishing with Weibull function (that takes into account so called "juvenile" effect of the early tree growth) and other ARIMA models or polynomials with special filters (Gaussian, for example), etc. (Cook and Kairiuksis (Eds), 1990)

Since the cores were taken approximately at the breast height, the "juvenile" effect is not present in the series, and it is seen declining tendency similarly to a negative exponential function. In the simplest case we could take out the exponential age tendency applying logarithmic transformation to the raw TRW series data. In order to get the greatest similarity to the data, other fitted models or smoothing lines can be applied. For example, doing more adjusted fitted regression to the research data, the best options are the polynomial curve or Box-cox power transformation [5] as seen in Figures 8 and 9, carried out with the use of

[5] *Box-Cox transformation uses power transformation as* $I=\frac{(y)^{\lambda}-1}{\lambda y_m^{(\lambda-1)}}$ *(6), where* y_m *is a geometrical mean (source: Internet, Wikipedia on-line: http://en.wikipedia.org/wiki/Powe_transform), and* λ *is a power found by regression.*

STAGRAPHIC and MINITAB programs respectively. Box-cox transformation regression is done for power (λ) of 0.57, with the significant p-value of 0.0000, and very high negative correlation coefficient of -0.971, and R^2=89.7 which means that this regression explains about 90% of the whole data variability.

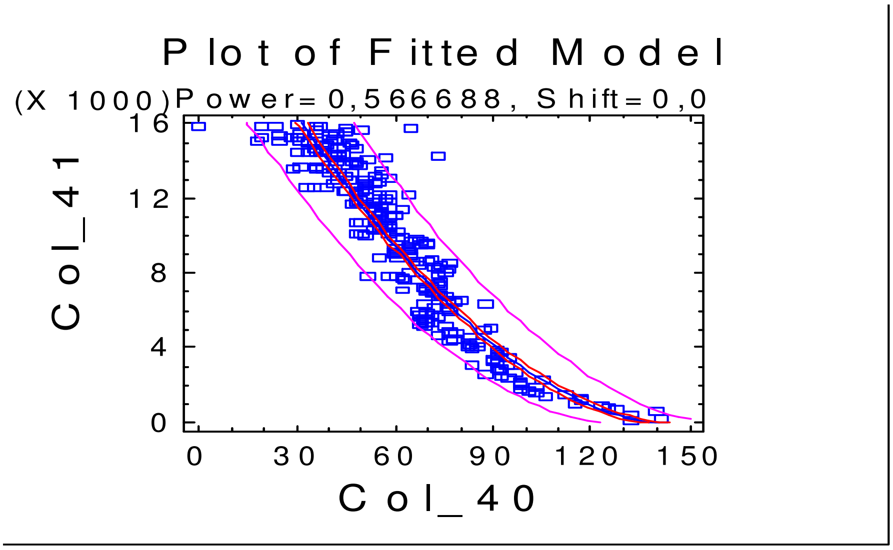


Figure 8. Box-cox approximation of the sample data of RCS (statgraphic plot)[6].

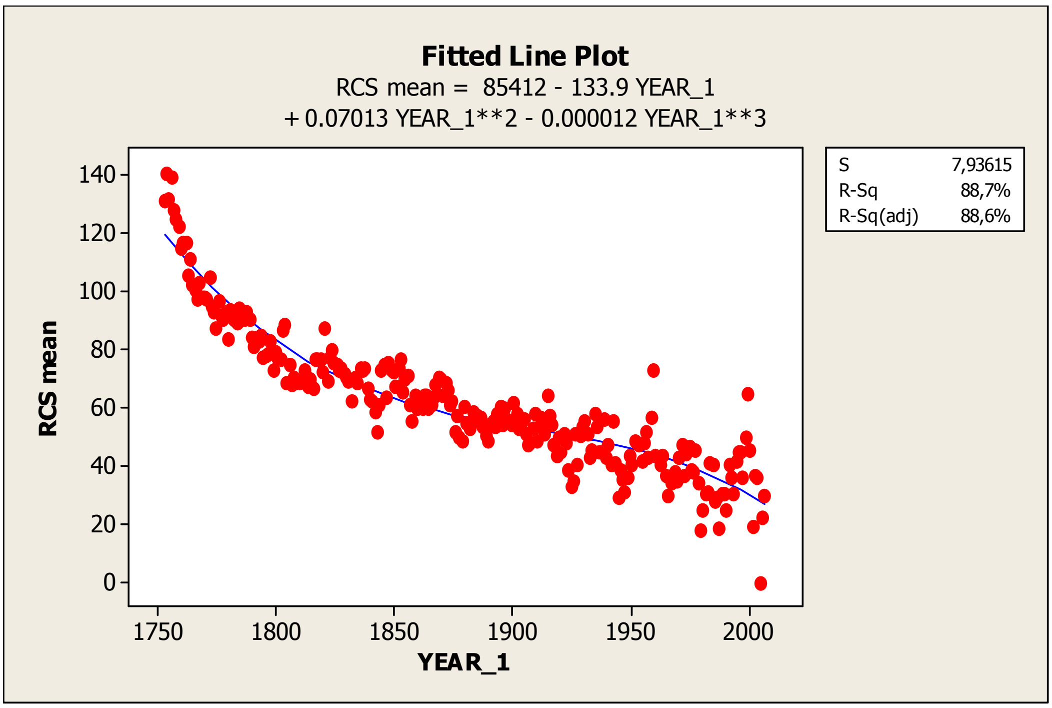


Figure 9. The fitted polynomial curve for the RCS mean value of TRW.

[6] *Here the raw TRW values data were transformed using box-cox power transformation (power=0.57) and presented in y-axis versa time (years in the x-axis), corresponded col_41 and col_40 of statgraphic* calculus *sheet correspondently.*

As for the polynomial regression fitted to the model, a polynomial of the 3rd order was used and gave similar results for the fitting parameters (a little bit less in comparison with box-cox transformation) for R^2 value (88.7%) while the lineal regression gave the minor value of all compared, but still quite high (R2=81.5%, p=o.oooo) as shown below:

Regression Analysis: RCS mean versus YEAR_1

```
The regression equation is
RCS mean = 602.2 - 0.2871 YEAR_1


S = 10.1097   R-Sq = 81.5%   R-Sq(adj) = 81.4%


Analysis of Variance

Source        DF      SS      MS        F      P
Regression     1  113887  113887  1114.28  0.000
Error        253   25858     102
Total        254  139745
```

Polynomial Regression Analysis: RCS mean versus YEAR_1

```
The regression equation is
RCS mean = 85412 - 133.9 YEAR_1 + 0.07013 YEAR_1**2 - 0.000012 YEAR_1**3


S = 7.93615   R-Sq = 88.7%   R-Sq(adj) = 88.6%


Analysis of Variance

Source        DF      SS       MS       F      P
Regression     3  123937  41312.2  655.93  0.000
Error        251   15809     63.0
Total        254  139745


Sequential Analysis of Variance

Source      DF      SS        F      P
Linear       1  113887  1114.28  0.000
Quadratic    1    6291    81.02  0.000
Cubic        1    3759    59.68  0.000
```

Summarizing 3 regressions done for the research data, the best application is to use Box-cox power transformation or polynomial regression of the 3rd order.

As a result of single (or double in many cases) removal of age trend and smoothing data values via splines (smoothing line) or other techniques to obtain of the TRW indexes that are standardized normally in their mean (=1) and more or less stable variance (Cook and Kairiuksis (Eds.), 1990). The comparative example of the raw and standardized indexes is seen in Figure 10, where the raw data with decline age tendency are converted onto indexes with mean of 1. The simplest method of taking out of the exponential tendency is taking LN of the raw values and followed standardization by the commonly used mean, for example.

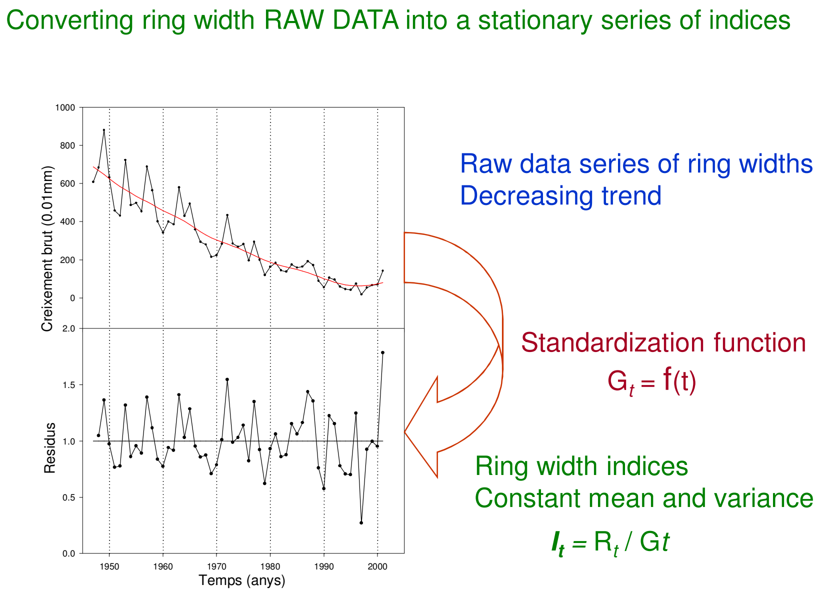


Figure 10. Conversion of the raw TRW data into stationary indexes.

(Source: E. Gutiérrez classes on dendrochronology, phD course, summer session, June 2007)

2.2.4.2. Regional Curve Standardization (RCS)

Regional Curve Standardization (RCS) is one of the advanced methods for taking out the age trend in tree-ring chronologies that has already been successfully applied to several large TRW data sets (Esper, J. et al, 2003; Helama et al., 2004). This method consists of aligning the individual TRW series by cambial age instead of the biological one and the curve obtained (RCS) describes the functional form of the overall, age related, growth trend for given samples (i.e. for given site and species). It is quite effective method, and in our case give less variance in comparison with mean series, as is shown in Figure 11 below, and has a clearer negative exponential trend (Figure 13) then the mean series tendency (Figure 12) since in the latter case the dispersion is greater due to different time-spine of the tree cores that reflect the different ages of the sampled trees.

However an even better result is obtained via double detrending with the use of the ARSTAN program whose indexes are more stable in variance in comparison with those obtained via RCS method ones (see Figure 14).

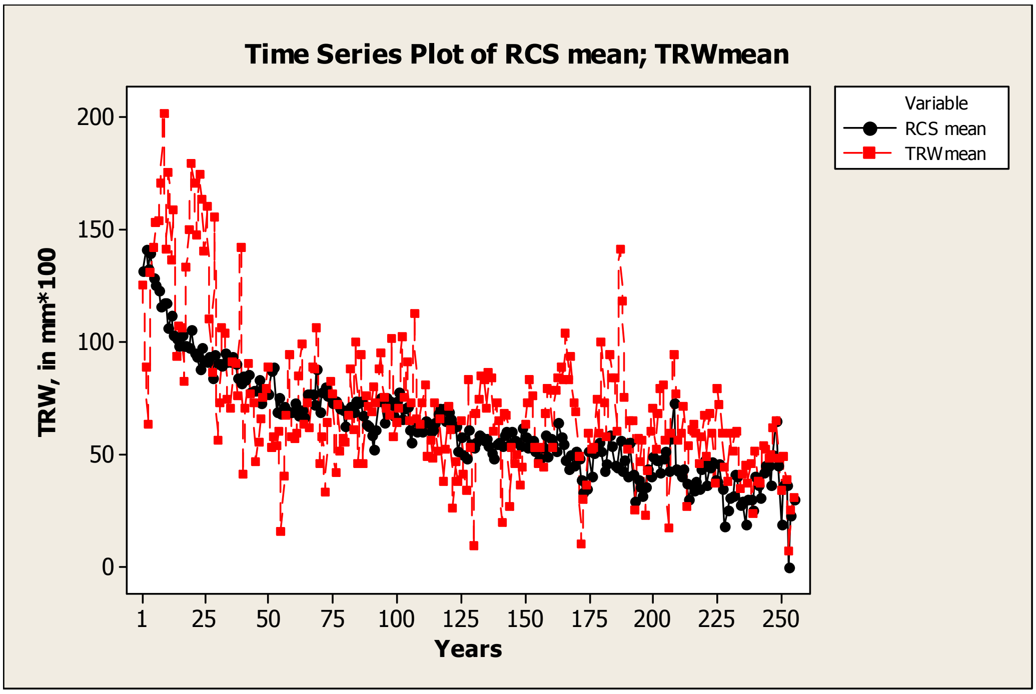


Figure 11. Comparative graphic of two methods: mean and RCS[7].

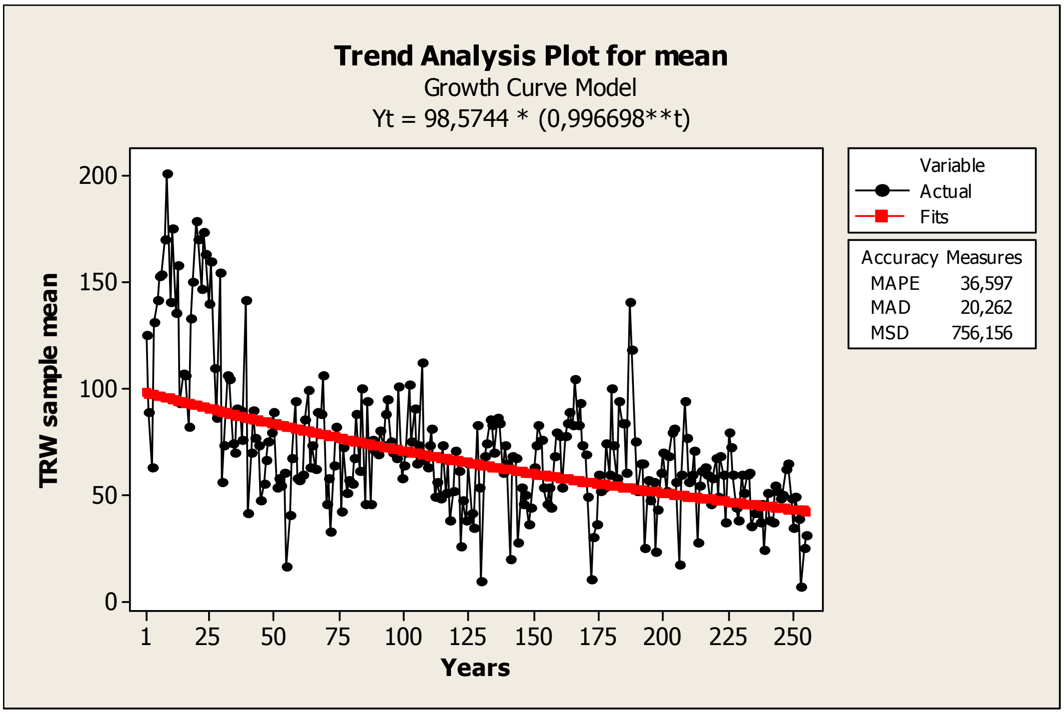


Figure 12. Trend Analysis Plot for TRW mean value[8].

[7] *The mean values obtained with use of RCS data are less in their variance in comparison with simple mean of raw data and better to interpret and use for further analysis.*

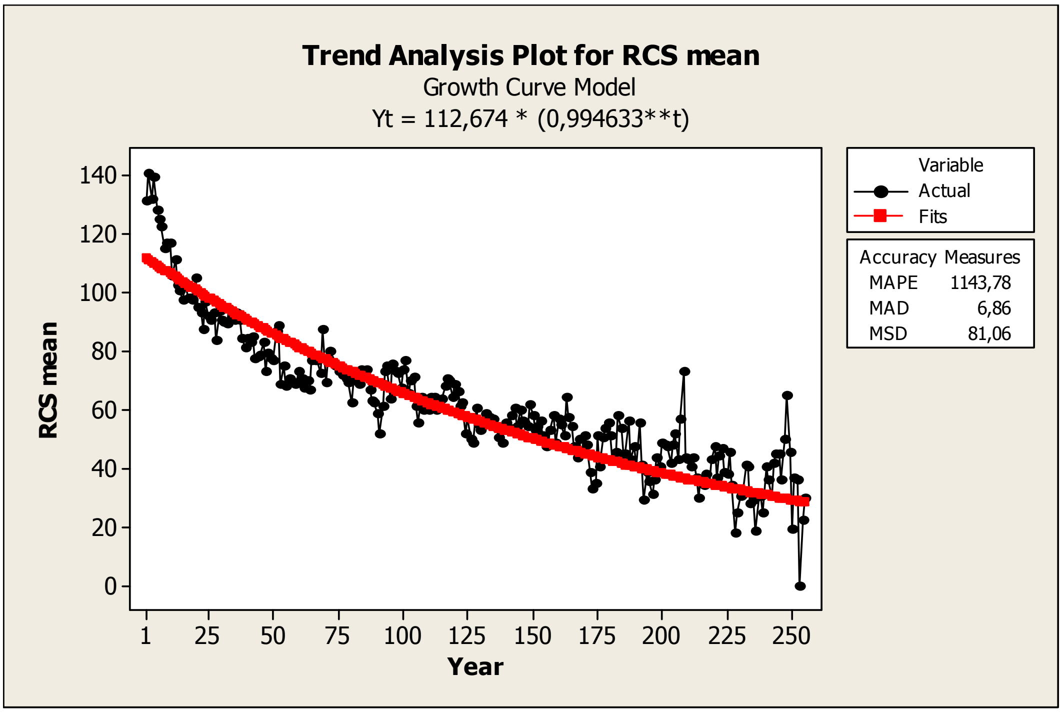


Figure 13. Trend Analysis Plot for RCS mean[9].

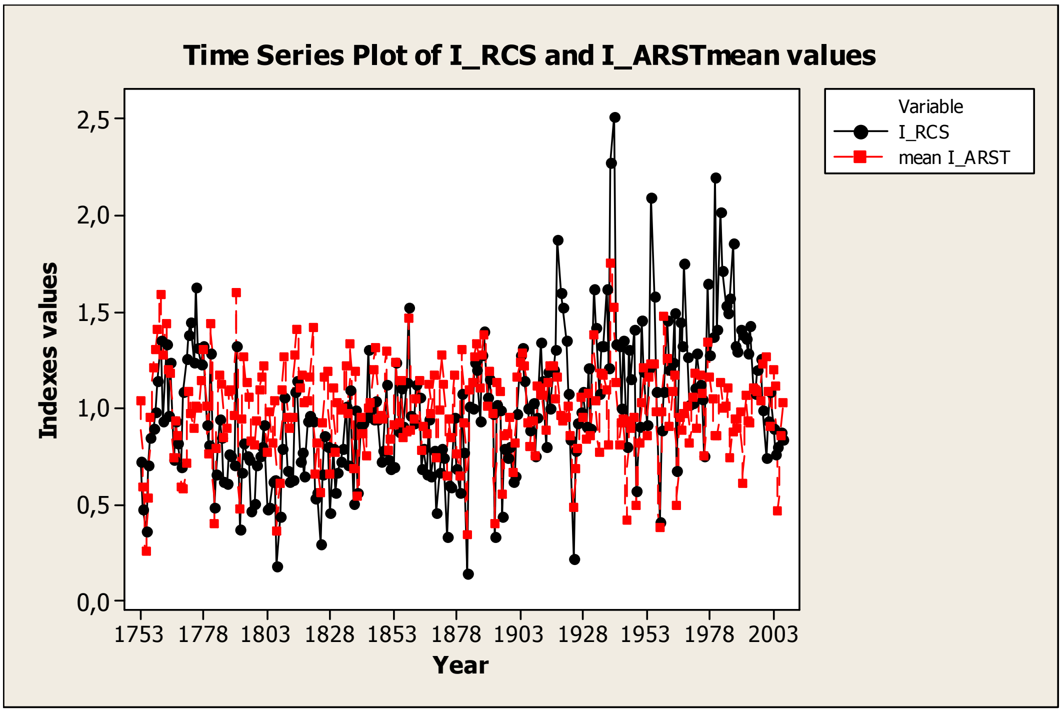


Figure 14. Comparative plot of TRW indexes received by various methods (RCS and program ARSTAN: power transformation and smoothing line of 32 years)[10].

[8] *Trend analysis plot for TRW mean values shows a very general declining tendency reflecting a common sense of tree rings growth due to geometrical and physiological limitation with time.*

[9] *Mean data of values obtained via RCS method is more adjust to the current research growth curve (a negative exponential) as it was shown in the preliminary analysis of data.*

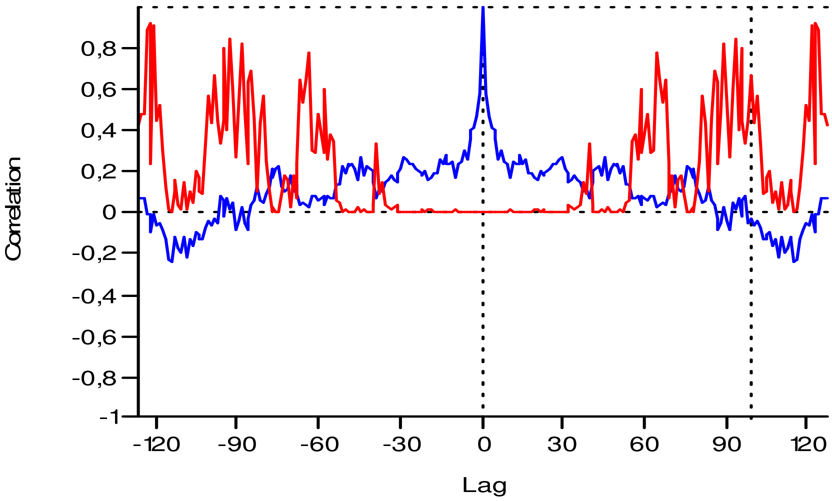


Figure 15. Cross-correlation between TRW indexes values obtained by different methods (RCS and ARSTAN program).

lag	correlation	p-value
-5	0.35	1.06E-08
-4	0.40	3.55E-11
-3	0.41	7.98E-12
-2	0.47	1.96E-15
-1	0.57	1.01E-23
0	1	0
1	0.57	1.01E-23
2	0.47	1.96E-15
3	0.41	7,98E-12
4	0.40	3.55E-11
5	0.35	1.06E-08

Table 2. Significant correlation coefficient for two types of TRW indexes (RCS and ARSTAN).

Interestingly two different methods (RCS and ARSTAN with double detrending) that use different approaches of raw data treatment, have a 100% correlation between each other as seen from Figure 15 and Table 2 with p-values for it. That means that both types of indexes statistically identical in their pair values with a maximum correlation

[10] *Comparing TRW indexes obtained by RCS methods and double detrending with use of ARSTAN program, generally they are quite similar, however, double detrended (PT+spline of 32 years) by ARSTAN are more stable in their mean and variance as shown in the plot of this Figure.*

coefficient (=1) and minimum p-value (=0) in comparison with their delay values in lags.

2.3. Time series analysis and other statistical methodologies

Since TRW and climate data, which are used in this research, are time series, mainly the time series analysis methods were used, such as autocorrelation, partial correlation functions for the separate series data and correlation between series just for preliminary study, and cross-correlation for the pair of data (TRW – climate variable) for the main study.

Initially the time series are to be determined if they are stationary and if they have any significant seasonality that needs to be modeled under a Box-Jenkins model (*source*: http://www.itl.nist.gov/div898/handbookhandbook/pmc/section4/pmc446.htm), that can be assessed from a run sequence plot (should show constant location and scale). As well non-stationarity can be seen from the autocorrelation plot when the graphics has very slow decay. Seasonality (or periodicity) can be seen from the autocorrelation plot or a spectral plot. Generally after addressing stationarity and seasonality, the order of the autoregressive and moving average terms (p and q) should be defined and further the autocorrelation and partial correlation plots are to be compared to the theoretical behavior. The order of the autoregressive process (p), especially for AR(1) process, the sample autocorrelation function should have an exponentially decreasing appearance while for higher-order AR processes are often a mixture of exponentially decreasing and damped sinusoidal components.

For higher–order autoregressive processes, the autocorrelation function (ACF) is to be complemented with a partial autocorrelation function (PACF) plot. The PACF of an AR(p) process becomes zero at lag p+1 and greater, thus, the sample partial autocorrelation function should be examined if there is evidence of a departure from zero. This is usually determined by placing a 95% confidence interval ($\pm 2/\sqrt{N}$ with N denoting the sample size) on the partial correlation plot.

Order of Moving Average Process (q) is determined from the autocorrelation function of a MA(q) process when it is zero at lag q+1 or greater with the 95% interval as well.

Depending on shape of autocorrelation function, one or other type of model is recommended to use (Table 3) (*source*: seen on-line in the 26th of May http://www.itl.nist.gov/div898/handbookhandbook/pmc/section4/pmc446.htm).

Table 3. Summary of the indicated model to use depending on shape of autocorrelation function.

SHAPE	INDICATED MODEL
Exponential decaying to zero	Autoregressive model. Use the partial autocorrelation plot to identify the order of the autoregressive model
Alternating positive and negative, decaying to zero	Autoregressive model. Use the partial autocorrelation plot to help identify the order
One or more spikes, rest are essentially zero	Moving average model, order identified by where plot becomes zero
Decay, starting after a few lags	Mixed autoregressive and moving average model
All zero or close to zero	Data is essentially random
High values at fixed intervals	Include seasonal autoregressive term
No decay to zero	Series is not stationary

Mixed models that are difficult to indentify are normally reflected in random variables of ACF and PACF and do not give the same picture as the theoretical functions and more complicate.

In this research, there were used specially designed programs for dendrochronological analysis and the statistical validation of cross-dating and obtaining treated TRW indexes, such as COFECHA, ARSTAN and Turbo ARSTAN. Moreover, for the raw data treating, fitting the data to the definite model, time series analysis and graphical presentation of data, there were used MINITAB, Excel, PAST, R, STATGRAPHIC and TSAP.

COFECHA is a quality-control program used to check the cross-dating and overall quality of tree-ring chronologies. There are three parts of the output:

1. the statistical measures and summary information for the chronology (Header);
2. the "correlation matrix" that shows the correlations of each series segment with the master chronology (Correlation of Series by Segments);
3. the summary statistics provided for each series in the chronology, and averaged over all series (Descriptive Statistics).

ARSTAN (and more flexible new version turbo ARSTAN), the concept and methodology of which were developed by Dr. Edward R. Cook at the Tree-Ring Laboratory, Lamont-Doherty Earth Observatory of Columbia University, Palisades, New York Cook, E. and Holmes, R., 1986), produces chronologies from tree-ring measurement series by detrending and indexing (standardizing) the series, then applying a robust estimation of the mean value function to remove effects of endogenous stand disturbances. Autoregressive modeling of index series often enhances the common signal. Extensive statistical analysis of a common time interval provides characterization of the data set. Three versions of the chronology are produced, intended to contain a maximum common signal and a minimum amount of noise.

PAST is a free easy-to-use data analysis package originally aimed at paleontology but now also popular in ecology and other fields; it includes common statistical, plotting and modeling functions and was used for calculus and plotting of cross-correlations of paired data.

Chapter 3. Results

3.1. General model description and limitations

Generally series of growth indexes that can be represented by multiple regression as

$$I_t = b_0 + b_1X_{1t} + b_2X_{2t} + \dots + b_nX_{nt} + e_t \qquad (7)$$

where t – the tree ring (one tree ring=one year)

I_t - the series growth indexes (TRW Indexes)

$b_0, b_1, \dots$ - coefficients of regression

$X_{1t}, X_{2t}, \dots$ - climatic variables.

The main problem of such type of regression is that there is the colineality (interdependency) both between and inside of the variable from one side, and the difficulty of "conversion" regression in the reconstruction. The multivariate models exist but they are more difficult to use in the reconstruction regressions.

As well the simple model $I_t = f(C_t)$ is used widely in the dendrochronological study where standardized indexes of TRW values are regarded as a function of climate value. In the current research the TRW indexes are compared with climate values one by one (month or annual data of temperature (mean, minimum or maximum) and precipitation (or by a grouped value, for example temperature of several months) via cross-correlations coefficients showing their significance by the correspondent p-values.

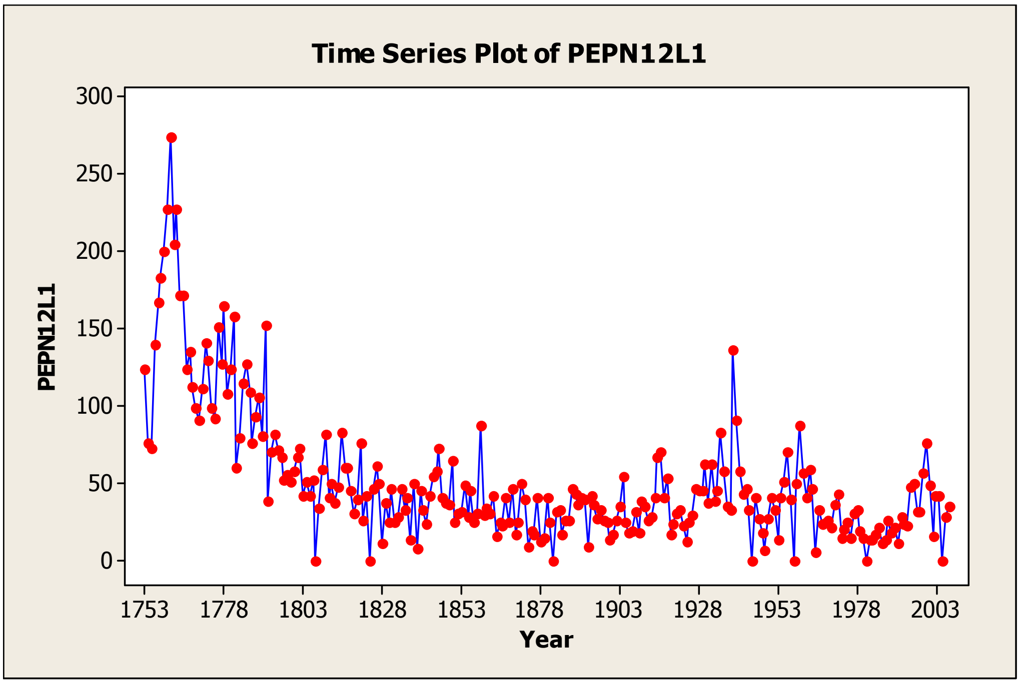


Figure 16. Time Series Graphic for the core PEPN12L1 (the oldest tree).

Generally, time series are obtained from observations of a phenomenon over time (Cryer, 1986) like values of TRW data for different years (Figure 16) and they can be used for further analysis independently.

One of the important features of time series data is their autocorrelation, estimated as a function:

$$r_k = \frac{\sum_{t=1}^{n-k}(Z_t-\bar{Z})(Z_{t+k}-\bar{Z})}{\sum_{t=1}^{n-k}(Z_t-\bar{Z})^2}, \qquad (8)$$

where $Z_1, Z_2, \ldots Z_n$ are observed series (Cryer, 1986).

For example, it is possible to see the order if significant autocorrelation between values in order to see the dependency of values of the previous ones. It is important for further "whitening" of data with the goal of obtaining "pure" signal for the corresponded time value. As is clearly seen on the Figure 17, autocorrelation in the core 12L1 is very strong and steady for the quite long lag of this tree due to the physiological and geometrical limitation of tree growth, and last rings are the thinnest ones and have very slight differences in their sizes. In this case the order of autocorrelation is high due to little annual increment because of tree age.

In the case of another sample core 02L1, due to the young age, ring formation depends mainly on other factors (endogenous or exogenous), and do not have the physiological and geometrical limitation as the core 12L1 (Figure 18) and the autocorrelation of 02L1 is of less order (AR(1)) in comparison with the core 12L1 (AR(15)). Young trees grow quickly since do not have growth limitation and thus do not depend on values of many previous years, but only the last one.

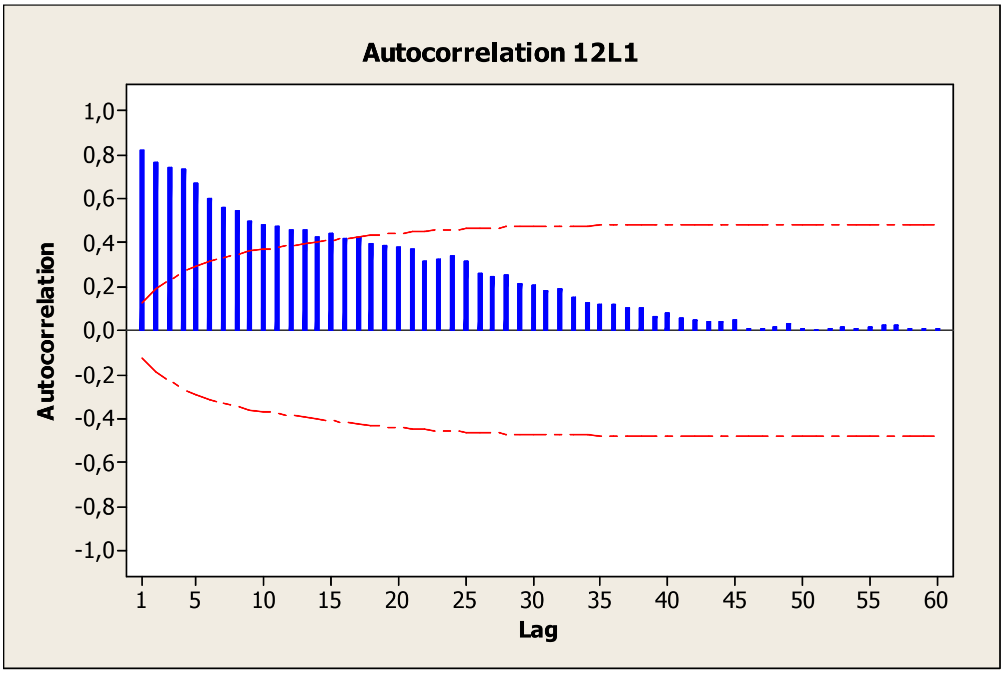


Figure 17. Autocorrelation Graphic of the core PEPN12L1 (the oldest tree).

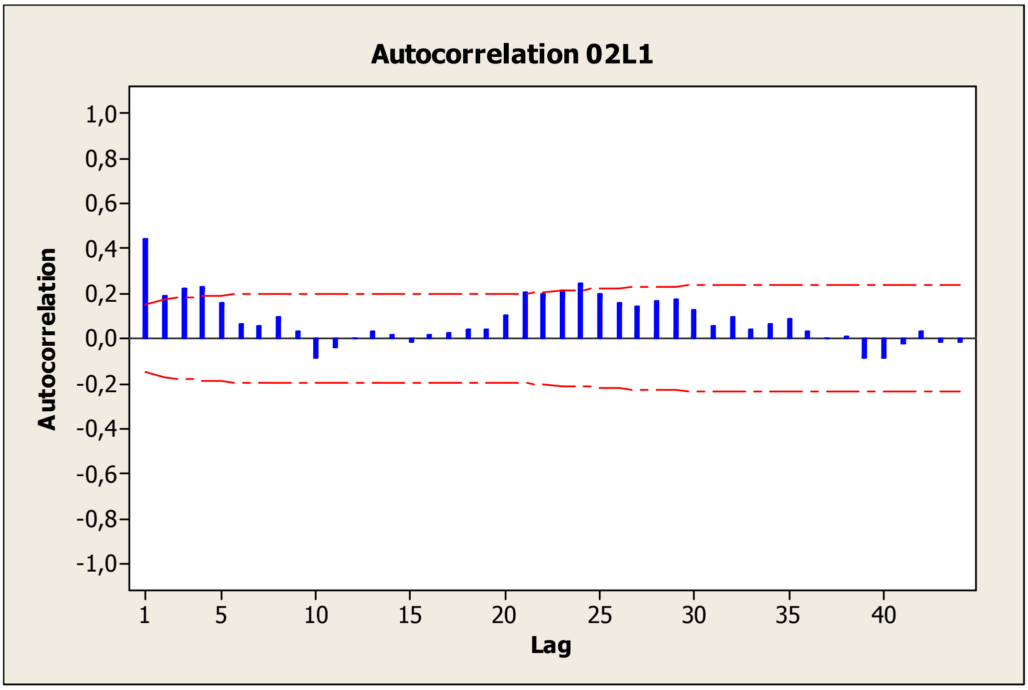


Figure 18. Autocorrelation Graphic of the core PEPN02L1 (the young tree).

Autocorrelation function can be applied both to data and to their residuals; an example of ACF of residuals foe mean TRW value is shown at the plot below (Figure 19), indicating a negative correlation at lag 1.

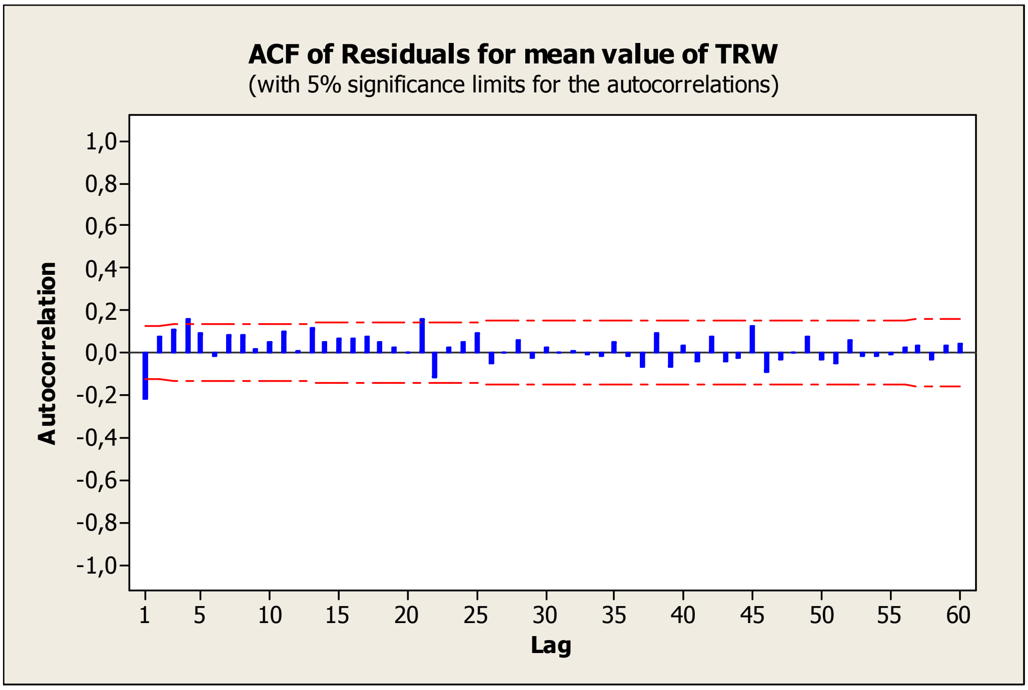


Figure 19. ACF of Residuals Graphic of the mean value of TRW chronologies.

Partial autocorrelation function is another parameter that can be analyzed similar to autocorrelation function since AR(p) series do not remain zero after a certain number of lags (Cryer, 1986) and sometimes can be useful to define some cycles in the data over the time (if they exist) and their frequency. In the example below there are highest positive correlations in lag 3, 4 and 5 and 45 (Figure 20).

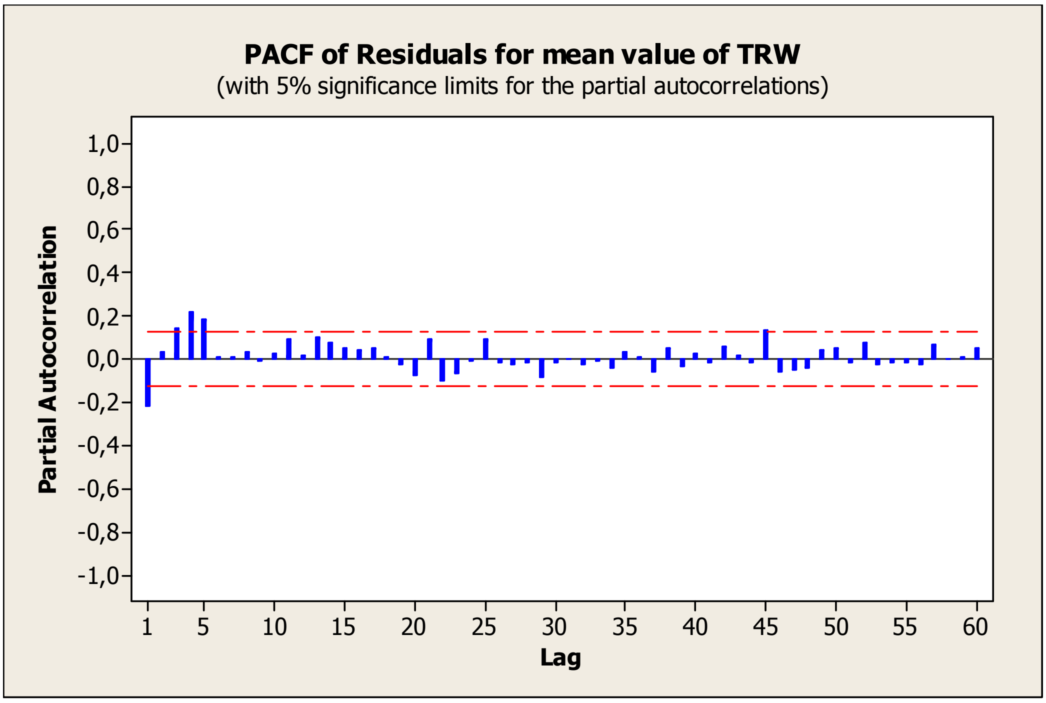
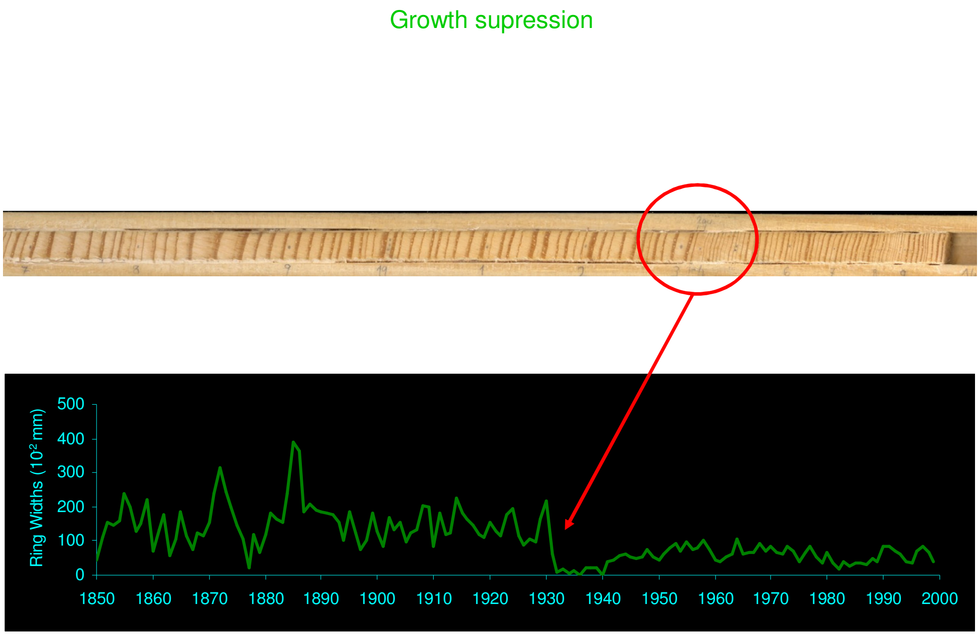


Figure 20. PACF of Residuals Graphic of the mean value of TRW chronologies.

Summarizing, after checking the autocorrelation functions (cores of trees A2 and A12 were taken as examples of the youngest and the eldest tree), autocorrelations of a higher order in the oldest tree were observed that can be logically explained by physiologically-geometrical growth limitations that do not permit a big dispersion in the TRW values for the last years (see Figures 17 and 18).

Since autocorrelation analysis is not the objective of this research, more detailed investigations were not carried out; however, generally it is important to understand the dependence of data from previous years and can be used in the "whitening" of data or in other prediction models as well (Cook and Kairiukstis (Eds.), 1990).

A part of the autocorrelation problem that can influence on proper "pure" value for the concrete point of time, there is another kind of "noise" in data due to a particular reaction to some factor of endogenous or exogenous origin. If this is exogenous factor and is reflected in all samples of the site, it is more difficult to detect and remove. Changes in increment of TRW values in many samples can be caused by some external event (for example due to opening of a ski station and deforestation of the site) and not to climate changes for the observed period. Sometimes growth suppression or deliberation can be caused by growth completion of the nearest trees. An example of growth suppression is shown in Figure 21, reflected both in the real ring width values of the core (photo of the core in the upper part) and in their graphical presentation above with significant decline.



Source: E. Gutiérrez classes on dendrocronology, phD course, summer session, June 2007.

Figure 21. Growth supression in the TRW series.

As for any endogenous influence for the specific tree, it can be detected easier just comparing with the master or mean series by differences (or dissimilarities) in correlations and variances.

At the contrary, similarities in "behavior" of data can be seen graphically by analogy of curves or min and max values for the first visual estimation, as is shown in the Figure 22, where time series of A2 and A12 trees are represented. Another method to see the degree of similarity between series is their correlation. An example of correlation between TRW raw values of A2 and A12 trees is seen in Figure 23 that have a maximum correlation at lag 0.

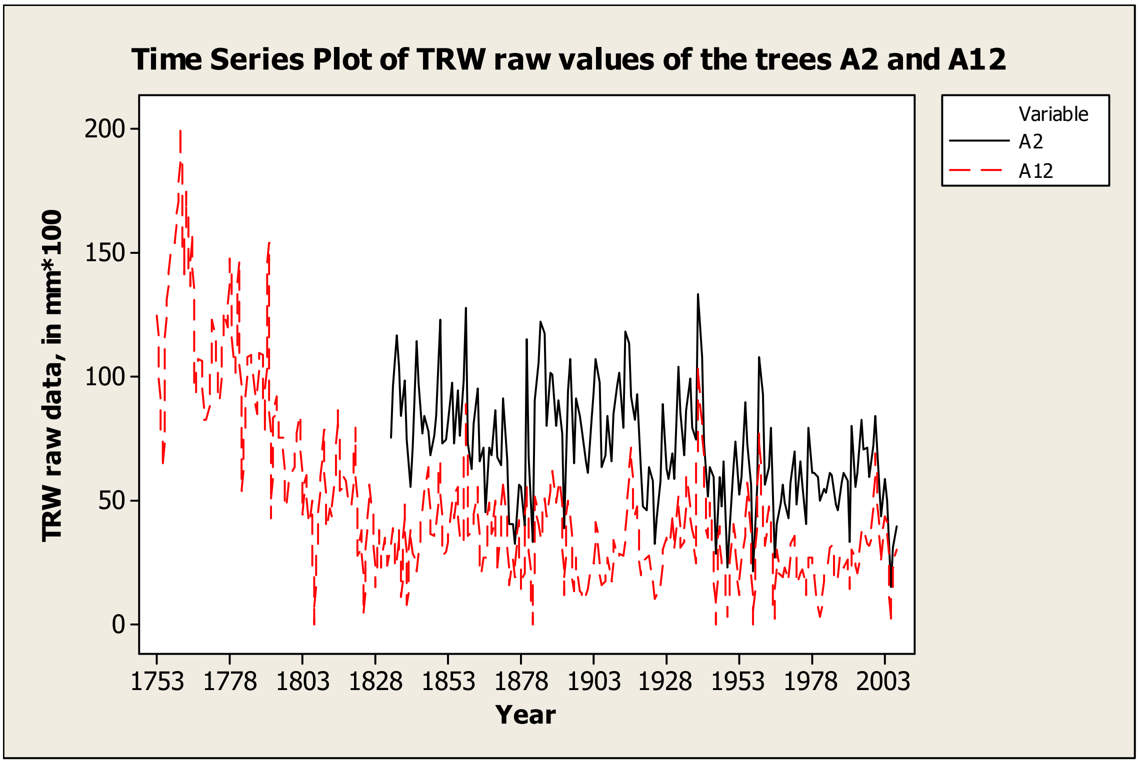


Figure 22. Time series plot of TRW raw data of the trees A2 and A12.

Figure 23. Correlation between two series for the common period of time for trees A2 and A12 (1833-2007).

Thus, there are several limiting factors in the representation of samples, and if on the one hand the sample size is important for reliability of the chronology and the maximum samples are needed to be included in the chronology, on the other hand, some samples can be some kind of "outliers" and differ more from the remaining majority, for example as is seen in Figure 24, the trees A6 and A15 have more dispersion and their raw values then other represented ones. This particular growth of some trees can influence on the average or mean chronology making it less "pure" as a climatic signal, and one of the solutions to it is to use weighted filters for different trees or even for some periods of TRW (see Figure 21 with partial growth suppression that can be caused due to endogenous factors such as tree growth competition, for example) where their correlation with a master series is low, while the trees A2 and A12 have quite high correlation (Figure 23) and visual agreement in the sample data (Figure 22).

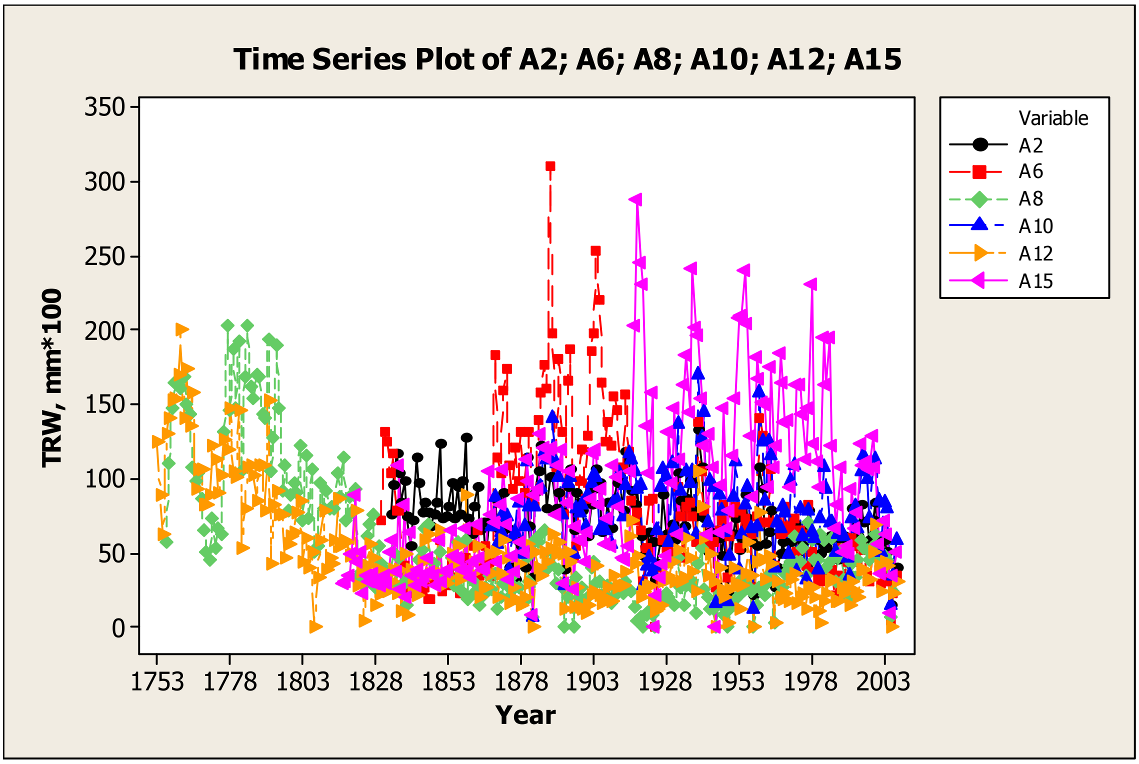


Figure 24. TRW time series plots of trees A2, A6, A8, A10; A12 and A15.

3.2. Simulation and obtaining of the cross-correlation between TRW indexes and climate variables

In order to see if there is any correlation between tree ring width growth and climate variables, the cross-correlations are done for different ones (mean, maximum and minimum annual temperatures, precipitation), using the data from different sources.

Cross correlation is a standard method of estimating the degree to which two series are correlated. Consider two series x(i) and y(i) where i=0, 1, 2 ... N-1. The cross correlation r at delay d is defined as

$$r = \frac{\sum_i[(x(i)-m_x)(y(i-d)-m_y)]}{\sqrt{\sum_i(x(i)-m_x)^2}\sqrt{\sum_i(y(i)-m_y)^2}} \qquad (9)$$

Where m_x and m_y are the means of the corresponding series. If the above is computed for all delays d=0, 1, 2, ... N-1 then it results in a cross correlation series of twice the length as the original series.

$$r(d) = \frac{\sum_i[(x(i)-m_x)(y(i-d)-m_y)]}{\sqrt{\sum_i(x(i)-m_x)^2}\sqrt{\sum_i(y(i-d)-m_y)^2}} \qquad (10)$$

As for analysis for cross-correlations of TRW indexes with Spanish data of Pallars region (see the full Table of p-values for cross-correlation coefficients in the Annex 6), analyzed for the common period of time 1941-1994; there were found some significant correlations with mean temperature: all the positive ones (0.31 (p=0.03) in lag -7; 0.35 (p=0.01) in lag 2; 0.52 (p=9.33*10-5) in lag 6, 0.58 (p=1.55*10-5) in lag 7 and 0.37 (p=0.024) in lag 19) and with annual precipitation data: all negative except one coefficient (0.4 (p=0.03) in lag -26, -0.37 (p=0.009) in lag -6, -0.27 (p=0.04) in lag -1, -0.29 (p=0.03) in lag 2 and -0.40 (p=0.005) in lag 7.

In both cases the maximum correlations are observed in the lag 7 (0.58 for the mean annual temperature and -0.40 for the mean annual precipitation) as can be seen in Figures 25 and 26.

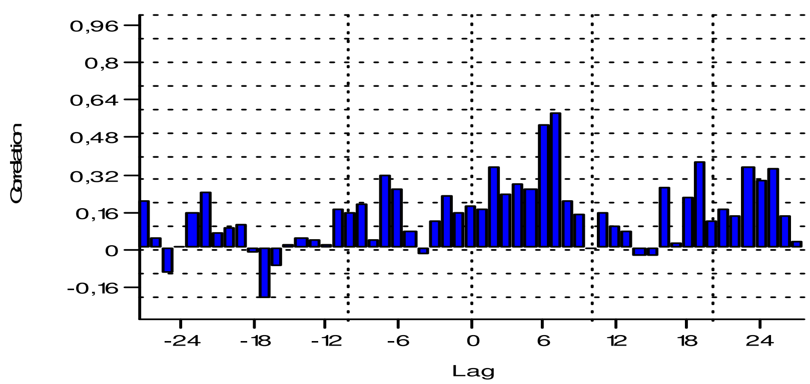


Figure 25. Cross-correlation of TRW_I time series with annual temperature mean of Pallars region (1941-1994).

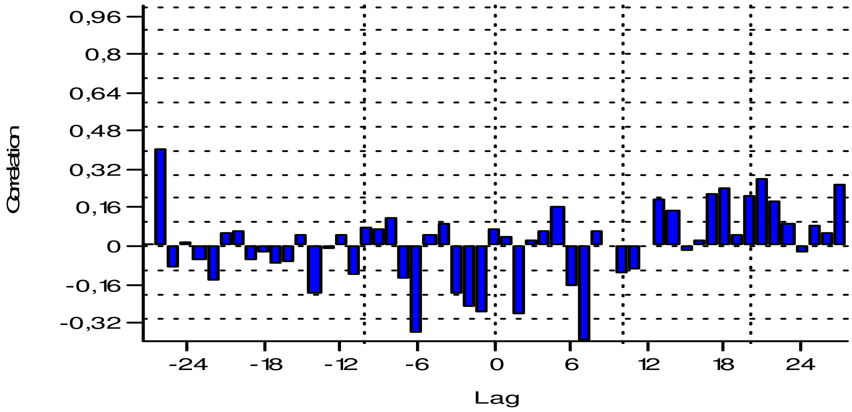


Figure 26. Cross-correlation of TRW_I time series with annual mean of precipitation of Pallars region (1941-1994).

Similarly other cross-correlations TRW mean indexes with climate data (annual, month or grouped period of month) were analyzed, and the highest significant cross-correlations were found with the Spanish climate data (maximum and minimum temperature and annual precipitation) of the meteorological station of Seu d'Urgell while there were no significant correlation links of TRW growth and climate data with the other nearest locality (Vielha meteorological station for the same period of time, 1998-2006) that can be related with greater similarity of the site where the samples were taken. The same tendency in the correlation sign is observed here (Seu d'Urgell station in comparison with Pallars historical climate data analyzed above), if for the temperature values TRW data have a positive correlation, for the precipitation, a negative one.

Table 4. Correlation between annual T mean of Seu d'Urgell station and TRW indexes.

lag	correlation	p-value
-5	0.65	1.19
-4	0.52	0.24
-3	-0.11	0.79
-2	-0.07	0.85
-1	0.23	0.52
0	0.51	0.11
1	0.61	0.07
2	0.12	0.75
3	-0.56	0.16
4	0.19	0.68
5	0.96	0.005[11]

[11] *The highest significant correlation (all significant correlations are marked with yellow color in this and other tables).*

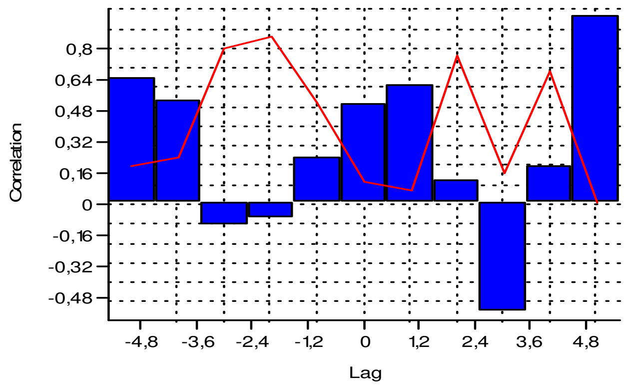


Figure 27. Cross-correlation of TRW indexes with annual mean temperature of Seu d'Urgell station.

Table 5. Crosscorelations between annual T max of Seu d'Urgell and TRW indexes.

lag	correlation	p-value
-5	0.27	0.61
-4	0.41	0.36
-3	0.22	0.59
-2	0.03	0.93
-1	0.04	0.91
0	0.43	0.19
1	0.73	0.02
2	0.19	0.63
3	-0.46	0.25
4	0.20	0.67
5	0.77	0.09

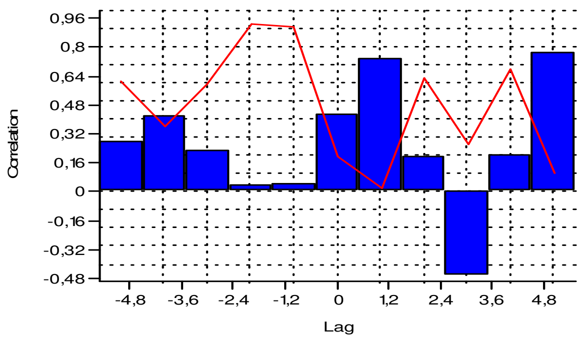


Figure 28. Cross-correlation of TRW indexes with annual maximum temperature of Seu d'Urgell station.

Table 6. Cross-correlation between annual Tmin of Seu d'Urgell and TRW indexes.

lag	correlation	p-value
-5	0.80	0.07
-4	0.50	0.27
-3	-0.45	0.26
-2	-0.26	0.50
-1	0.29	0.41
0	0.52	0.10
1	0.44	0.21
2	-0.05	0.90
3	-0.53	0.18
4	0.24	0.60
5	0.96	0.004

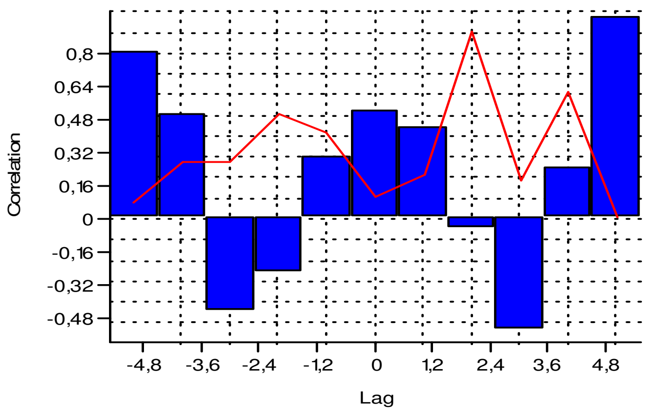


Figure 29. Cross-correlation of TRW indexes with annual minimum temperature of Seu d'Urgell station.

Table 7. Cross-correlation between annual precipitation of Seu d'Urgell and TRW indexes.

lag	correlation	p-value
-5	0.62	0.21
-4	0.36	0.43
-3	-0.64	0.09
-2	-0.68	0.047
-1	-0.34	0.34
0	-0.11	0.73
1	-0.05	0.88
2	-0.15	0.70
3	-0.53	0.19
4	-0.39	0.40
5	0.52	0.31

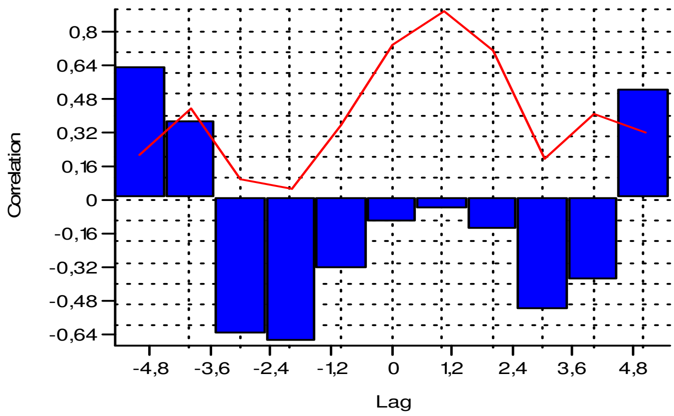


Figure 30. Cross-correlation of TRW indexes with annual precipitation of Seu d'Urgell station.

As for the rest of the data (taken from the regions with higher distance in case of extrapolation of data used in phD student work and with possible greatest error due to the manual extrapolation and less precision of the data format presentation), there some other pictures of correlation function "behavior", there were observed some cycles with a negative and positive halves of divided lags, as is shown in Figures 31 and 32.

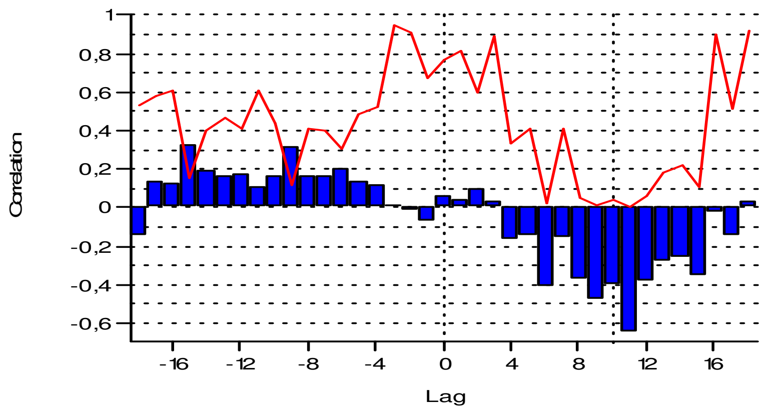


Figure 31.Cross-correlation TRW with annual T mean of Perpignan region (climate data from UK).

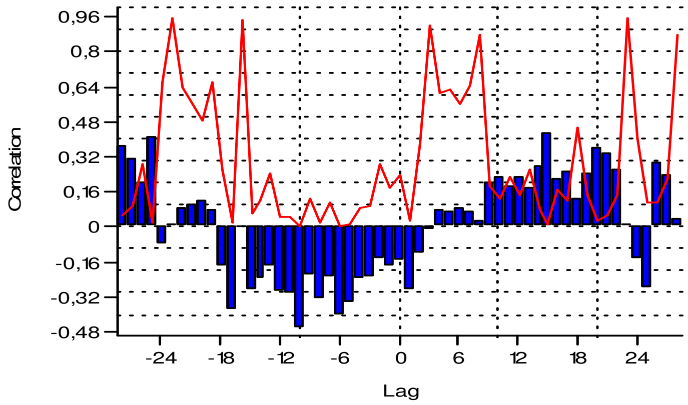


Figure 32. Cross-correlation TRW with annual mean temperature (1951-1994) of Vielha data extrapolated from phD data.

3.3. Future application of the findings (reconstruction of climate in the past).

Since the findings of correlations in some lags (delays) were significant they can be used for the climate reconstruction of the past. Below is an example of predicted values of precipitation versa real ones (Figure 33).

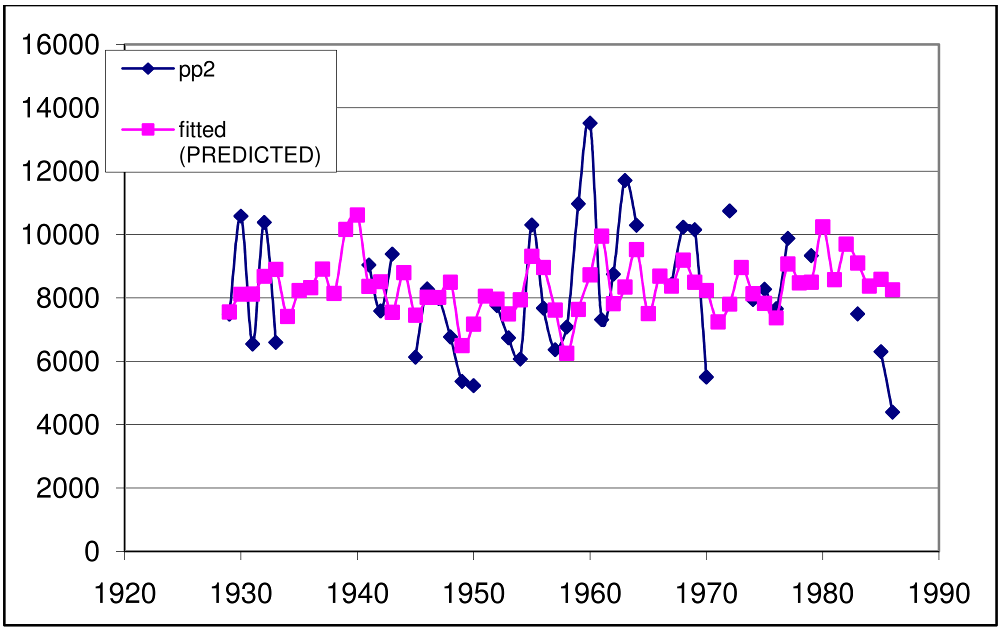


Figure 33. Comparative plot of the fitted values of precipitation (predicted by model) and real pp2 (UK climate data).

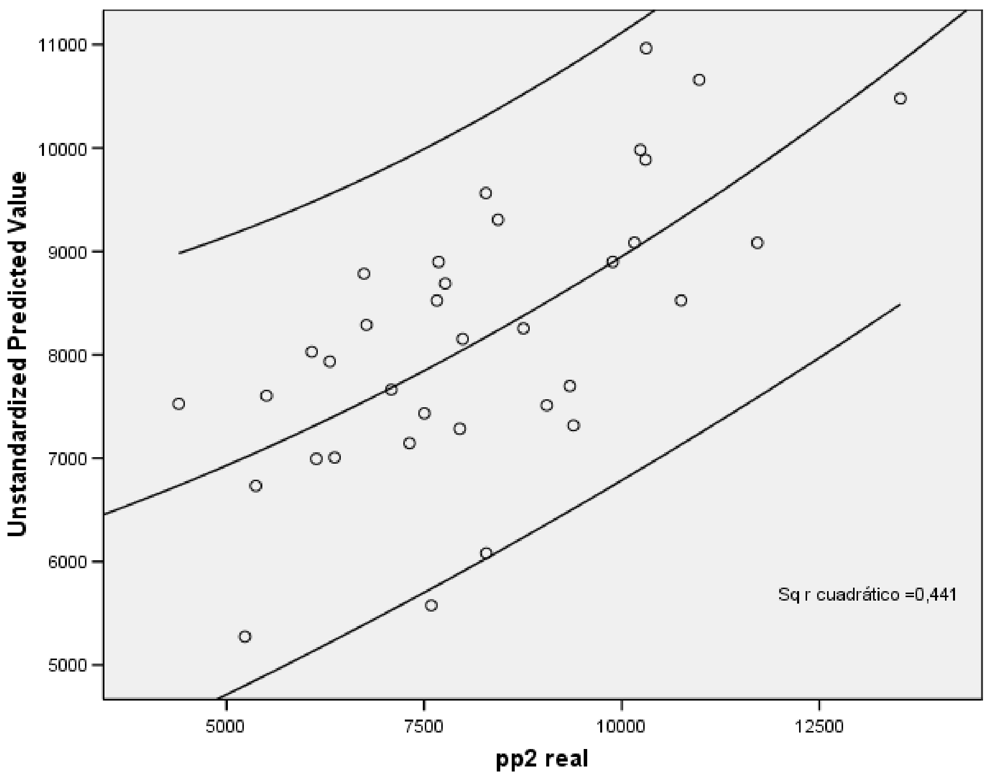


Figure 34. No standardized predicted value of precipitation versa real (pp2, x-axis). The 95% prediction confidence interval is drawn.

Coefficients(a)						
Model		No est. coefficients		Stand. coefficients	t	Significance
		B	Typical Error	Beta		
1	(Constant)	10992.0413	981.594909		11.1981442	8.841E-13
	delay10	-2291.24527	763.194116	-0.46317415	-3.0021789	0.00507859
2	(Constant)	13068.4639	1246.91475		10.4806394	7.1003E-12
	delay10	-2131.64156	714.154872	-0.43091034	-2.98484495	0.0053994
	delay6	-1665.62881	679.77406	-0.3537356	-2.45026827	0.01992609
3	(Constant)	14979.5006	1425.51098		10.5081622	9.6824E-12
	delay10	-2163.09511	669.105613	-0.43726866	-3.23281567	0.00290566
	delay6	-1594.58057	637.489243	-0.33864683	-2.50134506	0.01786395
	delay2	-1508.75324	645.169611	-0.31532465	-2.33853737	0.02598435
a	Dependent Variable: pp2					

Resum of the model(d)				
Model	R	R sqr.	corrected R sqr	Typical error of estimation
1	0.46317415	0.2145303	0.19072819	1829.44812
2	0.58190912	0.33861822	0.29728186	1704.76089
3	0.6616625	0.43779726	0.38339054	1596.90096
a	Variables for prediction: (Constant), delay10			
b	Variables for prediction: (Constant), delay10, delayt6			
c	Variables for prediction: (Constant), delay10, delay6, delay2			
d	Dependent Variable: pp2			

Table 8. Lineal regression model for the pp2 data.

Model of lineal regression was applied with prediction variables of different delays (lags) that gave the highest significant correlations with the use of pp2 precipitation data (CRU data, UK). As a result of including different delays, the 3rd (the most complete) model has the highest predictive capacity with R^2 of 0.44 (Table 7).

The estimated model is:

$$R_t = \beta_1 lag10_t + \beta_2 lag6_t + \beta_3 lag2_t + C + \varepsilon_t \tag{11}$$

where

- Rt – annual increment ring measurement (TRW)
- Lag10 – growth variations due to climate common signal in the year -10
- Lag6 – growth variations due to climate common signal in the year -6
- Lag2 – growth variations due to climate common signal in the year -2
- C – model constant
- ε_t - random variance. (see Cook and Kairiuksis (Eds.), 1990a)
- t – index related to a common year.

The values of the coefficients were found as the following ones:

C	14979.5006
β_1	-2163.09511
β_2	-1594.58057
β_3	-1508.75324

Although it is not a very ideal result, it is a result and proof that the data can be used for reconstruction or future prediction. Using different standardization methods for TRW data and choosing the most appropriate climate variable for the model, it is possible to construct finally the optimum model and have predictions more adjusted and reliable. Regarding the current research work, is seen from Figure 34, all predicted values (except one outlier) are within calculated 95% confidence interval that means that constructed model is a good predictor model and can be validated as a good predictor model of changes of climatic parameters or to be used for the cross validation, however it was not used due to little common spine of samples and climatic data available.

Chapter 4. Discussion and Conclusions

Dendrochronological analysis requires a lot of time mainly due to obtaining data. There are limitations in both types of data: as dendro (sampling, preparing and cross-dating requires entire weeks of the concentrated work), as well as climate data since there is no complete historical registers for all localities studied covering at least 50-100 years backward (to have enough for validation and reconstruction) on the one hand, and extrapolation or previous calculations (from daily to month and annual values, for example) on the other hand. In addition, the study of methodologies, used both in the experimental and analytical stages, requires a special narrow preparation in this field and constitutes the first endpoint on the current research.

Complicity exists not only with obtaining data and reliable data, but as well with choosing the method of their treatment and standardization that it is still one of the most important problems of dendrochronological analysis in order that during the process of removal the age tendency or data standardization the climate signal is to be left as much as possible. However, taking into account the particular behavior of the tree growth or knowing any additional information about its “history” can help to interpret the data more exactly even if it is costs extra to find forces and time.

In the current research the tree ring widths (annual growth increments) of 32 samples (cores) belonging to 15 trees of the same locality were analyzed after their special standardization in order to obtain the climate signal and further comparative analysis with climate data (temperature values and precipitation) that were provided a part.

Although different types of standardization of raw data were applied in this research, the RCS (regional curve standardization) and indexes achieved with use of the ARSTAN program (double detrending: power transformation and spline of 32 years for smoothing) were the most appropriate to the fitted data models. Interestingly, that they were 100% correlated between them as it was shown via cross-correlation procedure giving unique maximum in lag 0 with a significant value of $p<0.001$.

Analyzing the cross-correlations between obtained tree ring width indexes and climate data, significant correlations ($p<0.05$) were observed in some lags, as for example, annual precipitation in lag -1 (previous year) had negative correlation with TRW growth in the Pallars region data. Some significant correlation coefficients between 0.27-0.51 (with positive or negative signs) were detected for many cases, corresponding to a medium correlation value, met in other research works, of about 0.44 (Macia et al., 2006). Regarding the recent (but very short period) climate data of Seu d’Urgell meteorological station, some significant correlation coefficients were observed, of the order of 0.9, which are very high and can be explained by the precision of climate data (modern and precise tools of measuring) as well as by the approximation of localities and similarity of climate between sampled site and meteorological station. In comparison, for another recent meteorological station (Vielha) there were not observed any significant correlations for the same period of time (1998-2006).

The time series research, applied in the current research, has different levels: starting with the simplest one, univariate model, like autoregressive model of order 1 AR(1) for tree 02L1; then passing to bivariate models with cross-correlations between TRW and one climatic parameter series; finalizing with multivariate model in order to predict the climate of the past with different lags with highest correlations. The lineal multivariate model is commonly used in dendrochronological analysis for the more complex and complete study as it was explained before:

$$\mathbf{C}_t = \mathbf{R}_t + \mathbf{G}_t + +\delta\mathbf{D}_{1t} + \delta\mathbf{D}_{2t} + \varepsilon_t \,, \qquad (12)$$

where

- Rt – annual increment ring measurement (TRW)
- Gt – the age –related growth trend
- Ct – growth variations due to climate common signal in the year *t*
- D_{1t} – the occurrence of disturbance factors *within* the forest stand
- D_{2t} – the occurrence of disturbance factors *outside* the forest stand
- δ – indicates either a “0” for absence or “1” for presence
- ε_t - random variance. (see Cook and Kairiuksis (Eds.), 1990a)
- *t* – index related to a common year.

In the current research analysis performed there were found high time correlations between raw values of tree ring width values with a mean series (ca. 0.70) that means the common behavior in the annual increment growth of sampled trees. Sample size for the statistical analysis was considerably reliable (> 30 samples), and with EPS ≥ 0.85 for the total time spine except on the first lag of 25 years, covering total significant time spine then 1800-2006. Different statistical types of raw data treatments were shown in this work in order to compare different outputs, and the box-cox transformation and power transformation plus smoothing lines (with lags of 32 years) were the most suitable ones for removal the age trend (a negative exponential function). Obtained standardized indexes were cross-correlated with different climate variables (one by one) from different meteorological stations and there were observed significant correlations in lags, in delays that can be used in further analysis for reconstruction of past climate or in the prediction of the future (the last one cannot be validated only).

In a sum, the results obtained from the current research are positive, and there were found the significant correlations between TRW indexes and climate data that proves the hypothesis of using tree rings width data sampled in an adequate place (under special limiting factors and away of urbanized or industrialized areas where the environmental pollution can interfere the growth as well) can be used for taking out of the climate signal. In continuation the corresponded climatic parameters (with higher significant correlation) can be used in the models for the reconstruction of the past climate or in the prediction of the future one that is to be done in continuation of research. Moreover, there is no research done with the Pallars locality until now and can contribute to the data bank at Spanish or European level. Actually a lot of investigation work is carried out and still go on in this direction since the climate change is one of the major environmental problems nowadays.

REFERENCES

Baillie, M.G.L. 1982.Tree-Ring Dating and Archaeology. Croom Helm Ltd, London; Great Britain.

Biondi, F. and Waikul, K. 2002. DENDROCLIM2002: A C++ program for statistical calibration of climate signals in tree-ring chronologies, University of Nevada, Reno, USA.

Broecker, W. 2006. Abrupt climate change revisited. Global and Planetary Change, 54: 211-215.

Campelo, F. at al. 2006. Climatic significance of tree-ring width and intra-annual density fluctuations in Pinus Pinea from a dry Mediterranean area in Portugal. Ann. For. Sc. 64: 229-238.

Climate Change 2001: Impacts, Adaptation, and Vulnerability. 2001. Edited by McCarthy, J.J., Canziani, O.F., Leary, N.A., Dokken, D.J., and White, K.S. Press syndicate of the University of Cambridge, Cambridge, UK.

Cook, E.R. and Kairiuksis, L.A. (Eds). 1990. Chapter 6. The Statistics of Ring-Width and Climatic Data, Interational Institute for Applied Systems Analysis, the Netherlands.

Cook, E.R. and Peters, K. 1997. Calculating unbiased tree-ring indices for the study of climatic and environmental change. The Holocene, 7(3): 361-370.

Cook, E.R., Briffa, K.R., Meko, D.M., Graybill, D.A., and Funkhouser, G. 1995. The segment length curse in long tree-ring chronology development for paleoclimatic studies. The Holocene, 5(2): 229-237.

Cryer, J. 1986. Time series analysis. PWS publishers, USA.

Douglass, A.E. 1940. Tree-Ring Dates from the Foresdale Valley, East-Central Arizona. Tree-Ring Bulletin, 7(2).

Fritts, H.C. and Swetnam, T.W. 1989. Dendroecology: A Tool for evaluationg variations in past and present forest environments. Advanced Ecological Research, 19: 111-188.

Giorgi, F., Bi, X., and Pal, J.S. 2004. Mean, interannual variability and trends in a regional climate change experiment over Europe. I. Present-day climate (1961-1990). Climate Dynamics, 22: 733-756.

Helama, S., Lindholm, M., Timonen, M., and Eronen, M. 2004. Detection of climate signal in dendrochronological data analysis: a comparison of tree-ring standardization methods. Theor. Appl. Climatol., 79: 239-254.

Llasat, M.-C. and Quintas, L. 2004. Stationary of Monthly Rainfall Series since the Middle of the XIXth Century Application to the case of peninsular Spain. Kluwer Academic Publishers, The Netherlands.

Macias, M. et al. 2006. Increasing aridity is enhancing silver fir (*Abies Alba Mill.*) water stress in its south-western distribution limit. Climate Change, 79: 289-313.

Martin-Vide, J. and Lopez-Bustins, J.-A. 2006. The Western Mediterranean Oscillation and rainfall in the Iberian peninsula. Int. J. Climatol., 26: 1455-1475.

Methods of dendrochronology: applications in the environmental science. 1990. Edited by E. Cook and L. Kairiukstis. Kluwer Academic Publishers, Dordrecht, The Netherlands.

Morales, P. at al. 2005. Comparing and evaluating process-based ecosystem model predictions of carbon and water fluxes in major European forest biomes. Global Change Biology, 11: 2211-2233.

Norrant, C. and Douguédroit, A. 2006. Monthly and daily precipitation trends in the Mediterranean (1950-2000). Theor. Appl. Climatol., 83: 89-106.

Rodó, X., Baert, E. and Comin, F.A. 1997. Variations in seasonal rainfall in Southern Europe during the present century: relationships with the North Atlantic Oscillation and El Niño-Southern Oscilation. Climate Dynamics, 13: 275-284.

Romero, R., Guijarro, J.A., Ramis, C., and Alonso, S. 1998. A 30-year (1964-1993) daily rainfall data base for the Spanish Mediterranean regions: first exploratory study. International Journal of Climatology, 18: 541-560.

Schweingruber, F.H. 1988. Tree rings: bases and applications of dendrochronology. D. Reidel publishing company; Dordrecht, Holland.

Stahle, D.W. at al. 1998. Experimental Dendroclimatic Reconstruction of the Southern Oscillation. Bulletin of the American Meteorological Society, 79(10): 2137-2152.

Summer, G.N., Romero, R., Homar, V., Ramis, C., Alonso, S., and Zorita, E. 2003. An estimate of the effects of climate change on the rainfall of Mediterranean Spain by the late twenty first century. Climate Dynamics, 20: 789-805.

Strumia, G. 2005. Temperature variations of the last 700 years reconstructed from a tree-ring chronology of the Central Alps. Natura bresciana. Ann.Mus. Civ. Sc. Nat. Brescia, 34:41.

Tree rings, environment and humanity (Proceeding of the International Conference; Tucson, Arizona, 17-21 May 1994). 1996. Edited by Jeffrey S. Dean, David M. Meko; Thomas W. Swetnam. Radiocarbon, The University of Arizona, Tucson, Arizona, USA.

Wigley, T.M.L., Briffa, K.R. and Jones, P.D. 1984. On the Average Value of Correlated Time Series, with Applications in Dendroclimatology and Hydrometeorology. Journal of Climate and Apllied Meteorology, 23: 201-213.

Yamaguchi, D. 1990. A simple method for cross-dating increment cores from living trees. Can. J. For. Res., 21: 414-416.

ANNEX 1. Absent rings listed by series:

PEPN01LD 3 absent rings: 1924 1958 2005

PEPN01U1 6 absent rings: 1924 1958 1981 1986 2005 2006

PEPN03UR 2 absent rings: 1882 1924

PEPN04L1 1 absent rings: 2005

PEPN04R1 1 absent rings: 2005

PEPN05L1 1 absent rings: 1924

PEPN05U1 1 absent rings: 1924

PEPN06L1 1 absent rings: 1924

PEPN06U1 2 absent rings: 1924 2005

PEPN07L1 2 absent rings: 1920 1924

PEPN07L2 2 absent rings: 1920 1924

PEPN07R1 3 absent rings: 1920 1924 1986

PEPN08R1 8 absent rings: 1893 1896 1920 1924 1945 1949 1958 1965

PEPN08U1 14 absent rings: 1877 1882 1893 1896 1918 1919 1920 1923 1924 1938 1945 1948 1949 1958

PEPN09D1 2 absent rings: 1896 1924

PEPN09D2 2 absent rings: 1896 1924

PEPN09U1 2 absent rings: 1896 1924

PEPN11N1 3 absent rings: 1919 1924 2005

PEPN11S1 2 absent rings: 1896 1924

PEPN12L1 7 absent rings: 1807 1824 1882 1945 1958 1981 2005

PEPN12R1 12 absent rings: 1807 1882 1896 1898 1899 1925 1926 1945 1949 1958 1965 2005

PEPN13D1 5 absent rings: 1882 1893 1923 1949 1958

PEPN13U1 4 absent rings: 1807 1837 1882 2005

PEPN14D1 4 absent rings: 1824 1871 1882 1924

PEPN14U1 2 absent rings: 1882 1924

PEPN15U1 4 absent rings: 1882 1896 1924 1945

PEPNG1LD 3 absent rings: 1924 1958 2005

PEPNG1U1 5 absent rings: 1924 1949 1958 1981 1986

PEPNG3UL 1 absent rings: 1882

PEPNG3UR 2 absent rings: 1882 1924

107 absent rings 1.532%

ANNEX 2. Time spine of the sampled cores.

```
1750 1800 1850 1900 1950 2000 2050 Ident   Seq Time-span  Yrs
   :    :    :    :    :    :    :    :    :    :    :    :    :
  .    . <=================>    . PEPN01LD   1 1820 2006  187
  .    . <=================>    . PEPN01U1   2 1820 2007  188
  .    .  <================>    . PEPN02L1   3 1833 2007  175
  .    .  <================>    . PEPN02U1   4 1833 2007  175
  .    .  <================>    . PEPN03UL   5 1835 2007  173
  .    .<==================>    . PEPN03UR   6 1818 2007  190
  .    .   <===============>    . PEPN04L1   7 1844 2007  164
  .    .    <==============>    . PEPN04R1   8 1855 2007  153
  .    .<==================>    . PEPN05L1   9 1818 2007  190
  .    .    .<=============>    . PEPN05U1  10 1860 2007  148
  .    .    .<=============>    . PEPN06L1  11 1869 2007  139
  .    .  <================>    . PEPN06U1  12 1830 2007  178
  .    .  <================>    . PEPN07L1  13 1830 2007  178
  .   <====================>    . PEPN07L2  14 1792 2007  216
  .    .<==================>    . PEPN07R1  15 1812 2007  196
  <========================>    . PEPN08R1  16 1756 2007  252
  . <======================>    . PEPN08U1  17 1776 2006  231
  .    .    . <============>    . PEPN09D1  18 1871 2007  137
  .    .<==================>    . PEPN09D2  19 1815 2007  193
  .    . <=================>    . PEPN09U1  20 1821 2007  187
  .    .    .<=============>    . PEPN10N1  21 1868 2007  140
  .    .    .<=============>    . PEPN10S1  22 1868 2007  140
  .    .   <===============>    . PEPN11N1  23 1840 2007  168
  .    .   <===============>    . PEPN11S1  24 1840 2007  168
  <========================>    . PEPN12L1  25 1753 2007  255
  <========================>    . PEPN12R1  26 1753 2007  255
  . <======================>    . PEPN13D1  27 1778 2007  230
  . <======================>    . PEPN13U1  28 1778 2007  230
  . <======================>    . PEPN14D1  29 1770 2007  238
  . <=================>    .    . PEPN14U1  30 1770 1952  183
  .    .<==========>  .    .    . PEPN15D1  31 1817 1921  105
  .    . <=================>    . PEPN15U1  32 1821 2007  187
```

ANNEX 3. Master Bar Plot

15:41 Wed 12 Sep 2007

Year Rel value	Year Rel value	Year Rel value	Year Rel value	Year Rel value	Year Rel value
	1800-------B	1850----------F	1900-e	1950--c	2000----------E
	1801--------C	1851-d	1901--c	1951------A	2001-------B
	1802---------D	1852--b	1902--------C	1952--------C	2002---a
1753------B	1803-d	1853---a	1903---------D	1953--b	2003---------D
1754-d	1804-----@	1854----------E	1904----------E	1954--------C	2004-------B
1755m	1805--b	1855----a	1905---------D	1955---------D	2005o
1756--b	1806------A	1856---------C	1906---a	1956---------D	2006--c
1757-----A	1807j	1857--b	1907-c	1957-----A	2007------A
1758--------C	1808-e	1858---a	1908---a	1958n	
1759--------C	1809-------B	1859----------H	1909-d	1959-----@	
1760---------D	1810---------D	1860--b	1910------B	1960----------G	
1761----------F	1811----@	1861---b	1911-------B	1961---------D	
1762------B	1812---a	1862------A	1912-------B	1962---a	
1763----------E	1813----@	1863--------C	1913---a	1963------A	
1764--------C	1814---------D	1864-d	1914---------C	1964---------C	
1765---------C	1815----------E	1865---a	1915---------D	1965j	
1766-d	1816-------B	1866--c	1916---------D	1966----@	
1767---a	1817-------B	1867-------B	1917-----A	1967---a	
1768---a	1818------A	1868---a	1918--------C	1968-----@	
1769-f	1819------A	1869---------C	1919---a	1969------A	
1770g	1820--------C	1870-d	1920---a	1970--c	
1771-d	1821----------E	1871-----@	1921----@	1971------B	
1772-------B	1822-e	1872---------D	1922-----A	1972---------D	
1773-----@	1823---b	1873-------B	1923—b	1973--b	
1774---a	1824f	1874g	1924k	1974---------C	
1775-----A	1825----@	1875---a	1925-e	1975------B	
1776-----@	1826--------C	1876--b	1926-c	1976-f	
1777--------C	1827--------C	1877--------C	1927------A	1977----------F	
1778---------C	1828-e	1878-c	1928----@	1978--------C	
1779------A	1829------B	1879-e	1929--b	1979------A	
1780--b	1830-c	1880---------D	1930------B	1980--b	
1781----------F	1831----@	1881----@	1931—b	1981--c	
1782i	1832----@	1882l	1932----------F	1982-------B	
1783--b	1833-----A	1883-------B	1933------A	1983-----@	
1784--------C	1834---------D	1884--------C	1934--b	1984-----A	
1785-------B	1835-----@	1885---------D	1935--------C	1985------B	
1786--b	1836----------E	1886---------D	1936--------C	1986-f	
1787---a	1837-e	1887------B	1937-------B	1987--c	
1788------B	1838---------C	1888---------D	1938--b	1988----@	
1789------B	1839h	1889---------D	1939----------H	1989--b	
1790----@	1840----@	1890-----@	1940----------G	1990-----@	
1791----------H	1841---a	1891--------C	1941-------B	1991k	
1792h	1842-c	1892-----@	1942--b	1992-------B	
1793----@	1843------A	1893k	1943----@	1993---a	
1794---------D	1844----@	1894-------B	1944----@	1994---a	

1795-------C 1845--------C 1895------B 1945k 1995--------C

1796-----A 1846---------D 1896i 1946----@ 1996-------B

1797--c 1847----@ 1897---a 1947---a 1997-------B

1798--b 1848----@ 1898---a 1948----@ 1998------B

1799----@ 1849----a 1899----@ 1949k 1999---------E

ANNEX 4 . COFECHA Analysis output

Correlation with master series (in lags of 50 years, overlapped 25 years)

1	PEPN01LD	1820	2006			.66	.69	.74	.72	.82	.88	.82	.83
2	PEPN01U1	1820	2007			.77	.78	.91	.88	.89	.90	.66	.67
3	PEPN02L1	1833	2007				.63	.87	.85	.84	.90	.83	.84
4	PEPN02U1	1833	2007				.48	.69	.77	.89	.90	.82	.87
5	PEPN03UL	1835	2007				.84	.88	.86	.87	.91	.81	.85
6	PEPN03UR	1818	2007			.78	.82	.90	.87	.84	.87	.79	.85
7	PEPN04L1	1844	2007				.73	.69	.76	.76	.80	.76	.73
8	PEPN04R1	1855	2007					.75	.81	.76	.85	.75	.75
9	PEPN05L1	1818	2007			.73	.74	.75	.76	.76	.87	.82	.86
10	PEPN05U1	1860	2007					.75	.79	.83	.91	.83	.85
11	PEPN06L1	1869	2007					.31A	.29A	.72	.92	.87	.88
12	PEPN06U1	1830	2007				.73	.82	.76	.75	.79	.73	.76
13	PEPN07L1	1830	2007				.88	.92	.89	.88	.89	.79	.81
14	PEPN07L2	1792	2007		.77	.82	.83	.83	.87	.89	.90	.78	.82
15	PEPN07R1	1812	2007			.83	.88	.89	.89	.90	.92	.74	.80
16	PEPN08R1	1756	2007	.54	.56	.65	.78	.79	.72	.72	.66	.71	.76
17	PEPN08U1	1776	2006		.70	.76	.72	.69	.59	.56	.70	.75	.83
18	PEPN09D1	1871	2007					.65	.72	.88	.86	.81	.85
19	PEPN09D2	1815	2007			.43	.74	.77	.76	.85	.86	.80	.83
20	PEPN09U1	1821	2007			.66	.73	.83	.82	.78	.80	.81	.82
21	PEPN10N1	1868	2007					.77	.72	.72	.85	.77	.81
22	PEPN10S1	1868	2007					.82	.77	.71	.83	.74	.78
23	PEPN11N1	1840	2007				.76	.81	.79	.83	.94	.90	.90
24	PEPN11S1	1840	2007				.71	.71	.66	.72	.89	.84	.88
25	PEPN12L1	1753	2007	.78	.81	.86	.92	.84	.76	.82	.85	.83	.83
26	PEPN12R1	1753	2007	.75	.89	.88	.89	.85	.74	.73	.74	.65	.68
27	PEPN13D1	1778	2007		.86	.87	.80	.71	.60	.65	.78	.78	.85
28	PEPN13U1	1778	2007		.75	.72	.82	.83	.75	.75	.87	.83	.83
29	PEPN14D1	1770	2007	.76	.79	.81	.63	.57	.64	.68	.73	.70	.77
30	PEPN14U1	1770	1952	.71	.75	.79	.75	.79	.72	.73	.74		
31	PEPN15D1	1817	1921			.74	.71	.83	.75				
32	PEPN15U1	1821	2007			.46	.53	.60	.43	.27B	.35	.49	.61
33	PEPNG1LD	1822	2007			.74	.77	.78	.72	.83	.92	.80	.81
34	PEPNG1U1	1819	2007			.78	.81	.91	.86	.83	.87	.66	.47
35	PEPNG2U1	1836	2007				.68	.80	.85	.83	.89	.83	.87
36	PEPNG2UL	1839	2007				.57	.77	.82	.89	.91	.85	.86
37	PEPNG3UL	1824	1989			.76	.78	.89	.85	.85	.93	.82	
38	PEPNG3UR	1837	1989				.77	.82	.79	.83	.87	.84	
	Av segment correlation			.71	.77	.74	.75	.78	.75	.78	.84	.78	.80

Unfiltered --------\\ //---- Filtered -----

Seq	Series	Interval		No. Years	No. Segmt	No. Flags	with Master	Mean msmt	Max msmt	Std dev	Auto corr	Mean sens	Max value	Std dev	Auto corr	AR ()
1	PEPN01LD	1820	2006	187	8	0	.786	.65	2.67	.401	.764	.392	2.48	.385	-.043	1
2	PEPN01U1	1820	2007	188	8	0	.804	.59	1.89	.441	.836	.453	2.43	.350	-.020	1
3	PEPN02L1	1833	2007	175	7	0	.797	.67	1.40	.234	.447	.299	2.67	.468	-.029	2
4	PEPN02U1	1833	2007	175	7	0	.772	.75	1.44	.260	.534	.279	2.76	.453	-.012	3
5	PEPN03UL	1835	2007	173	7	0	.847	.97	2.34	.504	.629	.409	2.56	.403	-.016	2
6	PEPN03UR	1818	2007	190	8	0	.846	.74	1.98	.376	.675	.401	2.69	.473	-.024	1
7	PEPN04L1	1844	2007	164	7	0	.751	1.22	2.97	.573	.568	.366	2.63	.453	-.021	2
8	PEPN04R1	1855	2007	153	6	0	.773	1.03	2.59	.437	.513	.358	2.49	.325	-.011	1
9	PEPN05L1	1818	2007	190	8	0	.774	.85	2.08	.449	.673	.361	2.48	.297	.018	1
10	PEPN05U1	1860	2007	148	6	0	.807	.86	1.96	.447	.662	.353	2.60	.390	-.043	1
11	PEPN06L1	1869	2007	139	6	2	.716	.93	4.41	.660	.701	.375	2.82	.448	-.030	1
12	PEPN06U1	1830	2007	178	7	0	.763	.81	2.67	.515	.731	.390	2.62	.329	-.009	1
13	PEPN07L1	1830	2007	178	7	0	.854	.55	1.73	.285	.587	.437	2.70	.444	-.040	1
14	PEPN07L2	1792	2007	216	9	0	.809	.69	2.86	.451	.764	.402	2.75	.533	-.046	1
15	PEPN07R1	1812	2007	196	8	0	.816	.70	2.31	.396	.645	.446	2.63	.434	-.006	1
16	PEPN08R1	1756	2007	252	10	0	.743	.67	3.37	.634	.901	.459	2.58	.375	-.043	2
17	PEPN08U1	1776	2006	231	9	0	.739	.43	2.29	.446	.872	.500	2.57	.417	-.012	1
18	PEPN09D1	1871	2007	137	6	0	.776	.61	1.31	.275	.524	.406	2.51	.314	.023	2
19	PEPN09D2	1815	2007	193	8	0	.707	.67	2.19	.345	.644	.383	2.50	.340	.000	1
20	PEPN09U1	1821	2007	187	8	0	.751	.68	1.91	.324	.647	.380	2.44	.275	.004	1
21	PEPN10N1	1868	2007	140	6	0	.761	.84	2.45	.369	.390	.415	2.56	.345	-.037	1
22	PEPN10S1	1868	2007	140	6	0	.785	.73	1.68	.304	.403	.411	2.72	.496	-.037	3
23	PEPN11N1	1840	2007	168	7	0	.823	.75	1.97	.410	.677	.419	2.55	.404	-.023	1
24	PEPN11S1	1840	2007	168	7	0	.796	.70	1.87	.330	.561	.432	2.68	.418	.017	3
25	PEPN12L1	1753	2007	255	10	0	.811	.51	2.74	.436	.821	.499	2.61	.320	-.023	1

26	*PEPN12R1*	*1753*	*2007*	*255*	*10*	*0*	*.798*	*.46*	*1.55*	*.323*	*.699*	*.515*	*2.62*	*.399*	*-.020*	*1*
27	*PEPN13D1*	*1778*	*2007*	*230*	*9*	*0*	*.809*	*.45*	*2.46*	*.319*	*.576*	*.523*	*2.82*	*.452*	*-.058*	*1*
28	*PEPN13U1*	*1778*	*2007*	*230*	*9*	*0*	*.823*	*.51*	*1.57*	*.266*	*.443*	*.496*	*2.66*	*.443*	*-.061*	*1*
29	*PEPN14D1*	*1770*	*2007*	*238*	*10*	*0*	*.716*	*.64*	*2.23*	*.366*	*.691*	*.412*	*2.66*	*.434*	*.016*	*1*
30	*PEPN14U1*	*1770*	*1952*	*183*	*8*	*0*	*.771*	*.74*	*3.61*	*.533*	*.731*	*.437*	*2.81*	*.474*	*.035*	*1*
31	*PEPN15D1*	*1817*	*1921*	*105*	*4*	*0*	*.735*	*.88*	*3.26*	*.558*	*.585*	*.467*	*2.69*	*.455*	*-.001*	*1*
32	*PEPN15U1*	*1821*	*2007*	*187*	*8*	*1*	*.577*	*.81*	*2.50*	*.597*	*.773*	*.437*	*2.75*	*.388*	*-.038*	*1*
33	*PEPNG1LD*	*1822*	*2007*	*186*	*8*	*0*	*.817*	*.64*	*1.67*	*.365*	*.682*	*.416*	*2.43*	*.368*	*-.027*	*1*
34	*PEPNG1U1*	*1819*	*2007*	*189*	*8*	*0*	*.752*	*.58*	*2.82*	*.455*	*.793*	*.460*	*2.45*	*.313*	*-.023*	*1*
35	*PEPNG2U1*	*1836*	*2007*	*172*	*7*	*0*	*.816*	*.84*	*2.21*	*.400*	*.715*	*.302*	*2.52*	*.375*	*-.002*	*1*
36	*PEPNG2UL*	*1839*	*2007*	*169*	*7*	*0*	*.796*	*.81*	*2.16*	*.330*	*.613*	*.296*	*2.71*	*.395*	*-.003*	*1*
37	*PEPNG3UL*	*1824*	*1989*	*166*	*7*	*0*	*.825*	*.97*	*2.82*	*.482*	*.571*	*.400*	*2.77*	*.462*	*.038*	*1*
38	*PEPNG3UR*	*1837*	*1989*	*153*	*6*	*0*	*.823*	*.69*	*1.70*	*.336*	*.614*	*.416*	*2.54*	*.370*	*-.013*	*1*

--- -------- --------- ----- ----- ----- ------ ----- ----- ----- ----- ----- ----- ----- ----- --

Total or mean: 6984 287 3 .781 .71 4.41 .410 .660 .416 2.82 .400 -.017

- = [COFECHA PEP25COF] = -

ANNEX 5. ARSTAN outputs

[] P R O G R A M   A R S T A N

Version 6.05P 26555

PROGRAM ARSTAN : Summary of chronology statistics [13Sep07-0834]

Chronology time span 1753 to 2007 255 years 3 trees 38 radii

Chronology type	STNDRD	RESID (AR 1)	ARSTAN
Mean	.9863	.9966	.9919
Median	.9820	.9875	.9792
Mean sensitivity	.3179	.3491	.3057
Standard deviation	.2986	.2874	.2952
Skewness	.0072	-.0692	.0050
Kurtosis	1.3019	1.3183	1.0208
Autocorrelation order 1	.2715	-.0113	.2763
Partial autocorr order 2	.0321	-.0933	-.0578
Partial autocorr order 3	.0998	.0455	.0881

Common interval time span 1872 to 2006 135 years 3 trees 34 radii

Mean correlations:	Detrended series	Residuals (white noise)
Among all radii	.557	.609
Between trees (Y variance)	.549	.597
Within trees	.567	.625
Radii vs mean	.752	.780
Signal-to-noise ratio	3.645	4.435
Agreement with population chron	.785	.816
Variance in first eigenvector	57.51%	62.62%
Chron common interval mean	.981	.990
Chron common interval std dev	.330	.308

ANNEX 6. Tables for p-values and cross-correlations of TRW data with climate data.

1. TRW versa T annual mean Pallars

lag	correlation	p-value
-27	0,20462	0,29664
-26	0,043479	0,82286
-25	-0,10288	0,58868
-24	0,0091197	0,96118
-23	0,15382	0,40083
-22	0,23865	0,18139
-21	0,069777	0,69505
-20	0,087344	0,61794
-19	0,10435	0,54486
-18	-0,020903	0,90229
-17	-0,21251	0,20046
-16	-0,07482	0,65085
-15	0,018485	0,90988
-14	0,046183	0,77437
-13	0,038105	0,81068
-12	0,020012	0,89866
-11	0,17214	0,26401
-10	0,15376	0,31337
-9	0,18817	0,21061
-8	0,039352	0,79287
-7	0,31288	0,030478
-6	0,25355	0,078907
-5	0,077873	0,59095
-4	-0,024197	0,86617
-3	0,12135	0,39154
-2	0,22468	0,1059
-1	0,15375	0,26708
0	0,18206	0,18352
1	0,1686	0,22306
2	0,3529	0,0095977
3	0,23642	0,091649
4	0,27547	0,050517
5	0,25437	0,074786
6	0,52974	9,33E-05
7	0,58111	1,55E-05
8	0,20445	0,1682
9	0,14558	0,33448
10	-0,0025474	0,98675
11	0,15833	0,3048
12	0,096554	0,53803
13	0,076629	0,62964

2. TRW versa annual PREC. Pallars

lag	correlation	p-value
-27	0,003535	0,98576
-26	0,40004	0,031865
-25	-0,09484	0,61827
-24	0,014413	0,93868
-23	-0,06512	0,72336
-22	-0,154	0,39241
-21	0,052853	0,76663
-20	0,058844	0,73711
-19	-0,062495	0,71735
-18	-0,034257	0,84051
-17	-0,082297	0,62337
-16	-0,076299	0,6444
-15	0,046364	0,77638
-14	-0,20737	0,19347
-13	-0,022117	0,88945
-12	0,045913	0,77005
-11	-0,12946	0,4024
-10	0,077734	0,61183
-9	0,066694	0,65971
-8	0,11246	0,45178
-7	-0,14533	0,32445
-6	-0,37124	0,0086945
-5	0,040526	0,77994
-4	0,090888	0,52595
-3	-0,20167	0,15179
-2	-0,26334	0,056865
-1	-0,27945	0,040809
0	0,063906	0,64302
1	0,039399	0,77731
2	-0,2926	0,033586
3	0,022254	0,87558
4	0,056187	0,69538
5	0,16142	0,26287
6	-0,17131	0,23935
7	-0,39812	0,0051177
8	0,057654	0,70033
9	-0,0022202	0,98832
10	-0,12102	0,42852
11	-0,10398	0,50186
12	-0,0055671	0,97174
13	0,19019	0,22785

14	-0,03585	0,82394	14	0,14489	0,36624
15	-0,0353	0,82883	15	-0,023393	0,88609
16	0,26626	0,10157	16	0,020197	0,90289
17	0,024755	0,88274	17	0,21534	0,19438
18	0,21766	0,19587	18	0,24153	0,15008
19	0,37421	0,024739	19	0,041155	0,81168
20	0,11606	0,5069	20	0,20879	0,22899
21	0,17129	0,33298	21	0,27972	0,10942
22	0,138	0,44395	22	0,18536	0,302
23	0,34742	0,051697	23	0,086147	0,63933
24	0,28897	0,11526	24	-0,035861	0,84816
25	0,34107	0,065495	25	0,083289	0,66182
26	0,14175	0,4635	26	0,047328	0,80746
27	0,030098	0,87921	27	0,25477	0,19122