Mediterranean Forests in Transition (MEDIT): Deliverable No1

Title: Report on the results of the tree-rings meta-analysis

Due to Project Month 6, Date: 30/09/2012

Introduction

This manuscript summarises the work done during the first 6 months of the Medit Project, dealing in particular with the tree-rings database developed and analysed within component C1 ("Literature Review and Metadata Collection"). This report summarises the development and analysis of the tree-rings database. An accompanying report (Deliverable No2) summarises the functional traits dataset development and meta-analysis.

Within Deliverable No1 I have gathered and analysed tree-rings data from 512 sites across Europe (Fig. 1). These data are publicly available at Tree-Ring Data portal.

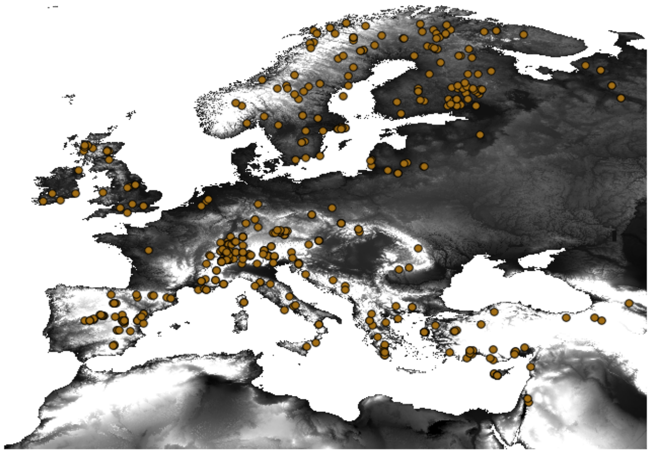

Figure 1: Spatial extent of the tree rings data gathered and analysed in Deliverable 1

I selected tree species with a wide distribution, commonly found in Greece and Europe. The aim of this data meta-analysis is to derive optimum-growth functions to be used in the small scale GREFOS vegetation dynamics model (Fyllas et al. 2007, 2010). I expect that using this data constrained model developments an improvement of the predictive ability of the model will be achieved.

Methods

Data from the Tree Rings Data Portal

The 13 tree taxa included in this analysis are mainly coniferous species. Table 1 summarises the species of interest and the number of sites that were found. *Pinus sylvestris and Picea abies* are the most common species found in the tree rings dataset, found in more than half of the study sites.

Within the 13 taxa *A.cephalonica, F. Sylvatica, P brutia, P halepensis, P nigra* and *Q frainetto* are the ones most commonly found in Greece. For these species however there was a limited number of sites where tree rings data were available, identifying the need for additional sampling as envisaged in MEDIT.

Species	No Sites
Abies alba	53
Abies borisii-regis	1
Abies cephalonica	5
Fagus sylvatica	3
Picea abies	125
Pinus brutia	14
Pinus halepensis	2
Pinus leucodermis	4
Pinus nigra	61
Pinus pinea	7
Pinus sylvestris	225
Quercus frainetto	1
Quercus petraea	11

Statistical Analysis

The main aim of this meta-analysis was to fit optimum growth curves for each one of the 13 species of interest. Optimum growth curves are defined here as the radial increment (as a function of diameter at breast height [*dbh*]) that an individual of a species would achieve given no limitation due to competition or resource availability. An optimum growth model has been proposed and used by Zeide (1993) and it is described by the equation:

$$g = G_{opt}\, e^{-\frac{1}{2}\left\{\frac{\log(dbh/D_0)}{D_b}\right\}} \quad (1)$$

Where g is the optimum growth an individual of size (*dbh*) can achieve, G_{opt} the maximum value of g during the lifetime of an individual of a species, D_o the *dbh* at which G_{opt} is achieved and D_b the shape parameter of the curve. For each one of the 512 sites I estimated the population level G_{opt}, D_0 and D_b parameters. Furthermore the 13 spp were classified to a successional status (S) (i.e. 1 early successional, 2 mid successional, 3 late successional) based on the forestry literature. Based on the successional status of the species I explored for potential differences of the three growth curve estimates using ANOVA.

A second step was to try to explore the variation of the three optimum growth parameters based on the long-term climatic profile of each region, in order to identify potential systematic variation of species specific optimum growth curves with climate. For each site I extracted long term climatic parameters from the Worldclim database at a spatial resolution of approximate 1km http://www.worldclim.org/. I then used Pearson's full and partial correlation coefficients to identify potential relationships between the optimum growth curve parameters and key climate variables. As most climatic parameters are usually intercorellated, I also used a partial-correlation analysis, in order to control for potential intercorrelations.

All analysis and graphs were performed with the R statistical language (R Development Core Team, 2012).

Results

Table 2 summarises the growth curve estimates for the species of interest. These estimates will be used to re-parameterise the growth algorithm of the GREFOS v2 model.

Species	G_{opt}	D_0	D_b	S
Abies alba	1.11	8.1	2.1	3
Abies borisii	1.15	8.5	2.1	3
Abies cephalonica	1.21	7.5	1.6	2
Fagus sylvatica	0.93	14.2	2.1	3
Picea abies	1.02	14.4	2.3	2
Pinus brutia	1.40	4.9	1.4	1
Pinus halepensis	1.43	7.4	1.5	1
Pinus leucodermis	0.97	5.1	2.0	2
Pinus nigra	1.25	4.3	1.7	1
Pinus pinea	1.59	10.8	0.6	1
Pinus sylvestris	0.96	9.8	2.0	2
Quercus frainetto	1.07	1.1	2.1	2
Quercus petraea	0.65	4.8	1.9	3

Table 2. Mean values of the growth curve coefficients estimates across all study site of a species occurrence

Figure 2 summarises the differences in G_{opt}, D_0 and D_b between the three successional status groups. The mean G_{opt} estimate was higher for early successional species (F=21.81, p<0.001) with a posthoc Tukey HSD test identifying no difference between mid and late successional species. No statistical difference was identified for D_0 between the three successional statud groups (F=2.604, p=0.08), while D_b was lower in early successional species (F=8.813, p<0.001) with a posthoc Tukey HSD test identifying no difference between mid and late successional species.

Figure 2: Boxplots of G_{opt}, D_0 and D_b between the three successional status groups. Early successional species (1) seem to achieve a higher G_{opt} compared with mid (2) and late successional (3) species. Furthermore the width of the growth curve seesm to be smaller for early successional species compared with the mid and late succcessional groups.

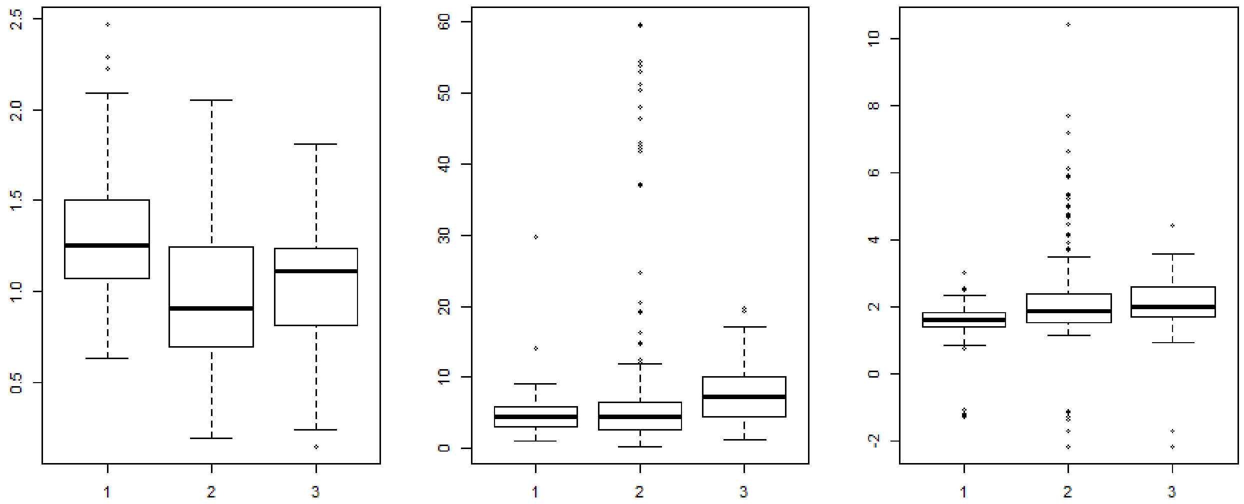

Table 3 summarises the Pearson's correlation coefficients between G_{opt} and the altitude, average annual temperature and total annual precipitation of the site. For 5 out of 11 tree species a positive correlation between mean annual temperature and G_{opt} were identified, leading to higher optimum growth rates in warmer environments. Precipitation was not a significant predictor of G_{opt} in most cases. These results are also visualised in Figure 3.

Table 3. Pearson's correlation coefficients between G_{opt} and the altitude, mean annual temperature and annual precipitation of the site.

	Altitude	p	Temperature	p	Precipitation	p	N(sites)
Abies alba	**-0.424**	0.003	**0.383**	0.007	-0.112	0.447	48
Abies cephalonica	***-0.861***	0.061	**0.869**	0.056	-0.420	0.482	5
Fagus sylvatica	0.170	0.891	0.344	0.777	0.949	0.204	3
Juniperus excelsa	-0.112	0.857	0.247	0.688	0.692	0.195	5
Picea abies	**-0.269**	0.005	**0.467**	0.000	***-0.177***	0.064	110
Pinus brutia	-0.384	0.176	-0.010	0.972	0.013	0.965	14
Pinus leucodermis	0.204	0.796	-0.149	0.851	0.868	0.132	4
Pinus nigra	**-0.318**	0.015	**0.444**	0.000	-0.084	0.532	58
Pinus pinea	-0.690	0.129	0.638	0.172	0.544	0.265	6
Pinus sylvestris	0.116	0.108	**0.249**	0.000	0.083	0.253	192
Quercus petraea	0.498	0.172	-0.097	0.804	-0.173	0.657	9

Figure 3: Scatterplots of optimum growth rate and mean annual temperature. Statistically significant positive correlations were identified for *A. alba*, *A. cephalonica*, *P. abies*, *P. nigra* and *P. sylvestris*.

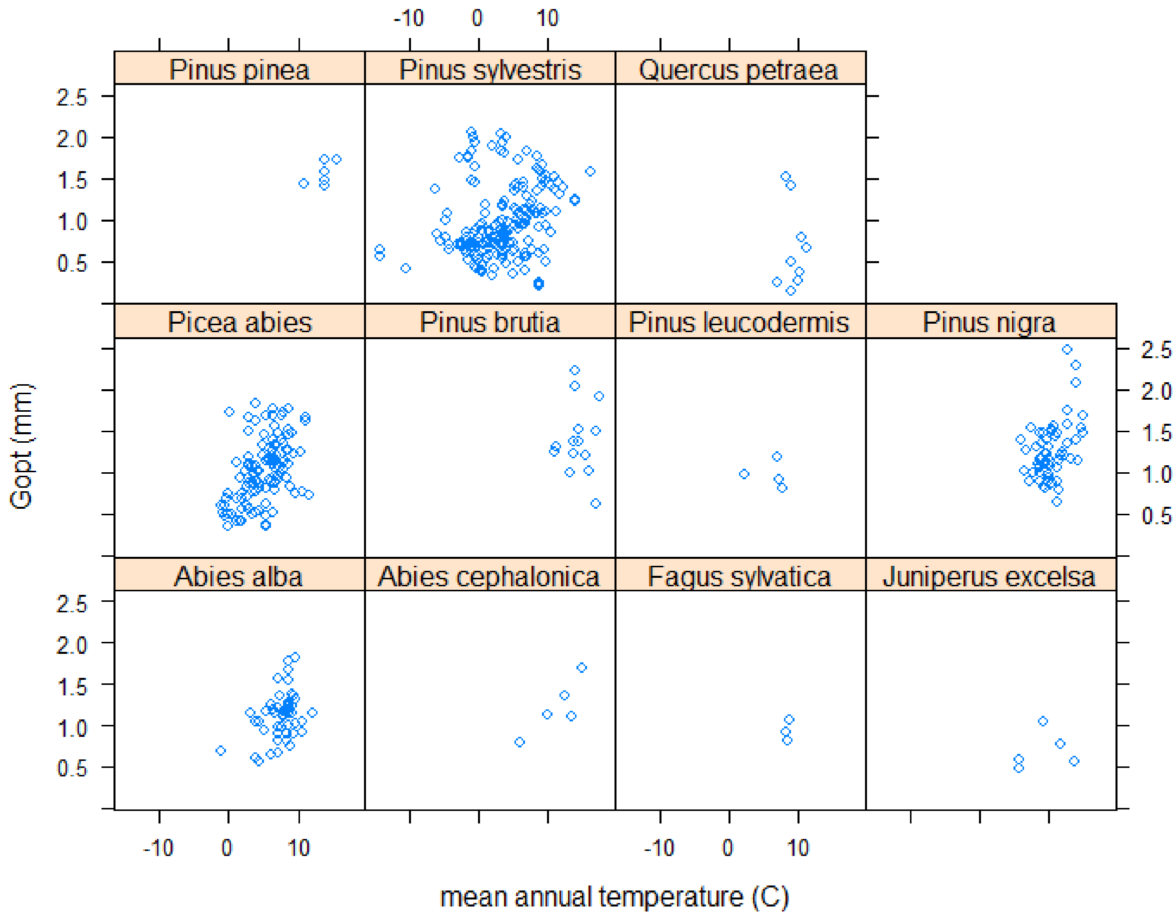

Table 4 summarises the Pearson's partial correlation coefficients between the three optimum growth curve parameters and some important climatic parameters. GDD stands for Growing Degree Days, a measure of thermal energy availability of a site. SPI stands for Standard Precipitation Index a measure designed to enhance the detection of onset and monitoring of drought (Guttman 1999). Site specific calculation of SPI were made using data from the Climate Research Unit (CRU_ts3) covering the period 1901-2009 at 0.5^{o} spatial resolution (http://www.cru.uea.ac.uk/cru/data/hrg/). As expected a smaller amount of statistically significant correlations are identified in this analysis, which takes into account potential intercorrelations between the climatic variables.Temperature remained a strong predictor of G_{opt} for *P. abies* and *P. nigra*.

Table 4. Pearson's partial correlation coefficients between the optimum growth curve parameters and the long term(1901-2009)climate parameters of a site

	Parameter	G_{opt}	D_0	D_b
Abies alba	Temp	-0.03	-0.15	**0.30**
	Prec	-0.11	-0.11	0.09
	GDD	0.07	0.10	-0.30
	SPI	-0.14	0.11	-0.25
Picea abies	Temp	**0.40**	**0.21**	0.05
	Prec	**-0.31**	**-0.21**	-0.10
	GDD	**-0.29**	-0.19	-0.07
	SPI	-0.13	0.01	**0.20**

Pinus brutia	Temp	0.49	-0.56	-0.36
	Prec	-0.03	0.54	-0.19
	GDD	-0.50	0.57	0.30
	SPI	-0.33	0.40	0.59
Pinus nigra	Temp	**0.30**	0.18	-0.12
	Prec	0.05	-0.02	-0.02
	GDD	-**0.32**	**-0.20**	0.15
	SPI	0.21	0.03	-0.27
Pinus sylvestris	Temp	0.08	0.01	0.04
	Prec	0.06	-0.05	-0.07
	GDD	0.01	-0.03	-0.08
	SPI	0.01	-0.01	-0.03
Quercus petraea	Temp	-0.41	**-0.97**	-0.65
	Prec	0.42	0.25	0.16
	GDD	0.62	**0.97**	0.83
	SPI	0.55	0.69	0.28

Conclusions

By developing and analyzing the tree-rings data base we managed to calculate data constrained coefficients for the optimum growth curve. These estimates are expected to lead to a more accurate model performance. The next step is to use the new species specific growth curves in GREFOS v2 and simulate the dynamics of the most dominant forest types in Greece.

Furthermore I identified data gaps-in terms of tree-rings availability for the dominant forest types in Greece. In particular there is an urgent need of tree rings data for the following species*: A. cephalonica, F. sylvatica, P. halepensis, Q. frainetto, Q. cerris.* I expect to cover this need with fieldwork envisaged in C4 of the Medit project.

References

Fyllas, N.M., Phillips, O.L., Kunin, W.E., Matsinos, Y.G., Troumbis, A.I., 2007. Development and parameterization of a general forest gap dynamics simulator for the North-eastern Mediterranean Basin (GREek FOrest Species). Ecological Modelling 204, 439–456.

Fyllas, N.M., Politi, P.I., Galanidis, A., Dimitrakopoulos, P.G., Arianoutsou, M., 2010. Simulating regeneration and vegetation dynamics in Mediterranean coniferous forests. Ecological Modelling 221, 1494–1504.

Guttman, N.B., 1999. Accepting the Standardized Precipitation Index: A Calculation Algorithm1. JAWRA Journal of the American Water Resources Association 35, 311–322.

R Development Core Team, 2012. R: A language and environment for statistical computing R Foundation for Statistical Computing, Vienna Austria. ISBN 3-900051-07-0, URL http://www.R-project.org.

Zeide, B., 1993. Analysis of Growth Equations. Forest Science 39, 594–616.