

# Were there significant changes in the overall condition of the CONECOFOR plots over the 1995 -2005 period?

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*Accepted 08 February 2008*

**Abstract** – Since 1995 the CONECOFOR programme is collecting data on a number of attributes of forest ecosystems in 20 permanent plots in Italy. In this paper, different multivariate methods were used to detect possible changes and deviations in the overall biological and chemical-physical status of the CONECOFOR plots as compared to defined reference periods. The reference periods were set-up taking into account the data availability and were as follows: 1997-1999 for biological status; 1999-2002 for chemical-physical status. Changes of the biological conditions of the plots were identified only in a few cases over the period 2000 - 2004 and were due to low values in transparency and basal area increment of the intermediate and dominated layer. On the other hand, several changes were detected in relation to the chemical and physical status over the period 2003-2005. Some few regularities were identified: (i) change/deviations concentrated on few plots; (ii) high ozone (O<sub>3</sub>), low sulphur deposition and low precipitation were the attributes more consistently related to changes/deviations; (iii) most deviations were due to changes in the correlation structure of the attributes; and (iv) there is no consistent timing of change/deviations among plots. These findings emphasise the need to evaluate the data at the plot level and this indicate the importance of obtaining a time series long enough to enable plot-wise integrated analysis.

**Key words:** *permanent plots, Italy, change, deviations, Mahalanobis, PARAFAC, Hotelling T<sup>2</sup>, Square Prediction Error.*

**Riassunto** – Ci sono stati cambiamenti significativi nelle condizioni complessive delle aree CONECOFOR nel periodo 1995-2005? Ormai dal 1995 il programma CONECOFOR sta raccogliendo dati su numerosi attributi degli ecosistemi forestali presso 20 aree permanenti localizzate in tutta Italia. In questo articolo, vengono utilizzati diversi metodi multivariati per identificare possibili cambiamenti e deviazioni nel complessivo stato biologico e chimico-fisico delle aree di osservazione in relazione a definiti periodi di riferimento. I periodi di riferimento sono stati definiti in relazione alla disponibilità dei dati e sono: 1997-1999 per lo stato biologico e 1999-2002 per lo stato chimico-fisico. Solo poche aree hanno mostrato cambiamenti nello stato biologico nel periodo 2000-2004, generalmente causato da bassi valori di trasparenza e di accrescimento negli strati intermedi e dominato. Invece sono stati riscontrati numerosi casi di cambiamento/deviazione dello stato chimico-fisico per il periodo 2003-2005. Sono state identificate alcune regolarità: (i) i cambiamenti/deviazioni sono risultati concentrati su poche aree; (ii) gli attributi più frequentemente e coerentemente coinvolti sono risultati alti livelli di ozono e bassi valori di precipitazione e deposizione di zolfo; (iii) in genere, le deviazioni rilevate sono dovute a cambiamenti nella struttura delle correlazioni; (iv) non esiste una coerenza temporale nell'accadimento di cambiamenti e deviazioni. Questi risultati enfatizzano la necessità di valutare i dati a livello di area ed indicano quindi l'importanza di ottenere serie di dati sufficientemente lunghe per permettere analisi integrate per ciascuna area.

**Parole chiave:** *aree permanenti, Italia, cambiamento, deviazioni, Mahalanobis, PARAFAC, Hotelling T<sup>2</sup>, Square Prediction Error.*

*F.D.C. 524. 634: 180 -- 05: (450)*

## Introduction

Since 1995, the intensive monitoring programme CONECOFOR is collecting data about several ecosystem's attributes on 20 permanent plots scattered throughout Italy. This offers the chance to evaluate if, and at what extent, changes have occurred in the status of these plots. There are three questions of interest when assessing changes occurring in forest

ecosystems over time: (i) changes in individual attributes, (ii) changes in the "overall status" of the plot (see below), and (iii) deviation from expected changes due to "common-cause" variation. As for question (i), a number of papers in this report provided evidence of several, statistically significant, temporal changes in individual attributes measured at the CONECOFOR plots (see AMORIELLO and COSTANTINI, BUSSOTTI *et al.*, CAMPETELLA *et al.*, CECCHINI *et al.*, FABBIO *et al.*,

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MANGONI and BUFFONI, MARCHETTO *et al.*, this volume). They identified different trends, according to the indicator and the plot considered. It is therefore of interest to concentrate on question (ii) and (iii), *i.e.* evaluate whether reported changes in individual attributes resulted in a change in the “overall status” of the concerned plot (FERRETTI *et al.* 2000) and if there are “deviations” from expected changes. With “overall status” we refer to the status of a given plot as measured by different attributes of its biological, chemical and physical status. Let the status  $\mathbf{S}$  of a given plot  $\mathbf{P}$  ( $P_1, P_2, P_3, \dots, P_n$ ) at time  $\mathbf{t}_k$  ( $t_1, t_2, t_3, \dots, t_k$ ) be measured by several attributes  $\mathbf{I}_m$  ( $I_1, I_2, I_3, \dots, I_m$ ) and denoted by  $\mathbf{S}_{p,t}$ . Such a status can be identified by a vector in an  $m$ -dimensional space, each dimension being one measured indicator of the ecosystem status. The status of the  $n$ -plot  $\mathbf{P}_n$  at subsequent times  $\mathbf{t}_{1,2,3, \dots, k}$  is therefore  $\mathbf{S}_{p=n, t=1, 2, 3, \dots, k}$ . Thus, the distance between  $\mathbf{S}_{p=n, t=1}$  and  $\mathbf{S}_{p=n, t=2}$  can be measured to assess whether a significant change has actually occurred. In this paper we will consider selected attributes and we will combine them into a synthetic metric to figure out whether the plot of concern is still within the set of “reference condition”. As “reference condition” we define the condition identified by the attributes measured at the beginning of the monitoring period, *i.e.* the set of expected condition in case no change have occurred. By this way we intend to avoid value judgement (*e.g.*, “healthy”, “unhealthy”, “improvement”, “worsening”) and refer only to the measured conditions at the time the plot was installed. “Change” from such condition will be considered in statistical terms only (FERRETTI *et al.* 2000).

However, a certain degree of change is inherent to forest ecosystem. For example, ageing is a directional process affecting stand dynamics (and therefore plots status) at every plots. For this reason, not only changes, but also deviation from expected change is of interest. Here “deviation” is defined in relation to the (expected) common pattern of variation (“variation which affects the process all the time and is essentially unavoidable within the current process”). Concepts derived from the statistical process control (SPC, *e.g.*, KOURTI and MAC GREGOR 1995) are useful in this context. The objective of SPC “is to monitor the performance of a process over time to verify that it is remaining in a ‘state of statistical control’”. Such a state of control is said to exist if certain process or product variables remain close to their expected values and the only

source of variation is ‘common-cause’ variation, that is, variation which affects the process all the time and is essentially unavoidable within the current process”. In our case, the “product variable” is the status of our monitoring plots and the “process variables” are the various environmental characteristics that determine such a status and that we measure through various attributes. In the terms reported above, a significant change/deviation is said to occur when defined statistical limits are exceeded.

This paper aims to assess whether “changes” and “deviations” were actually detectable from our data and - if yes - to identify what attributes are involved and when and where such a change/deviation have occurred.

## Methods

### Data sets

Availability of the data is driven by several factors. Firstly, the time schedule of the different investigations: from continuous data collection (*e.g.* meteo), to weekly (deposition and ozone -  $O_3$ ), annual (crown, vegetation), bi-annual (foliar), 5 yrs (growth) and 10 yrs (soil). Secondly, the starting time was different: soil and foliar started in 1995,  $O_3$ , crown condition assessment and ground vegetation in 1996, growth in 1996-1997 and meteo and deposition in 1998-1999. Thirdly, not all measurement are allocated to all the plots: for example, concurrent, reliable measurements of crown condition, deposition and meteo occurred only on 8 plots. These caused several restrictions for aggregating the data (FERRETTI 2000).

For the purposes of this paper we used three different datasets (Table 1 - 2). The first one refers to biological data and was denoted by B. It includes crown transparency (CT) and basal area increment (BAI) for different tree layers (upper, intermediate, lower). These attributes are indicators of forest health and productivity. The second dataset consider chemical and physical characteristics of the ecosystem and is denoted by C. It includes meteorological indicators like annual precipitation (PR), precipitation in the growing season (PRGI) and air temperature (AT) as well as  $O_3$  ( $O_3$ ) concentrations and deposition of H+, S and N (DepoH, DepoS and DepoN, respectively). The third dataset includes the C data plus tree crown transparency and is denoted by TC. Original data can be found in this volume in the papers of BUSSOTTI *et*

**Table 1** – Investigations contributing data, indicators selected, areas of concern and relevant metrics.  
*Indagini che hanno fornito dati, indicatori selezionati, area di interesse e metrica degli indicatori.*

Investigation	Indicator selected	Areas of concern	Metrics
Crown condition	Crown transparency (CT)	Forest health	% of a reference
Growth	Basal Area Increment (BAI) of the upper (s), intermediate (m) and lower (i) layers (BAI_s, m, i)	Forest productivity, C-sequestration, health	m <sup>2</sup>
Deposition	Throughfall of N, S and H+ (DepoN, DepoS, DepoH)	Air pollution	eq m <sup>-2</sup> yr <sup>-1</sup>
Meteo	Air temperature (AT), annual precipitation (PR), precipitation in the growing season (PRGI)	Climate	°C (AT); mm (PR, PRGI)
Ozone	O <sub>3</sub> concentration	Air pollution	ppb

**Table 2** – Datasets used. See text for more information.  
*Dataset utilizzati. Per maggiori spiegazioni, vedi il testo.*

Data set	Indicators	Plots (n) Years (n)	Reference period Training set Years (n)	Evaluation period Evaluation set
B-Biological status	Crown transparency, basal area increment of three layers (upper, intermediate, lower)	All plots (n=20)	1997-1999 (n=20)	2000-2004 (n=20)
C-Chemical-physical status	P, T, PRGI, DepoH+, DepoN, DepoS	CAL1, EMI1, EMI2, FRI2, LAZ1, PIE1, TOS1, TRE1 (n=8)	1999, 2000, 2001, 2002 (n=32)	2003, 2004, 2005 (n=24)
TC-Crown transparency+C	Crown transparency, P, T, PRGI, DepoH+, DepoN, DepoS	CAL1, EMI1, EMI2, FRI2, LAZ1, PIE1, TOS1, TRE1 (n=8)	1999, 2000, 2001, 2002 (n=32)	2003, 2004, 2005 (n=24)

al. (CT), FABBIO *et al.* (BAI), MARCHETTO *et al.* (DepoH, -S, -N), MANGONI and BUFFONI (O<sub>3</sub>) and AMORIELLO and COSTANTINI (PR, PRGI, AT).

Missing values occurred on a very limited basis. In case, they were reconstructed according to different methods in relation to the indicator considered: PCA was used for O<sub>3</sub> and meteo; correlation was used for crown transparency.

For each dataset, a “training set” and an “evaluation set” were considered. The training set was identified by the data belonging to the “reference period”, *e.g.* the period against which we wish to detect changes (see below). The training set was used to set-up the model. On the contrary the evaluation set is made up by those data collected subsequently and tested against model expectations.

For the B-set, the multi-annual frequency of growth measurements conditioned the aggregation of the data. Thus, the training set was built up by the data collected in the years 1997-1999 (reference period), while the evaluation set was built up by the data collected in the years 2000-2004. Crown transparency and basal area increment for different layers were averaged over

these periods to obtain comparable values.

For the C-set, data were aggregated on an annual basis. The training set was built up by the data collected in the years 1999, 2000, 2001, 2002 (reference period), while the evaluation set was made up by the years 2003, 2004, 2005.

For the TC-set, data were again aggregated on an annual basis. The training and evaluation sets were built up as for the C dataset.

#### **Assumptions and limitations**

As explained in other reports and papers of the I&C series (*e.g.* FERRETTI *et al.* 2000, 2003, 2006), a number of attributes averaged at plot level are used as predictor and/or response indicators. This approach requires a number of assumptions (FERRETTI and CHIARUCCI 2003). A first assumption concerns the ability of the available data to provide reliable, unbiased estimates of population parameters (*e.g.* mean plot crown transparency) at plot level. Another important assumption concerns the consistency of data through time. Although a huge effort has been placed to ensure maximum consistency, those surveys involving

visual assessment (*e.g.*, crown condition) are always subject to observer error. To carry out the analysis, we assumed that data were comparable through space and time, but we invite readers to be careful when considering this aspect.

### Statistical methods

Data were checked for normality and - when necessary - transformed to achieve normal distribution according to Box-Cox (Box and COX 1964). Since the variables were measured according to different metrics and in order to obtain equal variances, data were

$$Xstd_i = \frac{(x_i - \bar{x})}{s}$$

standardized by means of autoscaling:

where:

$Xstd_i$  is the standardized value of the variable  $i$ ,  
 $\bar{x}_i$  is the actually measured value of  $i$ ,  
 $\bar{x}$  is the mean value of  $i$  between the  $n$  sites,  
 $s$  is the standard deviation of  $x$  between the  $n$  sites.

Different statistical methods were used: to detect changes in the overall plot status, the Mahalanobis distance was used. To detect deviations from the common-cause variations, a set of different tools were used: Principal Component Analysis (PCA), Parallel Factor Analysis (PARAFAC), Tucker3 (3-way PCA). In order to better identify possible cause of oddness of individual observations, contribution plot were used.

### Mahalanobis distance

The independent variables of a data array define a multidimensional space, in which is possible to plot "mean point", also called centroid, that is the mean of all the independent variables. The Mahalanobis distance (MAHALANOBIS 1936) is the distance of a case from the centroid in the multidimensional space, defined by the correlated independent variables (if

$$d_{ab} = (\bar{x}_a - \bar{x}_b)^T \bar{S}^{-1} (\bar{x}_a - \bar{x}_b)$$

the independent variables are uncorrelated, it is the same as the simple Euclidean distance):

Thus, this measure provides an indication of whether or not an observation is an outlier with respect to the independent variable values. The covariance matrix inversion ( $S^{-1}$ ) allows the compression of the distance between cases located in a space defined

by correlated variables and downweights high variance variables.

### Principal Component Analysis (PCA)

PCA is a technique for concentrating the information in a data set into fewer dimensions (MASSART *et al.* 1997; JACKSON 1991; JOLLIFFE 1986). This is done by creating new variables, Principal Components (PCs), that are linear combinations of the original variables and which account for maximum possible variance in the data set. Each PC is constrained to be orthogonal to all previously extracted PCs (at right angles in the multidimensional space and therefore completely uncorrelated), and as a consequence they have no overlap in information content. Each PC thus represents a different fundamental property of a system, were all the original variables that are partially or largely redundant in information content influence the same PC in the same direction. This is evident in the loadings plot, which shows correlations between the PCs and the original variables. Moreover, it is possible to view how the objects of the data set are distributed in the space of the PCs by means of the scores plot. The number of significant PCs indicates the number of fundamentally different properties exhibited by the data set.

### PARAFAC and Tucker3 models

PARAFAC and Tucker3 are decomposition methods and they are both considered a generalization of PCA to higher order array (see BRO 1997; BRO *et al.* 1999; HENRION 1994; MUNCK *et al.* 1998; PRAVDOVA *et al.* 2002; SMILDE *et al.* 2004 for a detailed description of the properties and characteristics of these two multi-way techniques). Briefly, a 3-way array  $\underline{\mathbf{X}}$ , of dimension  $I \times J \times K$ , is decomposed into a triplets of loadings vectors. Each triplet is called Component or Factor or Latent Variable (LV). For the PARAFAC, the decomposition can be mathematically expressed by the following equation:

$$x_{ijk} = \sum_{f=1}^F t_{if} w_{if}^j w_{kf}^k + e_{ijk}$$

Where:

$F$  is the number of components (not orthogonal) used in the PARAFAC model, which has to be equal for the three modes;  
 $\mathbf{T}$  ( $I \times F$ ) with element  $t_{if}$  is the first mode score matrix;

$\mathbf{W}^J (J \times F)$  with element  $w_{ij}^j$  and  $\mathbf{W}^K (K \times F)$  with element  $w_{ip}^k$ , are the second and the third modes weights, respectively;  
 $e_{ijk}$  is a residual term containing all the unexplained variation.

The equation for the Tucker3 is as follows:

$$x_{ijk} = \sum_{p=1}^P \sum_{q=1}^Q \sum_{r=1}^R t_{ip} w_{jq}^j w_{kr}^k g_{pqr} + e_{ijk}$$

where:

$t_{ip}$ ,  $w_{jq}^j$ ,  $w_{kr}^k$  and  $e_{ijk}$  are, as discussed in PARAFAC case, the elements of the loading matrices  $\mathbf{T}$ ,  $\mathbf{W}^J$ ,  $\mathbf{W}^K$ , and of the residual array, respectively;

$P$ ,  $Q$  and  $R$  are the number of components (orthonormal) extracted for each mode;

$g_{pqr}$  is the element of the core matrix  $\mathbf{G}$  of order  $P \times Q \times R$ ;

The array  $\mathbf{G}$  is called core array and represents the value by which the single component product is weighted. Therefore, the value and the sign of each core element, gives information about the entity of the interaction among the components of the different modes. The squared elements of the core matrix are proportional to the variation explained by the combination of the components corresponding to their indices, *i.e.* if  $g_{112}$  is the largest core element, special attention in interpreting the model has to be given to the interaction between component 1 of mode 1, component 1 of mode 2 and component 2 of mode 3.

One of the main advantages of the multi-way techniques lies in the improvement of the visualization and interpretation of the results. In fact, separate loading plots are displayed for each mode: one for the objects, one for variables and one for the conditions, allowing distinct analysis of each source of variability, without 'flattening' or loosing any type of information.

#### *Statistical limits to detect "deviations"*

Detection of changes: for the purposes of this paper, we calculated the Mahalanobis distance for the training set and the relevant statistics (mean and its standard deviation,  $S$ ) without considering the outliers. Secondly, we calculated the distance of each point of the evaluation set from the centroid of the training set. Thirdly, we compared such a distance with the mean distance of the training set augmented by 2 times  $S$ . Points falling outside this limit were considered outliers.

Detection of deviations: statistics like Hotelling's  $T^2$  (HOTELLING 1947) and  $Q$  (also defined as SPE, square prediction error, NOMIKOS and MAC GREGOR 1995) are used in order to establish confidence limits in a multivariate space and to detect "out-of-control" situations. They are calculated on the basis of a model from principal component analysis (PCA) or partial least squares (PLS), and give superior performance to the univariate quality control methods which monitor one variable at a time.

Hotelling's  $T^2$  statistic measures variations in the PCs. This will only detect whether or not the variation in the variables in the plane of the first PC is greater than can be explained by common cause. If a totally new type of special event occurs which was not present in the reference data used to develop the "in-control" PCA model, then new PCs will appear and the new observation will move off the plane. Such new events can be detected by computing the squared prediction error ( $Q$ ) of the residuals of a new observation. The  $Q$  index measures the projection of the sample vector on the residual subspace.

Although both  $Q$  and  $T^2$  are used, *i.e.*, for process monitoring, it is necessary to point out that they measure different situations of the process, and their roles in process monitoring are not symmetric. The  $Q$  index measures variability that breaks the normal process correlation, which often indicates an "abnormal" situation. The  $T^2$  index measures the distance to the origin in the principal component subspace. Since the principal component subspace typically contains normal process variations with large variance that represent signals, and the residual subspace contains mainly noise, the normal region defined by the control limit for  $T^2$  is usually much larger than that of  $Q$ . Therefore it usually takes a much larger "deviation" to exceed the  $T^2$  control limit. On the other hand, deviations with small to moderate magnitudes can easily exceed the  $Q$  control limit.

While a fault can cause  $Q$  and  $T^2$  to increase, an increase in  $T^2$  alone indicates that the change is consistent with the model, *i.e.* observation with a high  $T^2$  show an unusual variation inside the model, while samples with a high  $Q$  value demonstrate an unusual variation outside the model. In the former case, the meaning is that, within the set of the variables considered, we observe an unusual numeric value of the resulting vector which is however consistent with the overall model used to explain the overall variation,

**Table 3** – Summary data for the various attributes used. Mean values for the training and evaluation sets are reported. The training sets are 1997-1999 for the B-set and 1999-2002 for the C and TC sets. Evaluation sets are 2000-2004 and 2003-2005, respectively. See text for details. *Sintesi dei dati per gli attributi usati. Vengono riportate le medie per i set di training e di valutazione. Il set training è il 1997-1999 per il set B ed il 1999-2002 per i set C e TC. I set di valutazione sono 2000-2004 e 2003-2005 rispettivamente. Dettagli nel testo.*

Data set	Indicator and time coverage	Lambda values for Box-Cox	Years	ABR1	BAS1	CAL1	CAM1	EMI1	EMI2	FRI1	FRI2	LAZ1	LOM1
<b>B</b>	CT 1997-2005	1	97-99	20,4	22,7	35,8	24,1	21,0	22,0	18,8	19,3	14,9	17,6
			00-04	22,5	21,2	32,8	22,8	30,5	27,1	20,2	17,0	24,3	19,2
	BAI_l 1997-2004	1	97-99	-7,8	-110,2	-134,3	6,6	306,2	-1092,6	74,7	151,9	-13,8	-54,3
			00-04	10,4	-658,3	-215,5	7,5	32,2	-759,0	-357,1	-26,5	-75,1	96,1
BAI_m 1997-2004	1		97-99	174,3	316,5	428,3	456,0	-761,8	-36,1	511,6	666,6	567,5	256,9
			00-04	85,4	423,4	399,6	247,2	-517,3	40,6	91,1	605,0	17,5	196,5
BAI_s 1997-2004	0		97-99	1645,0	593,9	593,7	756,5	642,0	1493,4	1335,4	1402,5	1407,1	2507,9
			00-04	1011,8	716,4	813,8	648,9	420,4	2125,8	806,9	1078,7	839,0	2227,8
<b>C, TC</b>	CT 1999-2005	0,5	99-02			35,8		23,8	25,7		18,7	20,8	
			03-05			27,5		39,1	21,3		14,8	22,3	
	AT 1999-2005	-	99-02			10,3		12,9	9,7		6,9	11,6	
			03-05			9,8		12,5	9,1		6,3	12,1	
	PR 1999-2005	-0,5	99-02			1545,2		891,3	1301,8		1705,3	895,8	
			03-05			2094,3		855,7	1642,7		1703,0	998,0	
	PRGI 1999-2005	-0,5	99-02			721,1		562,3	504,3		1018,3	427,8	
			03-05			790,0		510,3	481,0		1022,0	414,0	
	DepoN 1999-2005	0,5	99-02			46,3		162,2	12,2		81,9	56,0	
			03-05			53,9		153,8	6,9		87,3	49,4	
	DepoS 1999-2005	0,5	99-02			111,2		74,6	10,4		68,1	55,1	
			03-05			118,5		48,4	4,0		45,9	43,7	
	DepoH+ 1999-2005	0	99-02			6,5		1,9	1,0		10,9	3,1	
			03-05			7,1		1,3	0,4		2,9	3,2	
O3 1999-2005	-0,5	99-02			47,8		45,6	44,2		42,9	49,2		
		03-05			59,7		47,0	56,8		45,6	55,2		
Data set	Indicator and time coverage	Lambda values for Box-Cox	Years	MAR1	PIE1	PUG1	SAR1	SIC1	TOSI2	TRE1	UMB2	VAL1	VEN1
<b>B</b>	CT 1997-2005	1	97-99	18,5	25,6	19,1	20,2	12,5	35,8	13,0	24,3	25,2	18,9
			00-04	18,5	24,4	20,1	14,5	12,7	22,9	14,1	19,1	22,5	17,1
	BAI_l 1997-2004	1	97-99	316,5	-16,0	-653,5	-386,6	-256,6	-619,6	39,7	-86,8	5,6	42,6
			00-04	-108,4	2,9	-895,0	-742,1	-449,9	-450,7	-260,0	-331,5	65,1	-49,0
BAI_m 1997-2004	1		97-99	67,7	535,5	716,3	191,8	340,8	313,0	494,4	313,9	133,8	522,6
			00-04	-286,6	382,2	233,3	-18,4	-783,5	355,3	216,3	-4,4	102,1	226,5
BAI_s 1997-2004	0		97-99	1792,1	691,6	1141,9	1064,9	645,3	745,2	916,0	699,4	1414,2	836,4
			00-04	1114,0	528,4	1070,1	636,3	252,5	605,7	1168,6	527,6	1499,1	458,5
<b>C, TC</b>	CT 1999-2005	0,5	99-02			24,8			25,8	14,6			
			03-05			25,5			21,3	12,9			
	AT 1999-2005	-	99-02			7,6			12,8	4,9			
			03-05			7,0			9,4	4,7			
	PR 1999-2005	-0,5	99-02			2007,7			1088,7	1189,1			
			03-05			1451,3			1245,5	896,0			
	PRGI 1999-2005	-0,5	99-02			1307,6			415,3	476,3			
			03-05			838,3			566,0	306,7			
	DepoN 1999-2005	0,5	99-02			139,1			73,6	35,4			
			03-05			112,3			74,5	33,0			
	DepoS 1999-2005	0,5	99-02			72,1			106,6	26,4			
			03-05			38,3			74,2	13,4			
	DepoH+ 1999-2005	0	99-02			12,8			1,7	2,5			
			03-05			10,6			1,2	2,8			
O3 1999-2005	-0,5	99-02			48,6			41,2	48,7				
		03-05			64,0			49,9	63,0				

*i.e.* the expected correlations between the variables used. On the contrary, high Q values identify vector components that are outside the expected correlations between the variables used.

Once an observation has been detected as an outlier, it is very important to understand *why* it is an outlier. This can be done by computing the contribution of each variable to the calculated statistic (MILLER

*et al.* 1998; R. LEARDI, personal communication). A high contribution of a variable usually indicates a “problem” with this specific variable. Computing the contribution allows to split the global Q or T<sup>2</sup> into the contributions given by each variable and makes the interpretation much easier. The values used are the squared residuals, but in our case value of the contribution is multiplied by the sign of the residual. To give

an idea about the significance of the contributions (the actual numerical value has no “practical” meaning) a critical value for each variable is computed on the basis of the distribution of the contributions on the same variable, and corresponds to the 95<sup>th</sup> percentile of the distribution of the absolute values. By dividing each contribution by its critical value a normalized value is obtained, in which the value for each variable corresponds to how many times its contribution is greater than the critical value.

## Results

Table 3 summarizes the data for each plot, variable and datasets. In the following, results are discussed in relation to each dataset.

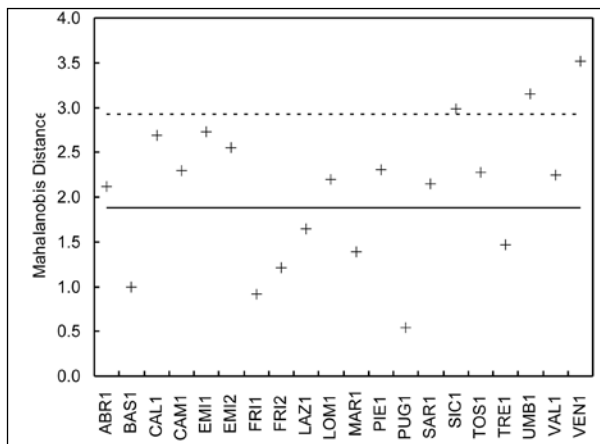
### **Biological status: crown transparency and basal are increment**

The Mahalanobis distance between 2000-2004 and 1997-1999 is reported for of each plot in Figure 1. Three outliers were identified: SIC1, UMB1 and VEN1. According to the original data (Table 3), these outliers seem mostly caused by reduced growth, especially at UMB1 and VEN1.

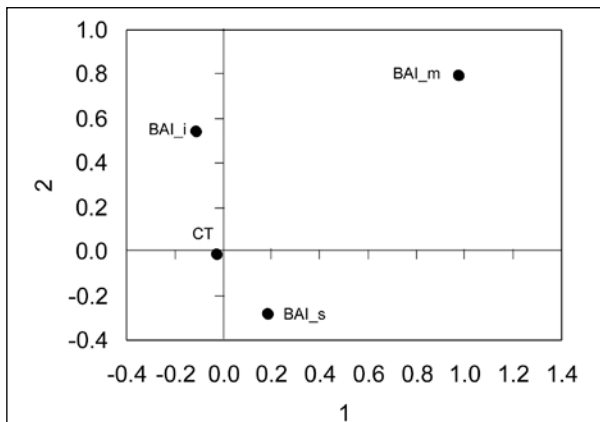
The PARAFAC identifies a three-linear model where 2 components explain 63.85% of the variance of the training set (Figure 2). The subsequent PCA analysis did not display outliers within the training set (Figure 3). When considering the evaluation set, four deviations with high Q values were obvious in comparison with the training set (Figure 3). Deviations occurred for the plots SAR1, SIC1, UMB1 and VEN1 and were due to high Q values, *i.e.* a possible change in the expected correlation structure. High Q were mostly due to low values for crown transparency and BAI in the intermediate layer (Table 4). These reflects the reduction of growth observed on these plots (particularly heavy in VEN1: -57% of annual increment in the intermediate layer as compared with the 1997-1999 value) which was accompanied by a slight decrease of transparency (BUSSOTTI *et al.*, this volume; FABBIO *et al.*, this volume) (Table 3).

### **Chemical and physical status: deposition, ozone and meteorology**

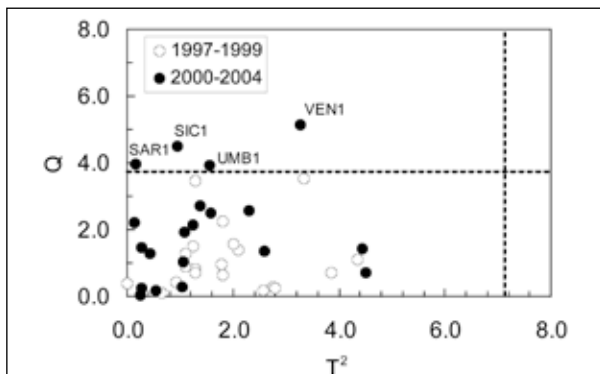
Figure 4 reports the Mahalanobis distance of the 2003-2005 data for each plot and year. Ten outliers were identified (Figure 6), namely the plots CAL1 (yrs 2003, 2004), EMI2 (2003, 2004), LAZ1 (2005), PIE1 (2003), TOS1 (2004), and TRE1 (all years). According



**Figure 1** - Mahalanobis distance, B-set, 2000-2004. The solid line indicates le mean distance from the centroid of the 1997-1999. The dashed line indicates 2 times S. *Distanza di Mahalanobis, set B, anni 2000-2004. La linea intera indica la distanza media dal centroide 1997-1999. La linea tratteggiata indica due volte S.*



**Figure 2** - B-set, 1997-1999, PARAFAC. The first two PCs explained 63.85% of the variance. *Set B, 1997-1999, PARAFAC. Le prime due PC spiegano il 63.85% della varianza.*



**Figure 3** - Datapoints of the B-set within the T<sup>2</sup>-Q diagram. The dashed lines indicate the critical values at p=0.05. Only datapoints having at least one diagnostic at p<0.05 are labelled with the plote code. *Dati del set B disegnati nel diagramma T<sup>2</sup>-Q. Le linee tratteggiate indicano il livello di significatività per p=0.05. Solo i dati che mostrano almeno un criterio diagnostico eccedente il livello di significatività sono indicati con il nome dell'area.*

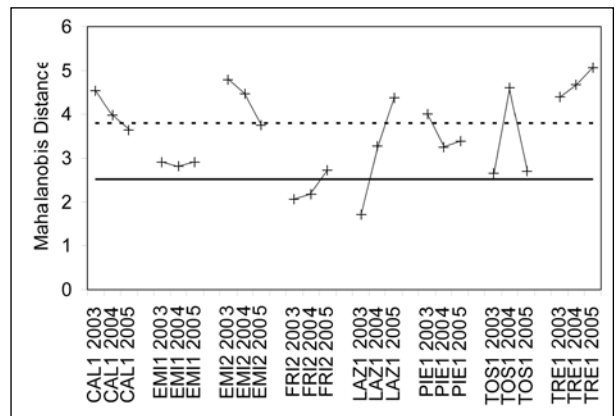
to the original data, different factors were involved: a strong reduction (-47%) in summer precipitation occurred at CAL1 in 2003, accompanied by an increase of O<sub>3</sub>. A similar situation occurred at EMI2, together with a reduction in sulfate, nitrate and H<sup>+</sup> deposition at EMI2, and an increase in annual precipitation. At LAZ1, high temperature, high O<sub>3</sub> and reduced summer precipitation appear to be the most important factors in determining the 2005 outlier, together with a high annual precipitation value. A particularly high deposition of N appeared responsible for the outlier value at TOS1 and increased O<sub>3</sub> and reduced precipitation for TRE1.

A three-linear PARAFAC model where 2 components explain 82.1% of the variance was identified. These two components are reported in Figure 5. The PCA analysis identifies only one minor deviation within the training set, the plot EMI2 at year 2002, characterized by slightly high Q values (Figure 6) caused probably by a high AT (mean annual value: 9.7 °C). When considering the evaluation set (2003-2005 data), strong deviation were observed for TRE1 at years 2004 and 2005, when both T<sup>2</sup> and Q critical values were exceeded (Figure 6). This indicates that at this plots and in these two years something was recorded that is out of the expected correlations structure and also with anomalous numerical values. The most likely reason for T<sup>2</sup> exceedance was high summer O<sub>3</sub> and low DepoS, while low AT and PRGI contributed to high Q values (Table 5). Exceedance of T<sup>2</sup> was observed also for PIE1 in 2003 (high O<sub>3</sub>), while exceedance of Q were reported for EMI2 (2003, high PR), CAL1 (2003: high PR and low PRGI; 2004: high PR and DepoS and low DepoN) and TOS1 (2004: low DepoH+) (Table 5).

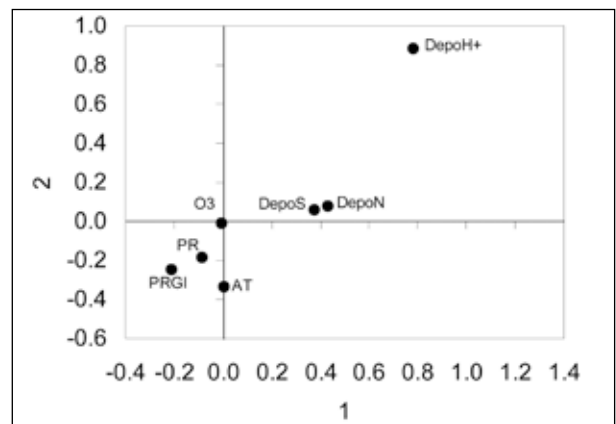
**Table 4 –** Normalized contribution for each variable in case of deviation for the B-data set. Variables that exceeded the value of 1 (in bold) have a significant contribution to the statistic considered.  
*Contributo normalizzato di ciascuna variabile nei casi di deviazione nel set B. Le variabili per cui viene superato il valore di 1 (in grassetto) hanno un contributo significativo alla statistica considerata.*

Indicator	Normalized contribution, Q			
	SAR1	SIC1	UMB1	VEN1
CT	-0.943	<b>-1.383</b>	<b>-1.325</b>	<b>-1.476</b>
BAI <sub>i</sub>	<b>-1.005</b>	-0.332	-0.075	-0.358
BAI <sub>m</sub>	<b>-1.433</b>	<b>-1.434</b>	<b>-1.232</b>	<b>-1.533</b>
BAI <sub>S</sub> *	-0.135	0.648	0.801	0.690

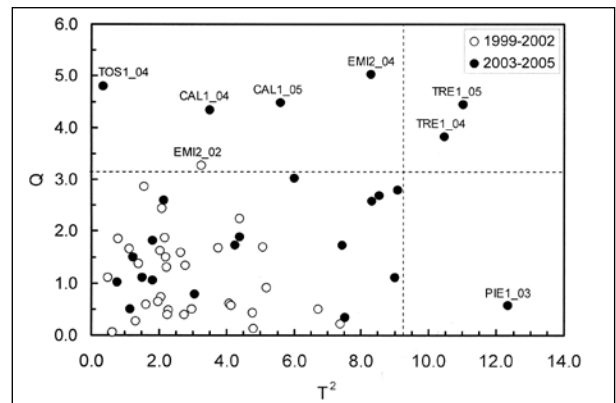
(\*)The sign of the contribution is reversed due to the negative lambda value of the Box-Cox transformation.



**Figure 4 -** Mahalanobis distance, C-set, 2003-2005. The solid line indicates the mean distance from the centroid of the 1999-2002. The dashed line indicates 2 times S.  
*Distanza di Mahalanobis, set C, anni 2003-2005. La linea intera indica la distanza media dal centroide 1999-2002. La linea tratteggiata indica due volte S.*



**Figure 5 -** C-set, 1999-2002, PARAFAC. The first two PCs explained 82.1% of the variance.  
*Set C, 1999-2002, PARAFAC. Le prime due PC spiegano l'82.1% della varianza.*



**Figure 6 -** Datapoints of the C-set within the T<sup>2</sup>-Q diagram. The dashed lines indicate the critical values at p=0.05. Only datapoints having at least one diagnostic at p<0.05 are labelled with the plote code.  
*Dati del set C disegnati nel diagramma T<sup>2</sup>-Q. Le linee tratteggiate indicano il livello di significatività per p=0.05. Solo i dati che mostrano almeno un criterio diagnostico eccedente il livello di significatività sono indicati con il nome dell'area.*



**Table 5** - Normalized contribution for each variable in case of deviation for the C-data set. Variables that exceeded the value of 1 (in bold) have a significant contribution to the statistic considered.  
*Contributo normalizzato di ciascuna variabile nei casi di deviazione nel set C. Le variabili per cui viene superato il valore di 1 (in grassetto) hanno un contributo significativo alla statistica considerata.*

Indicator	Normalized contribution, Q					Normalized contribution, T <sup>2</sup>			
	CAL1_03	CAL1_04	EMI2_03	TOS1_04	TRE1_04	TRE1_05	PIE1_03	TRE1_04	TRE1_05
DepoN	-0.881	<b>-1.136</b>	0.252	0.537	0.278	0.469	0.430	-0.732	-0.781
DepoS	0.933	<b>1.147</b>	0.112	0.569	0.156	0.304	-0.237	<b>-1.349</b>	<b>-1.416</b>
DepoH+	0.462	-0.546	-0.773	<b>-1.824</b>	0.951	0.665	0.599	-0.491	-0.472
O <sub>3</sub> *	-0.327	-0.382	-0.168	-0.183	0.053	0.025	<b>-2.807</b>	<b>-2.732</b>	<b>-2.789</b>
AT	0.289	0.607	0.432	-0.435	<b>-1.057</b>	<b>-1.355</b>	-0.312	-0.353	-0.435
PR*	<b>-1.000</b>	<b>-1.028</b>	<b>-1.294</b>	-0.725	0.621	0.586	-0.198	0.368	0.312
PRGI*	<b>1.129</b>	-0.004	0.339	-0.329	<b>1.144</b>	<b>1.229</b>	-0.623	0.370	0.333

(\*)The sign of the contribution is reversed due to the negative lambda value of the Box-Cox transformation.

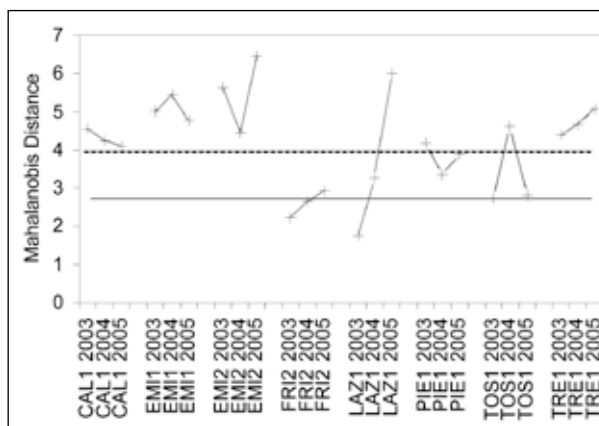
### Crown transparency, deposition, ozone and meteorology

The TC dataset includes the C-set one plus crown transparency and covers the years from 1999 to 2005. With respect to Mahalanobis distance, 15 outliers were identified (Figure 7). They were CAL1 (all years), EMI1 (all years), EMI2 (all years), LAZ1 (2005), PIE1 (2003), TOS1 (2004), and TRE1 (all years). With the exception of EMI1 and PIE1, plots are the same identified by the previous analysis. In addition to the likely factors already identified, changes appeared due to CT (reduced at CAL1, increased at EMI1), changes in PR (all), changes in DepoN (particularly at EMI2 and PIE1), a generalized decrease of DepoS (all plots, except CAL1), a generalized increase of O<sub>3</sub> (all plots) (Table 3).

A three-linear model where 2 components explain 80.45% of the variance was identified by the PARAFAC. These two components are reported in Figure 8. The subsequent PCA analysis identified two datapoints displaying high Q values, the plots EMI2 at yr 2001 and TOS1 at yr 2002. High Q values seemed caused by low O<sub>3</sub> (both plots) and low DepoH+ at TOS1. When considering the evaluation set (2003-2005 data), several deviations were observed, with two datapoints displaying high T<sup>2</sup> values and nine with high Q values (Figure 9). Most deviations were concentrated on three plots: EMI2 (2003, 2004, 2005), TRE1 (2003, 2004, 2005) and PIE1 (2003, 2005).

Overall, high O<sub>3</sub> was reported to be a significant factor in 9 out of the 11 deviations identified. The only two cases in which O<sub>3</sub> was not involved were EMI1 in 2005 and TOS1 in 2004. Note, however, that these two cases were very close to the limit of the statistical significance.

In the other cases, high O<sub>3</sub> was always reported as a significant factor leading to deviations: it contributed



**Figure 7** - Mahalanobis distance, TC-set, 2003-2005. The solid line indicates the mean distance from the centroid of the 1999-2002. The dashed line indicates 2 times S.  
*Distanza di Mahalanobis, set TC, anni 2003-2005. La linea intera indica la distanza media dal centroide 1999-2002. La linea tratteggiata indica due volte S*

to high T<sup>2</sup> for EMI2 at 2003 and 2004, and to high Q values for most of the remaining plot/year combinations (Table 6).

As far as the role of the other variables is concerned, low CT had a role at EMI2 and LAZ1 in 2005, while high value was reported for EMI2 in 2003. Low DepoS contributed to high T<sup>2</sup> values at EMI2 and high Q values at EMI1. DepoN contribution was due to high values at EMI1 and PIE1, and low values at EMI2. Low DepoH was reported for EMI2 and TOS1, while high AT (EMI2 and LAZ1 in 2005), low PR (PIE1 2005, TRE1 2004, 2005) and low PRGI (TRE1 2004, 2005) were identified as causing changes in the correlation structure of the variables. Reduced PR and PRGI were reported for PIE1 and TRE1.

## Discussion

When discussing the results, it is worthwhile to remind that the terms “change” and “deviation” do

**Table 6** - Normalized contribution for each variable in case of deviation for the TC-data set. Variables that exceeded the value of 1 (in bold) have a significant contribution to the statistic considered.  
Contributo normalizzato di ciascuna variabile nei casi di deviazione nel set TC. Le variabili per cui viene superato il valore di 1 (in grassetto) hanno un contributo significativo alla statistica considerata.

Indicator	T2		Q								
	EMI2_03	EMI2_04	EMI1_05	EMI2_05	PIE1_03	PIE1_05	LAZ1_05	TOS1_04	TRE1_03	TRE1_04	TRE1_05
CT	<b>1.299</b>	0.810	0.595	<b>-1.617</b>	-0.605	-0.120	<b>-1.664</b>	-0.294	-0.634	-0.682	-0.672
DepoN	<b>-2.120</b>	<b>-1.998</b>	<b>1.461</b>	0.287	<b>1.526</b>	<b>1.235</b>	0.442	0.538	0.962	0.765	0.912
DepoS	<b>-1.358</b>	<b>-1.480</b>	<b>-1.076</b>	0.396	-0.255	-0.576	0.293	0.684	0.461	0.383	0.566
DepoH+	<b>-1.098</b>	-0.761	-0.733	-0.884	0.299	0.573	0.832	<b>-1.813</b>	0.474	<b>1.069</b>	0.783
O3*	<b>-1.573</b>	<b>-1.499</b>	-0.419	<b>-1.534</b>	<b>-2.343</b>	<b>-1.689</b>	<b>-2.334</b>	-0.445	<b>-2.208</b>	<b>-2.245</b>	<b>-2.382</b>
AT	0.187	-0.371	-0.412	<b>1.476</b>	-0.106	-0.302	<b>1.194</b>	-0.246	-0.487	-0.376	-0.595
PR*	-0.078	-0.422	0.622	-0.637	0.847	<b>1.314</b>	0.023	-0.731	0.824	<b>1.050</b>	0.987
PRGI*	0.728	0.354	-0.651	-0.634	0.556	0.169	0.710	-0.343	0.950	<b>1.129</b>	<b>1.202</b>

(\*)The sign of the contribution is reversed due to the negative lambda value of the Box-Cox transformation.

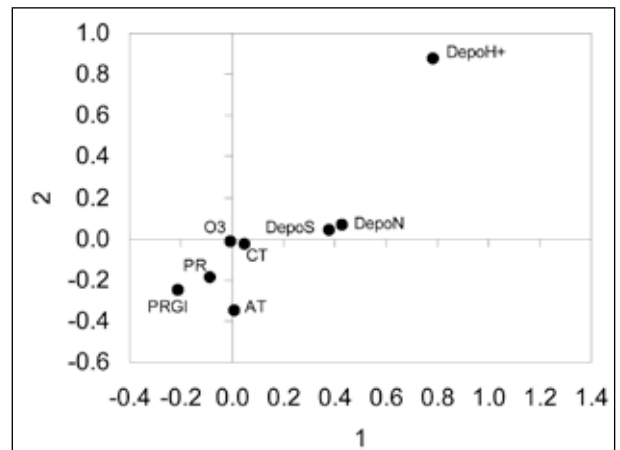
not imply any positive or negative value judgement. It is the reason behind that makes a change/deviation “good” or “bad”, “desirable” or “not desirable”.

The evaluation of the biological status (as defined by the crown transparency and basal area increment) identified 3 plots with a significant change and 4 with significant deviations. These plots are UMB1, SIC1 and VEN1 (change and deviation), plus SAR1 (deviation only) (Figure 1, Table 3). Changes and deviation were due for the most part to the reduction in growth observed over the period 2000-2004 especially in the intermediate layer (see FABBIO *et al.*, this volume). This seems to reflect internal stand dynamics: two plots were oak dominated transitory crops (UMB1 and SIC1) and one was a stored coppice (SAR1). The fourth one (VEN1) was a 130 yrs old beech high forest. It is worth noting that, due to the timing of growth data, the evaluation was carried out on data averaged over 3 and 5 years and this may have smoothed the occurrence of change/deviations episodes over these periods.

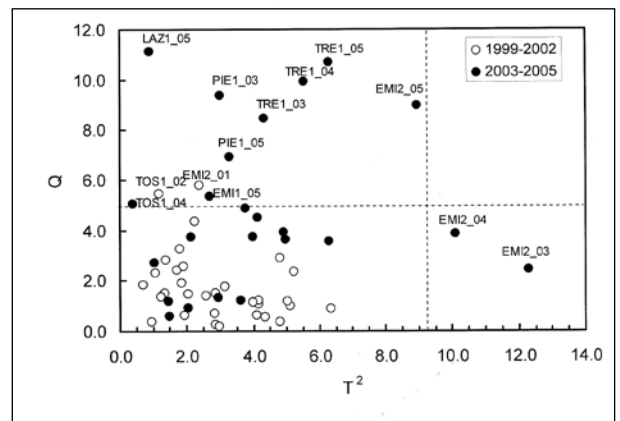
Most instances of change/deviations were reported for the C and TC datasets (Figures, 4, 7; Table 5, 6). It is therefore interesting to search for regularities in terms of plots concerned, attributes involved, nature of deviations, and timing of the events.

### Plots

Many significant changes were observed, but they were particularly frequent on 3 plots: CAL1, EMI2, and TRE1 (see Figure 4 and 7). On the other hand, deviations concentrated again on TRE1 and - to a lesser extent - on EMI2 (Table 5, 6). Although there were several other instances of significant/change deviations, these plots seemed the ones for which findings were particularly consistent.



**Figure 8** - TC-set, 1999-2002, PARAFAC. The first two PCs explained 80.45% of the variance.  
Set TC, 1999-2002, PARAFAC. Le prime due PC spiegano l'80.45% della varianza.



**Figure 9** - Datapoints of the TC-set within the T<sup>2</sup>-Q diagram. The dashed lines indicate the critical values at p=0.05. Only datapoints having at least one diagnostic at p<0.05 are labelled with the plote code.  
Dati del set TC plottati nel diagramma T<sup>2</sup>-Q. Le linee tratteggiate indicano il livello di significatività per p=0.05. Solo i dati che mostrano almeno un criterio diagnostico eccedente il livello di significatività sono indicati con il nome dell'area.

TRE1 is a 180-200 yrs-old Norway spruce plot located at 1775 m a.s.l. in Northern Italy. With respect to 1999-2002 period, the main signals apparent from the data 2003 - 2005 were:

- a reduction in PR and PRGI (-35%, see also AMORIELLO *et al.*, this volume), accompanied by a reduction in S deposition (-49%, see also MOSELLO *et al.*, this volume), that reached its minimum in 2004-2005. Reductions in AT were also reported;
- an increase in O<sub>3</sub> concentrations (+29%, see also MANGONI and BUFFONI, this volume) and - to a lesser extent - in DepoH+ (MARCHETTO *et al.*, this volume).

While most of the signals were consistently identified by the T<sup>2</sup> and Q statistics, O<sub>3</sub> was by far the most clear one (Table 5, 6). Interestingly enough, despite the reduction in precipitation and an increase in O<sub>3</sub>, an improvement of CT and an increase of annual BAI were reported for the upper canopy layer (+27%, see Table 3 and FABBIO *et al.*, this volume). In particular, over the investigated period, CT peaked in 2001 (CT=17%) and reached its minimum in 2005 (CT=12%),

EMI2 is located in a 45 yrs-old beech stored coppice at 975 m a.s.l. on the Apennines mountains in central Italy. Several changes were reported for this plot: on the average, a decrease in throughfall of S, N and H was obvious with values being reduced by 40-60%. Alongside, a significant increase in O<sub>3</sub> concentration (+28%) (MANGONI and BUFFONI, this volume) and a net increase in annual precipitation (+26%) were reported. Over the same period, crown transparency peaked in 2003 (mean plot value: 33%), at the time with the lowest precipitation during the growing season (302 mm between April and September). Later on, a significant improvement in crown transparency was obvious, with minimum values of 7% reached in 2005 (see BUSSOTTI *et al.*, this volume), a year characterized by relatively higher precipitation and cooler weather conditions. Note that crown transparency signals in 2003 and 2005 were recorded and identified also by the T<sup>2</sup> and Q statistics for this site (Table 6). Together with stand dynamics, increased precipitation can be considered likely factors leading to improved crown condition and augmented growth of the intermediate and dominant storey in this plot (+38% as compared to the 1997-1999 period) (see Table 3 and FABBIO *et al.*, this volume).

### Attributes

When considering the attributes most involved in determining change/deviations, three of them showed some regularity: O<sub>3</sub>, DepoS and PRGI. Ozone was by far the most frequent, the most consistent in direction, and with the highest scores: high O<sub>3</sub> values were reported for most of the investigated plots, thus contributing to significant changes/deviations from the expectations (Table 5, 6). Low values of DepoS were identified as causing high T<sup>2</sup> and Q values, the only exception being the site CAL1. Low values of PRGI causes high Q statistics at TRE1 and CAL1. Several other attributes were mentioned, but their role and direction were much less consistent and variable among plot and years and according to the dataset considered.

### Nature

Nature of deviations reported can be discussed in relation to the T<sup>2</sup> and Q statistics: significant Q values were much more frequent - in terms of plot-years-attribute combinations - that significant T<sup>2</sup> (Table 4, 5, 6). It means that most deviation were due to events that break the expected correlation process, rather than to extreme values of the attribute. All attributes were reported to cause significant Q values. On the contrary, high T<sup>2</sup> values were reported for 3 plots only (EMI2, PIE1 and TRE1) and were due to 4 attributes, with DepoS, and O<sub>3</sub> being the most frequent. In particular, unexpected high values were always reported for O<sub>3</sub>, and unexpected low values for DepoS.

### Timing

As far as the timing of the observed change/deviations, there is no clear pattern. They were distributed on the 2003-2005 period according to the plot: some plots (*e.g.* LAZ1, TOS1, and PIE1) showed change/deviations as single spots in different years (2005, 2004, 2003, respectively). Others, like CAL1, EMI2, TRE1 showed significant change/deviations across all the three years. All together, these findings suggest that - with very limited exceptions - there were only few common features in the detected changes and deviations. This support the need of evaluating the plots as individual case-studies, especially for cause-effect investigations.

### Conclusions

Different attributes of biological, chemical and physical status of the CONECOFOR plots were con-

sidered to investigate changes in their recent condition when compared to the condition at the beginning of the monitoring programme. On the average, significant changes in the biological status, as defined by crown transparency and basal area increment, in the period 2000-2004 are limited to few plots and are driven by a slight decrease of crown transparency and a decrease of growth, especially in the dominated and intermediate layers. Most of the detected changes/deviations were detected when considering the physical and chemical attributes of the plots. Some few regularities existed and concerned the plots (most deviation concentrated on few plots), attributes (unexpected high values reported for  $O_3$  and unexpected low values for DepoS) and nature of change/deviations (for the most part due to a change in the expected correlation structure). However, there was a considerable variation between plots, attributes involved and timing of change/deviations. When considered together with the results presented in individual papers of this volume, these findings emphasise the need to evaluate the data at the plot level and this indicate the importance of obtaining a time series long enough to enable plot-wise integrated analysis.

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