

## Chapter 16

# Characterization and Modelization of Surface Net Radiation through Neural Networks

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### ABSTRACT

*Artificial neural networks have shown to be a powerful tool for system modeling in a wide range of applications. In this chapter, the focus is on neural network applications to obtain qualitative/quantitative relationships between meteorological and soil parameters and net radiation, the latter being a significant term of the surface energy balance equation. By using a Multilayer Perceptron model an artificial neural network based on the above mentioned parameters, net radiation was estimated over a vineyard crop. A comparison has been made between the estimates provided by the Multilayer Perceptron and a linear regression model that only uses solar incoming shortwave radiation as input parameter. Self-Organizing Maps, another type of neural model, made it possible to get knowledge in an easy way on how the input variables are related to each other in the data set. The results achieved show the potential of artificial neural networks as a tool for net radiation estimation using more commonly measured meteorological parameters.*

DOI: 10.4018/978-1-61520-893-7.ch016

## INTRODUCTION

Artificial Neural Networks (ANN) applications on atmospheric science have experienced considerable growth in the last years if we consider the increasing number of publications in the topic. The most significant applications refer to solar radiation (Elizondo, Hoogenboom, & McClendon, 1994; Reddy & Ranjan, 2003), evapotranspiration (Landeras, Ortiz-Barredo, & López, 2008), ozone concentrations in urban areas (Yi & Prybutok, 1996; Prybutok, Yi, & Mitchell, 2000) or thunderstorms prediction (MacCann, 1992; Manzato, 2007), processing of Earth observation satellite data (Krasnopolsky & Schiller, 2003; Diego & Loyola, 2006), etc. But to the authors' knowledge, surface net radiation ( $Q^*$ ) estimation has not been attempted yet using ANNs. In effect, surface net radiation estimation is a complex problem because according to Venäläinen *et al.* (1998), there are complicated feedback mechanisms between the surface energy balance quantities and the surface characteristics. The usual approach to this problem has been through conventional statistical modeling techniques. In spite of finding successful applications by using regressions models to estimate  $Q^*$  (Glover, 1972; Iziomon *et al.*, 2000; Sentelhas & Gillespie, 2008), the input parameters used sometimes are difficult to obtain or measure. Thus, the objective of this chapter is to develop a *Multilayer Perceptron* ANN model, based on *in situ* measured micrometeorological and soil parameters, to estimate  $Q^*$  and compare and evaluate this model against the performance of a more commonly used  $Q^*$  linear regression model (LM) that only uses incoming solar radiation as input parameter. A *Self-Organizing Map* (SOM) was applied to extract knowledge of the possible relationships between the measured micrometeorological and soil parameters. The SOM, which is another neural model, preserves the topological relationships among the data while mapping this data into a two-dimensional map.

## BACKGROUND

The energy exchanges between the land surface and the atmosphere can be described by the surface energy balance equation given by the algebraic sum of fluxes over the surface

$$Q^* + Q_H + Q_{\lambda E} + Q_G = 0 \quad (1)$$

where  $Q^*$  is net radiation at surface,  $Q_H$  is the sensible heat flux,  $Q_{\lambda E}$  is the latent heat flux, a product of the evaporative rate  $E$  and the latent heat per unit quantity of water evaporated,  $\lambda$ , and  $Q_G$  is the soil heat flux, the rate at which heat is transferred from the surface downward into the soil profile, all in units of  $W m^{-2}$ . In Eq. (1), the fluxes are considered as positive if directed toward the surface and negative in the opposite case (Hillel, 2004) (See Figure 1).

In Eq. (1),  $Q^*$  is also the algebraic sum of net components of shortwave ( $K^*$ ) and longwave ( $L^*$ ) radiation, which can be written as

$$Q^* = K^* + L^* \quad (2)$$

where the symbol \* represents net flux. The  $K^*$  and  $L^*$  in Eq. (2) can be written as

$$K^* = K\downarrow - K\uparrow \quad (3)$$

and

$$L^* = L\downarrow - L\uparrow \quad (4)$$

finally resulting

$$Q^* = K\downarrow - K\uparrow + L\downarrow - L\uparrow \quad (5)$$

where the downward arrows ( $\downarrow$ ) and upward arrows ( $\uparrow$ ) indicate incoming and outgoing radiation components respectively, and the energy moving toward the surface is also considered positive and the energy moving away from the surface is considered negative.

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