Chapter 5

# Normalized Difference Vegetation Index Estimation in Grasslands of Patagonia by ANN Analysis of Satellite and Climatic Data

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## 5.1 Introduction

The Normalized Difference Vegetation Index (*NDVI*), derived from the red and infrared bands of the AVHRR on-board sensor of NOAA satellites, shows a high correlation with biophysical rates of the target area, such as transpiration or primary productivity (Sellers et al. 1992). *NDVI* has been shown to be a linear estimator of the fraction of the photosynthetic active radiation (PAR) absorbed by the canopy (Potter et al. 1993; Ruimy et al. 1994). Monteïth (1981) showed that the amount of PAR absorbed throughout the growing season is the major control of net primary production. *NDVI* data also allows the tracking of intra-annual changes in carbon gains (Lloyd 1990; Paruelo and Lauenroth 1995).

*NDVI* has also been shown to be strongly correlated to the Aboveground Net Primary Production (*ANPP*) in grassland and shrubland areas (Tucker et al. 1985; Box et al. 1989; Prince 1991a; Prince 1991b; Burke et al. 1991; Paruelo et al. 1997). *ANPP*, the rate of carbon accumulation in plants, is a key attribute of the ecosystem. It represents the amount of energy available to the upper trophic levels and integrates many important functional characteristics such as nutrient cycling, secondary production (McNaughton et al. 1989), and root biomass and soil organic carbon dynamics (Sala et al. 1997). The importance of *ANPP* is also related to applied reasons. For example, *ANPP* is the major control of forage availability for both domestic and wild herbivores in grasslands, savannahs and shrublands (Oesterheld et al. 1992; MacNaughton et al. 1993; Oesterheld et al. 1998). The understanding of the environmental controls of *ANPP* and the prediction of future values is, therefore, a crucial issue for both theoretical and applied ecologists. The development of predictive models of *ANPP* is clearly restricted by the availability of long-term data sets. The reason behind the lack of extensive databases is quite simple: estimation of *ANPP* is time-consuming, and therefore expensive (Lauenroth et al. 1986; Sala et al. 1988).

*NDVI* has been proved to be a reliable alternative in cases where long records for *ANPP* are unavailable (Paruelo et al. 1997). Several agencies have compiled and reprocessed original data to produce global databases of *NDVI* images at a spatial resolution of 8 × 8 km (i.e. James and Kalluri 1994; Tucker and Newcomb 1994). The NOAA/NASA EOS AVHRR Pathfinder data set include 36 images per year for the period 1981–1994. This database is specially suited to analysing the temporal dynamics of *ANPP*.

Southern Argentina is dominated by temperate, arid and semiarid steppes and semideserts (Soriano 1983; León et al. 1998). The design of sustainable systems for this area clearly depends on a better understanding of the structure and functioning of main ecosystems of the region (Soriano and Paruelo 1990). This area is characterized by scarce and variable precipitation, ranging from 700 mm toward the western edge of the region, to 150 mm in the centre of the area (Jobbagy et al. 1995). Most of the region is influenced by Pacific air masses (Prohaska 1976). The Pacific influence determines a clear concentration of precipitation during winter months. The area dominated by Pacific air masses corresponds to the Patagonian Phytogeographical Province (Paruelo et al. 1991). The north-eastern part of the region is also influenced by Atlantic air masses, which determine a more even distribution of precipitation (Paruelo et al. 1998). This area corresponds to the Monte Phytogeographical Province (León et al., 1998) and is covered by steppes dominated by evergreen shrubs of the genus *Larrea*.

Desertification has been a major concern for the scientific community, federal agencies and environmental groups for more than two decades (Soriano and Movia 1987). Sheep have grazed native vegetation since the beginning of the century (Soriano and Paruelo 1990). Grazing is blamed as the major determinant of vegetation degradation across the area (León and Aguiar 1985; Perelman et al. 1997). Aguiar et al. (1996) have showed, using simulation models, the impact of the structural changes associated to overgrazing on ecosystem functioning.

Jobbágy et al. (1999) have analysed long-term *NDVI* data for the Patagonia steppes using regression models. Even though regression models resulted in valuable tools to understand the system, they showed a low predictive power. A better knowledge of temporal dynamics of *NDVI* is advantageous in the management of natural resources. Predictive models of *NDVI* may also provide the basis for the development of "warning systems" for Patagonian rangelands. The objective of this paper is to investigate the temporal dynamics of the *NDVI* and its internal and external controls across northern Patagonia by using ANNs. We also explore the use of ANNs as predictive tools of the intra-annual dynamics of the *NDVI*.

## 5.2 Methodology

### 5.2.1 Artificial Neuronal Networks

Applications of ANNs to ecological and environmental problems have started early this decade, mainly through the use of feed-forward multilayer networks. Some examples are classification of remotely sensed data (Liu and Xiao 1991; Kanellopoulos et al. 1992; Foody et al. 1995), resource management (Gimblett and Ball 1995), ecosystems modelling (Lek et al. 1996; Recknagel et al. 1997; Paruelo and Tomasel 1997), weather forecasting (McCann 1992; Derr and Slutz 1994), prediction of daily solar radiation (Elizondo et al. 1994), and many others. In particular, there has been a clear interest in using ANNs for nonlinear prediction of time series. One of the most impressive results has been shown by Wan in the prediction of a chaotic time series through the use of a finite-duration impulse response (FIR) multilayer perceptron (Wan 1994). Although many of these ANNs are able to make very good predictions, training is in general based on availability of very long data sets. Unfortunately, this is not the common case in ecological modelling where, for example, population time series for terrestrial animals are usually composed of tens of samples (see, for example, Turchin and Taylor (1992) for a compilation of some of the longest data sets available on vertebrate and insects).

In this paper we use a feed-forward network, trained by a newly proposed learning technique based on Information Theory (IT). This direct learning approach has been shown to improve the performance of simple perceptrons, providing very good predictions based on a rather small quantity of known data (Diambra et al. 1995; Diambra and Plastino 1995). We will only outline the method here; the interested reader is encouraged to read the original references for an in-depth description of the procedures involved.

Following Diambra, Fernandez, and Plastino, let us consider a simple perceptron with $N$ inputs $I_i$ connected to a single output unit $O$ whose state is determined according to $O = g(h)$, where $g(x)$ is the activation function, $h = W_j I_j$ is the weighted sum of the inputs $I_i$, and repeated dummy indices imply a summation over those indices. In the structures discussed herein, we have chosen $g(x) = \tanh(x)$. For each set of weights $W$ the perceptron maps $I$ on $O$. The perceptron is trained with a set of $P$ examples, with input vectors $I^\mu$ and the corresponding outputs $O^\mu \equiv O(I^\mu)$. From here we can write

$$g^{-1}(O^\mu) = W_j I^\mu{}_j \tag{5.1}$$

where $I^\mu$ is an input patterns matrix and $g^{-1}(O^\mu)$ is a vector of components $g^{-1}(O^1), \ldots, g^{-1}(O^P)$, given by the output patterns, which constitute our available information. The central idea in this approach is to use an Information Theory approach to determine the weights $W$ on the basis of an incomplete information supply (rank $(I^\mu) < N$, in general). In order to determine weights consistent with Eq. 5.1, it is assumed that each set of weights $W$ is realized with probability $P(W)$. In other words, a normalized probability distribution is introduced over the collection of possible sets $W$. The normalization condition is written as

$$\int P(W)dW = 1 \tag{5.2}$$

where $dW = dW_1, dW_2, \ldots, dW_N$. Expectation values $<W_i>$ are defined as

$$<W_i> = \int P(W)W_i dW \tag{5.3}$$

The differential entropy associated with the probability density function $P(W)$ is written as

$$S = -\int P(W) \ln(P(W) / P_0(W))dW \tag{5.4}$$

where $P_0(W)$ is an appropriately chosen a priori distribution. The problem of determining the set of weights $W$ is now transformed into a constrained optimization problem: we must now determine the form of the probability density function for the differential entropy of $W$ to assume its largest value for the prescribed constraints of Eq. 5.1 and Eq. 5.2. The authors' central idea is to reinterpret Eq. 5.1 according to:

$$g^{-1}(O^\mu) = <W_j> I_j^\mu \tag{5.5}$$

where explicit account is taken of the fact that one is dealing with many sets of weights, each one being realized with a given probability, and borrowing from statistical mechanics the idea that measured data are to be reproduced by theoretical averages.

It can be shown that, after maximization of the differential entropy, the expectation vector $<W>$ can be expressed solely in terms of the training examples, and that it can be written as

$$<W> = g^{-1}(O^{\mu})I_{MP}[O^{\mu}] \tag{5.6}$$

where $I_{MP}(O^{\mu}) = (O^{\mu})^t[O^{\mu}(O^{\mu})^t]^{-1}$ is the Moore-Penrose pseudoinverse. The most probable configuration of weights, compatible with the constraints of Eq. 5.1, is thus given directly by the pseudoinverse matrix of $O^{\mu}$, with no iterative processes associated with the training of the network. IT-trained networks have been successfully applied to the prediction of some classical chaotic time series, even when a small quantity of examples was made available for the training process (Diambra and Plastino 1995).

## 5.2.2
## The Data Set

As we mentioned earlier in the introduction, *ANPP* has been shown to be strongly correlated with the *NDVI*. Therefore, an analysis of the *NDVI* cycles and their relationship with the climatic variables may translate into a better understanding of the environmental controls of *ANPP* and into a better predictive power. In this paper, we used *NDVI* from 10 sites covering a broad range of climatic conditions across northern Patagonia (Fig. 5.1, Table 5.1). These locations were selected based on the availability of precipitation data. We obtained the *NDVI* data from the Pathfinder AVHRR Land database (James and Kalluri 1994), from which data was available for a period of 11 years

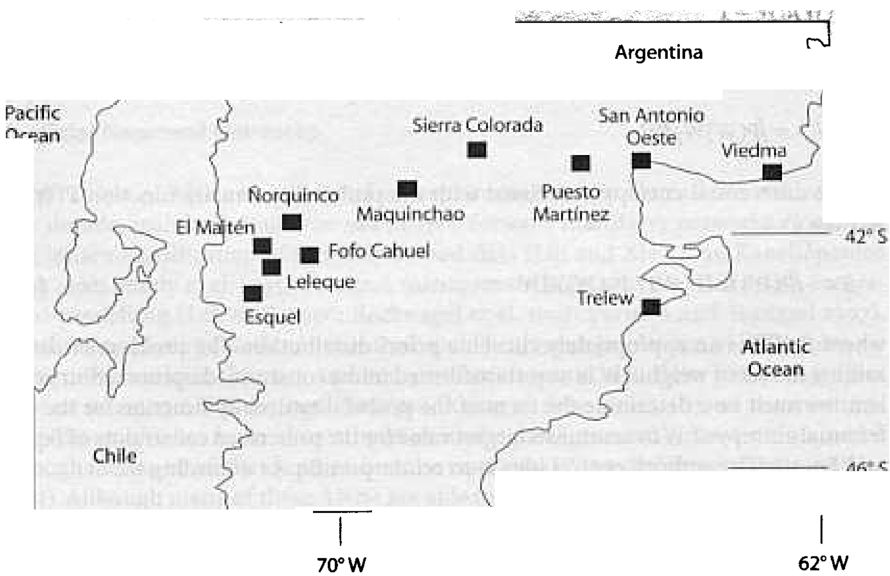


**Fig. 5.1.** Location of the sites used for this study. The sites cover a broad range of climatic conditions across northern Patagonia, with mean annual precipitation ranging from 130 mm in Fofo Cahuel to 420 mm in Leleque

**Table 5.1.** Characteristics of the precipitation regime for the sites selected for the present study. Mean annual precipitation ranges from 130 mm in the case of Fofo Cahuel to 420 mm in the case of Leleque

| Site | Mean annual precipitation (mm) | Precipitation falling in summer (%) |
|---|---|---|
| Leleque | 418 | 8 |
| El Maitén | 356 | 9 |
| Viedma | 328 | 21 |
| Esquel | 268 | 9 |
| San Antonio Oeste | 268 | 22 |
| Trelew | 214 | 20 |
| Sierra Colorada | 205 | 24 |
| Ñorquinco | 196 | 9 |
| Maquinchao | 173 | 18 |
| Puesto Martínez | 153 | 35 |
| Fofo Cahuel | 129 | 14 |

(1981–1991). For each year 36 images were available, each corresponding to a 10-day composite (Holben 1986). The spatial resolution of the images was 8 × 8 km., and every site was characterized by a single pixel (6 400 ha).

## 5.3 Results and Discussion

Our first approach to the problem was to analyse the predictive power of ANNs trained solely on $k$ past values of the *NDVI* time series. In this case, the training data were of the form

$$I^i = \{NDVI(t_i), NDVI(t_i - T), \ldots, NDVI(t_i - kT)\} \text{ and}$$
$$O^i = NDVI(t_i + mT), \; i = 1 : P \qquad (5.7)$$

where $P$ is the number of patterns used for training, $T$ is the sampling period and $m$ denotes a suitable number of time steps. So given $k$ past values of *NDVI*, the ANN was asked to extrapolate the value of the *NDVI* $m$ steps ahead.

On each site, an ANN was trained by using 8 years of data and tested on the remaining three. The dynamics of the *NDVI* time series was best captured when 36 past values (one year) of data were used as the input. Figure 5.2 shows the *NDVI* 9-step-ahead (three months) extrapolation for the case of sites Esquel, Leleque and Fofo Cahuel. Although the correlation between calculated and observed values of *NDVI* differed among sites, the results show that in general the agreement is very good. To evaluate the performance of our predictors, we calculate the mean square error,

$$MSE = E\{[NDVI_{\text{calc}}(t, kT) - NDVI_{\text{obs}}(t + mT)]^2\}$$

where $E$ is the expected value operator. For convenience in the comparison among sites, we normalize this by the mean square deviation of the data, $\sigma^2 = E\{(NDVI - E[NDVI])^2\}$,

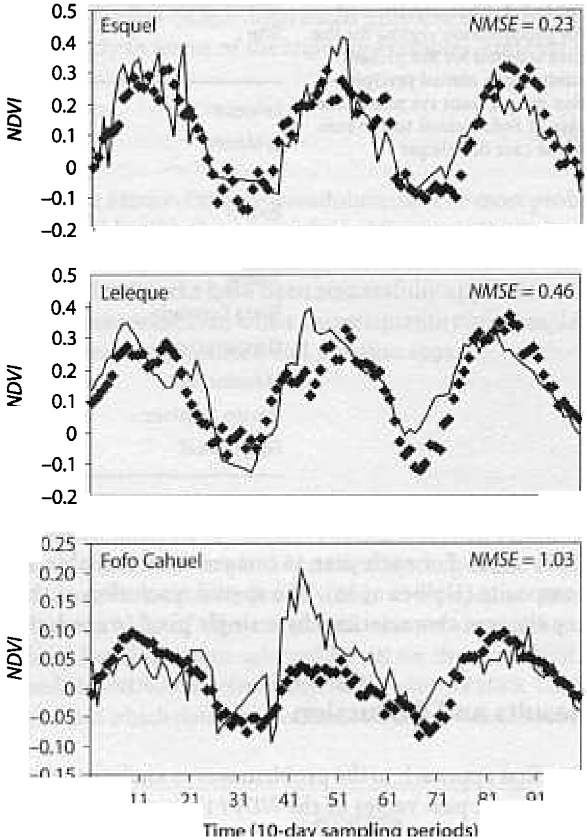


**Fig. 5.2.** Calculated (*square dots*) and observed (*solid line*) values of *NDVI* for the case of a 9-step-ahead extrapolation in sites Esquel, Leleque, and Fofo Cahuel. Values for the *NMSE* are indicated

forming the normalized mean square error $NMSE = MSE / \sigma^2$ (Farmer and Sidorowich 1987). In this way, smaller values of *NMSE* correspond to better predictions.

The *NMSE* values for the case of 9-step-ahead extrapolation ranged between 0.23 and 4.58 (Table 5.2). For sites with relatively small values of *NMSE*, extrapolation could be made up to 18 steps in advance (six months) without significant degradation of the forecasting error.

The results of calculating the *NDVI* from its internal dynamics highlight interesting aspects of the ecology of the different phytogeographical regions of Patagonia. Figure 5.3 shows that the *NMSE* strongly increases as the proportion of precipitation falling during summer increases. Sites located in the southwestern portion of the area analysed presented a better agreement between observed and calculated values than those located in the north-eastern area (Fig. 5.1). These two areas differ on the seasonal pattern of the precipitation. The southwestern area corresponds to the Patagonian Phytogeographical region. In this area, because of the strong influence of Pacific air masses, precipitation is mainly concentrated during winter. In contrast, the north-eastern portion of the region has a more evenly distributed precipitation regime. This area corresponds to the Monte phytogeographical region.

**Table 5.2.** Normalized mean square error for extrapolations based solely on *NDVI* data, and predictions based both on past values of *NDVI* and accumulated precipitation

| Site | *NDVI* trained | *NDVI* + PPT trained |
|---|---|---|
| Leleque | 0.46 | 0.47 |
| El Maitén | 0.45 | 0.46 |
| Viedma | 1.01 | 0.81 |
| Esquel | 0.23 | 0.24 |
| San Antonio | 4.58 | 1.39 |
| Sierra Colorada | 2.37 | 0.81 |
| Ñorquinco | 0.56 | 0.58 |
| Maquinchao | 0.94 | 0.94 |
| Puesto Martínez | 4.12 | 1.93 |
| Fofo Cahuel | 1.06 | 0.49 |

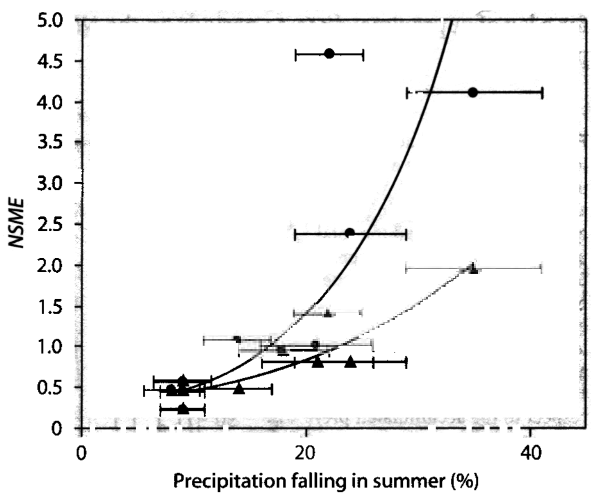


**Fig. 5.3.** Normalized mean square error as a function of percentage of precipitation falling in summer. *Circles* correspond to extrapolation based solely on past values of *NDVI* data, and *triangles* correspond to predictions based both on past *NDVI* data and accumulated precipitation *Solid lines* are exponential fits intended to show the general trend of the data

When ANNs are trained exclusively on past values of *NDVI* data, the *NMSE* provides a measure of the intrinsic predictability of the system. Areas showing a low *NMSE* would display a similar phenological pattern every year. Predictability is a very important attribute of the ecosystems. It would determine, for example, the kind of evolutive pressure that organisms will experience. Opportunistic strategies will be favoured in areas where the resources are not reliable in time or space. Predictability is also important for applied reasons: to define the stocking density on a given rangeland, the nutritional need of the flocks have to match as closely as possible the seasonal dynamics of forage availability. Given the same total production, the average stocking density will be higher in an environment where the timing of maximum and minimum forage availability is similar among years.

A winter concentration of precipitation seems to increase the predictability of the systems. Areas with winter precipitation in Patagonia showed a decoupling between the growing season and the wet season (Paruelo and Sala 1995). During winter, water is accumulated in the soil because transpiration losses are low. Soil water is then transferred from winter to spring. When temperature raises, this water becomes available to plants. In areas not extremely dry, the amount of water available at the beginning of the growing season is set by the holding capacity of the soil. Excess water is lost as deep drainage and/or runoff (Paruelo et al. 1998). Consequently, in areas with winter distribution of precipitation, a very stable component of the system (the soil) becomes the main control of water availability.

Predictive power increases when precipitation data are used along with *NDVI* past values as inputs. Precipitation was sampled in a 10-day period, corresponding to the sampling period of the *NDVI* data. Analysing the available data for precipitation, we observed that accumulated values are more relevant as inputs than ten-day values. When precipitation is accumulated by assigning to a given sampling period the precipitation of the past $k$ periods, it can be seen that for accumulations of 9–10 periods (about three months) a very well defined structure appears which shows a temporal correlation with the *NDVI* series (Fig. 5.4). The cross-correlation function shows a peak for a lag of approximately 11–14 periods on the *NDVI* with respect to the accumulated precipitation.

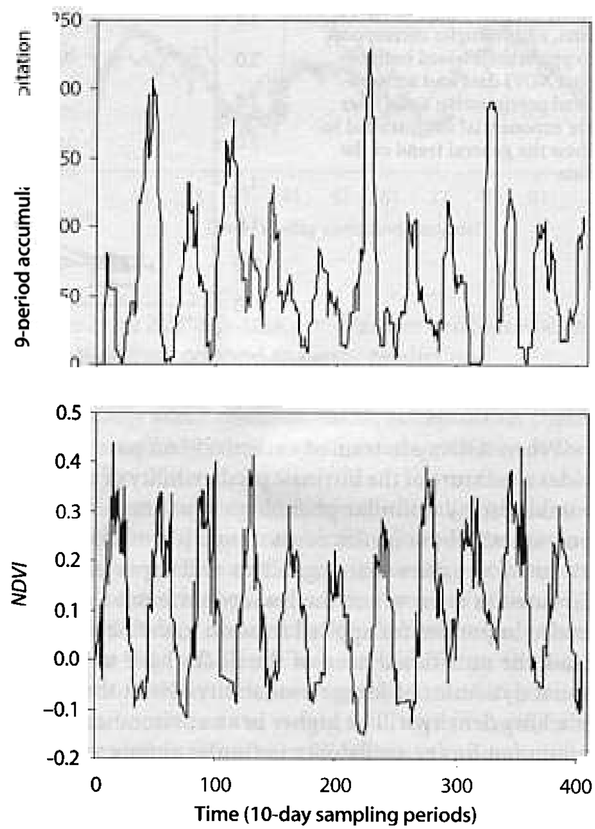


**Fig. 5.4. a** 9-period accumulated precipitation as a function of time for site Esquel. Values are obtained by assigning to a given sampling period the total precipitation of the past 9 periods; **b** *NDVI* data for site Esquel. Note the marked correspondence between the upper and lower parts of this figure, characterized by a lag of about 11 periods on the *NDVI* series respect to the accumulated precipitation

Augmenting the input vector with six past periods of accumulated precipitation (taken with a lag of 9 periods with respect to the predicted date) significantly improves the agreement between calculated and observed *NDVI* for most of the sites (Table 5.2, Fig. 5.4). Figure 5.5 shows a 9-step-ahead prediction for the case of sites Esquel, Leleque and Fofo Cahuel. In the case of site Fofo Cahuel, where the fraction of precipitation falling in summer is comparatively higher, the *NMSE* has been reduced by approximately 50%. Higher reductions in *NMSE* are observed in places with even lower summer precipitation, as it is the case of sites San Antonio, Sierra Colorada and Puesto Martínez (Table 5.2).

In summary, the study of the internal controls of the seasonal dynamics of the *NDVI* through ANN analysis of satellite and climatic data identified important differences between two phytogeographical areas (Patagonian and Monte steppes) and allowed for a satisfactory prediction of the *NDVI* values up to six months ahead.

ANN analysis is likely to become a valuable tool to be added to the standard toolbox of the researcher in ecological modelling. In particular, IT-trained ANNs appear as a promising approach for the analysis of time series in ecology. Preliminary results from a study we are presently undertaking also show promising results on the prediction of population time series through the use of IT-trained ANNs.

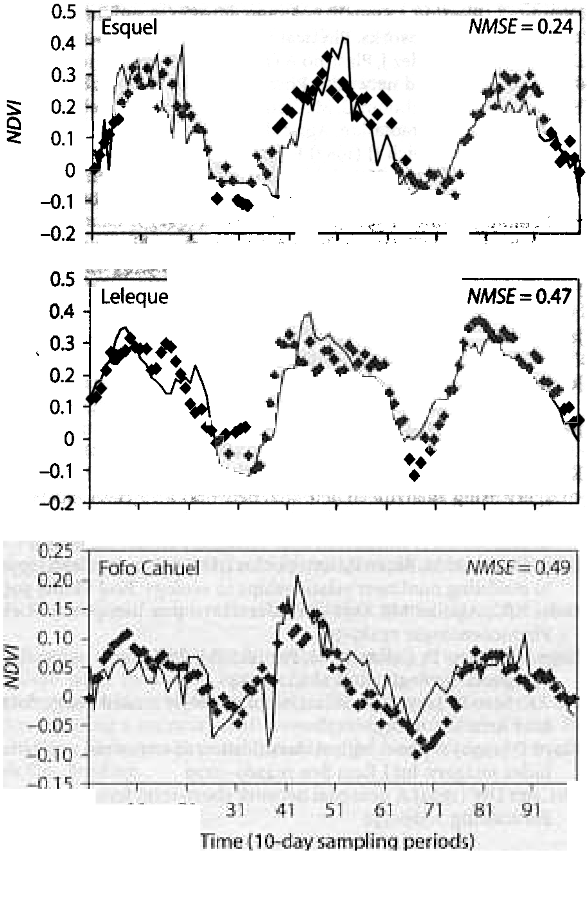


**Fig. 5.5.** 9-step-ahead prediction based on both past values of *NDVI* and accumulated precipitation for the case of sites Esquel, Leleque and Fofo Cahuel. Values for the *NSME* are indicated. Note that in Fofo Cahuel, where precipitation in summer is relatively higher, inclusion of precipitation data significantly improves the agreement between observed and predicted data respect to extrapolations based solely on *NDVI* data (see Fig. 5.2)

ANNs and satellite data also provide a very promising alternative for the prediction of *ANPP* and forage availability over extensive rangelands. Forecast of forage availability will provide to ranchers and natural resources managers a critical piece of information to devise sustainable systems in arid and semiarid lands.

## Acknowledgements

F.G. Tomasel would like to acknowledge A. Plastino for directing his attention toward pseudoinverse training techniques. This work was funded by Fundación Antorchas (Argentina) and the Inter-American Institute for Global Change Studies (IAI – ISP III # 3 077).

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