Journal of Hydrology 382 (2010) 64–71

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Estimating reference evapotranspiration (ETo) using numerical weather forecast data in central Chile

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ARTICLE INFO

Article history:
Received 17 March 2009
Received in revised form 16 November 2009
Accepted 12 December 2009

This manuscript was handled by K. Georgakakos, Editor-in-Chief, with the assistance of V. Lakshmi, Associate Editor

Keywords:
MM5 data
MOS corrections
Reference evapotranspiration
Maipo river basin

SUMMARY

Water demand at a basin level is influenced by many factors such meteorological variables, soil moisture, vegetation type and irrigation system. Among them, climate is the major driver, because weather conditions determine energy balances and vapor pressure deficits that affect the magnitudes of vapor flux from surface to atmosphere.

Monitoring evaporation is a great challenge since specific and costly equipments are required. As an alternative, agronomists and engineers use semi-empirical equations such as the Penman–Monteith formula to estimate potential evapotranspiration based on surface weather observations. Unfortunately weather stations are scarce and do not always have the instrumentation to measure relevant variables for its calculation.

In this work, we evaluate the use of numerical weather forecasts, obtained from MM5 model, as proxy for surface meteorological data with the specific objective of using them to estimate reference evapotranspiration (ETo) in the Maipo river basin. We compared three procedures to obtain ETo: (a) Raw MM5 estimates of latent heat flux; (b) calculation of ETo from Penman–Monteith equation, using raw MM5 outputs of weather variables; and (c) calculation of ETo from Penman–Monteith using MOS-corrected MM5 weather data. We used class A pan evaporation data and estimates of ETo using observed daily surface data to evaluate the precision of each method.

We found that the estimation of ETo based on MOS-corrected weather variables is usually the most effective method to estimate reference evapotranspiration. Since MM5 outputs in this region are available at 25 km grids, the number of monitoring sites can be increased substantially, improving the ability to capture spatial variability of water demands in the basin.

Introduction

In modern societies, potential water resource conflicts arise as a consequence of current multiple uses (i.e. industrial, agriculture, ecosystems, and human consumption) as well as increasing demand due to population growth (Rosegrant et al., 2000). In Mediterranean regions, the situation could become more critical since current imbalances between water supply and demand are aggravated as a consequence of climate change. Several models predict that precipitation is likely to be reduced in the next decades affecting runoff processes. In addition, temperature increases will produce changes in seasonality of streamflow associated with early snowmelt (Vicuña and Dracup, 2007; Bates et al., 2008).

For these reasons, it is necessary to develop systems that allow efficient operation of water resources, and water allocation policies that consider the increasing demand and multiple uses of water, climatic and spatial variability of water resources and climate change impacts on supply and seasonality.

Irrigated agriculture is one of the largest consumers of water resources (Ward and Trimble, 2004). For this reason, the knowledge of evaporation rates in a region is a critical issue that allows managers to develop strategies for efficient operation of water resources.

Unfortunately measurements of evapotranspiration are scarce and expensive. Real measurements of vapor fluxes require specialized instruments such as lysimeters (López-Urrea et al., 2006), Bowen ratio equipments (Jara et al., 1998) or specific instrumentation to calculate instantaneous fluxes of momentum and vapor to apply methods such as "Eddy covariance" (Rana et al., 2005).

Some equations have been developed to estimate vapor fluxes as a function of routine meteorological observations. These equations

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doi:10.1016/j.jhydrol.2009.12.018

introduce specific assumptions regarding the status and behavior of vegetation surfaces (generally under well watered conditions).

At regional level, there are methods that use satellite images and surface meteorological data to calculate both reference evapotranspiration and actual evapotranspiration. An example of these methods is SEBAL (Surface Energy Balance Algorithm for Land; Bastiaanssen et al., 1998, 2005), which has been used in regional water balance studies (Allen et al., 2007).

In any case, the correct estimation of crop evapotranspiration and therefore irrigation needs relies on the availability of routine meteorological information. Unfortunately weather stations are scarce and do not always have the instrumentation needed to measure all relevant variables.

Over the last years there have been improvements in objective weather forecasting based on mesoscale numerical models. These models not only provide forecast for commonly used variables such as temperature and precipitation. They also give information regarding other relevant variables such as pressure, wind speed and direction, specific humidity and solar radiation. All of these variables are required to calculate reference evapotranspiration, representing a potentially valuable source of information for water resources management.

The objective of this research is to evaluate the use of mesoscale model results as proxy for surface weather variables in places where there is no meteorological stations, and use these variables to estimate reference evapotranspiration.

Determining evapotranspiration

Because of its theoretical basis and effectiveness in assessing evapotranspiration rates, the Penman–Monteith equation (Monteith, 1965; Monteith and Unsworth, 1990) has been recommended by FAO as the most appropriate method to determine crop water requirements (Allen et al., 1998). The equation is:

$$\lambda E = \Delta\left((R_N - G) + \rho c_p \frac{(e_s - e)}{r_h}\right) \Big/ \left(\Delta + \gamma\left(1 + \frac{r_c}{r_h}\right)\right) \tag{1}$$

Here, λ is the latent heat of vaporization (2,500,000 J kg^{-1}), Δ is the rate of change of vapor pressure with temperature (Pa K^{-1}). R_N corresponds to net radiation (J m^{-2} day^{-1}), G is the soil heat flux (J m^{-2} day^{-1}). ρ is air density (kg m^{-3}). c_p is the specific heat at constant pressure (J kg^{-1} K^{-1}). e_s and e are the saturation vapor pressure and the actual vapor pressure of air (Pa). r_h is the aerodynamic resistance to heat flow (days m^{-1}). γ is the psycrometric constant (Pa K^{-1}). r_c is the canopy resistance (days m^{-1}).

When the crop experiences water stress, active mechanisms of regulation are trigged and vapor exchange is restricted via stomata closure. In Eq. (1) this is represented by increasing canopy resistance, which in turn reduces evapotranspiration. However, canopy resistance is very difficult to measure, unless soil water content is high enough so stomata are fully open and the resistance reaches its minimum value.

Reference evapotranspiration (ETo)

Due to the difficulties associated with the estimation of canopy resistances, environmental scientists have preferred to define a variable called reference evapotranspiration (ETo), which is the amount of water transpired by a short, dense vegetation growing under total satisfaction of its water requirements. Penman–Monteith equation is applied assuming that the canopy resistance is set to a known value close to zero. Allen et al. (1998) present this equation as a function of daily routine meteorological data.

$$\mathrm{ETo} = \frac{\left(0.408 \cdot \Delta \cdot (R_N - G) + \gamma \frac{900}{T+273} \cdot u_2 \cdot (e_s - e)\right)}{(\Delta + \gamma(1 + 0.34 \cdot u_2))} \tag{2}$$

In this case, net radiation (R_N) and soil heat flux (G) are expressed in MJ m^{-2} day^{-1}. Mean temperature is in Celsius (°C), and wind speed at 2 m height (u_2) is in m s^{-1}.

Reference evapotranspiration is regarded as a process that occurs without water stress, and represents the upper limit of grass water requirements when exposed to the observed meteorological conditions.

Empirical work (mostly carried on using lysimeters) has shown that water requirements of any crop are proportional to reference evapotranspiration. Therefore one can obtain crop potential evapotranspiration multiplying reference evapotranspiration by a crop coefficient (kc). As in the case of reference evapotranspiration, the application of this method is only possible when the crop does not experience water stress. To model actual evapotranspiration it is necessary to represent changes in canopy resistance as a function of water availability (Jarvis, 1976; Stewart, 1988). In some cases it is possible to model the crop coefficient value as a function of soil water content to represent impacts of water shortages on canopy resistance. Examples of this approach are found in Allen et al. (1994, 1998), and Meza (2005).

Class A evaporation pan

An alternative method to obtain reference evapotranspiration corresponds to the use of class A evaporation pan (Eb). This instrument has been standardized allowing the user to determine water evaporation measuring variations of the water table (Jensen et al., 1990; Allen et al., 1998). Since evaporation form an open source differs form the one occurring in crops, it is necessary to apply an empirical coefficient denominated pan coefficient (Kp). This value depends on wind speed and relative humidity in the surrounding environment. For a class A evaporation pan, Allen et al. (1998) give an equation to determine its value.

$$\mathrm{Kp} = 0.108 - 0.0286 \cdot u_2 + 0.0422 \ln(d) + 0.1434 \ln(\mathrm{RH}) - 0.000631(\ln(d))^2 \cdot \ln(\mathrm{RH}) \tag{3}$$

Here, RH corresponds to relative humidity (%), d is the distance between the instrument and crop (m), and u_2 corresponds to the wind speed measured at 2 m height. Once this value has been determined, reference evapotranspiration can be calculated as:

$$\mathrm{ETo} = \mathrm{Eb} \cdot \mathrm{Kp} \tag{4}$$

MM5 model

It is clear that surface weather observations are needed to calculate reference evapotranspiration either using Penman–Monteith or class A evaporation pan. Since it is not always possible to have these values, the use of other sources of information such as weather forecasts from numerical models appears as an interesting alternative.

MM5 is a non-hydrostatic, sigma coordinate, mesoscale model developed by the National Center for Atmospheric Research (NCAR) and Pennsylvania State University (PSU). The model has been designed to simulate and predict atmospheric circulation, based on the work of Anthes and Warner (1978). It is composed by a series of sub-models which represent several processes in the atmosphere such as conservation of mass and momentum, atmospheric thermodynamics, advection and divergence. In recent years, it has been possible to operate MM5 in a nested mode improving its spatial resolution (Dudhia et al., 2005).

The use of MM5 based forecasts for individual meteorological variables such as temperature, wind speed, and precipitation has been documented previously (Hart et al., 2004; Falvey, 2007; Oncley and Dudhia, 1995) and it has been used in several countries as a fundamental tool for objective weather forecasting. However, there is a rich body of information in MM5 simulations that can be fit within the framework of predicting evapotranspiration, since most of the variables requested in Eq. (2) are found in regular MM5 outputs. Moreover, MM5 gives information about latent heat flux (λE) at the surface, so it will be possible to use both, the direct assessment of evaporation and the one obtained combining surface meteorological information. MM5 uses a Land Surface Model (LSM; Chen and Dudhia, 2001) to represent feedback mechanisms between vegetation and the atmosphere, and calculates soil heat flux (G), sensible heat flux (H) and latent heat flux (λE), using a Penman-based energy balance approach with an stability-dependent aerodynamic resistance (Mahrt and Ek, 1984). Although this feature is recognized as a significant improvement in the ability of MM5 to represent land–atmosphere interactions, MM5-computed latent heat fluxes show important discrepancies with observed data when are applied to large regions (Marx et al., 2008).

MOS

It is widely recognized that MM5 forecasts (i.e. raw data) are far from perfect, and that the model has some limitations related to the coarse representation of the terrain, the numerical representation of the differential equations, and lack of high resolution upper air data for initialization. In some cases there are systematic errors that can be removed using statistically based post processing routines, training equations to obtain a better estimation of meteorological variables in specific locations. These types of procedures receive the common denomination of Model Output Statistics (MOS; Glahn and Lowry, 1972; Wilks, 1995) and have been used to obtain forecasts of daily surface weather variables form Numerical Weather Prediction models (NWP) for more than 30 years (Sokol and Rezacova, 2000). The method was proposed by Glahn and Lowry (1972), and it is described by the authors as an objective numerical weather forecasts technique that is based on determining the statistical associations between variables obtained from the numerical model (predictors) and the climatic variable of interest (predictand) for a specific time period.

The application of MOS to outputs of any Numerical Weather Prediction model (NWP) reduces forecasts errors, because the systematic deviation is removed and/or forecast variance is corrected (Neilley et al., 2002).

The general format of this procedure corresponds to a multiple linear regression model in which several NWP variables are included to obtain the best estimation of the forecasted variable (Eq. (6)).

$$Y_p = a_0 + a_1 \cdot p_1 + a_2 \cdot p_2 + a_3 \cdot p_3 + \cdots + a_n \cdot p_n \quad (5)$$

Here, Y_p is the MOS corrected predictand, a_i are the regression coefficients ($I = 1, 2, \ldots, n$), and p_i correspond to the predictors from a NWP model (Antolik, 2000). The optimum number of predictors is obtained using a screening procedure called stepwise fit regression. Basically this method chooses the predictor with highest correlation, then the pair of variables, including the predictor selected in the step before, with highest correlation and then the triplet, and so on. The process is repeated until the reduction of the root mean square error is no longer significant (Glahn and Lowry, 1972; Antolik, 2000; Wilks, 1995).

One disadvantage of MOS is that it requires a fairly long record of NWP outputs and observations to produce robust estimations (Antolik, 2000). It is also very likely that specific MOS equations have to be developed for different locations, making spatial generalization are very difficult task (Clark and Hay, 2004).

Even though there are evident limitations in mesoscale models and that MOS corrected forecast do not always achieve good results, it is important to recognize that these models contain information that can be used, especially in places where there is an insufficient network of meteorological stations and situation where only few meteorological variables are recorded.

Methods and procedures

Location

The area under study corresponds to the Maipo basin, located between latitudes 32°55′ and 34°15′ south, and longitudes 70–72 west. The basin has a surface of 15,157 km^2, 33% of that surface corresponds to mountains (Andes), 45% shows native forests, 30% is irrigated agriculture and the rest corresponds to urban areas (DGA, 2007).

The climate is regarded as Mediterranean with mean annual temperature of 14 °C and total precipitation of 350 mm in the valley. Rainfall shows strong seasonality with 80% of annual precipitation falling in austral winter. Snow accumulation occurs above 1500 m during winter.

Reference evapotranspiration varies from 6.5 mm day^{-1} in the austral summer to 1.5 mm day^{-1} in mid winter. The strong seasonal pattern is a consequence of the variability of solar radiation and temperature. High frequency variability (i.e. day to day) remains constant over the year, with a slight reduction in winter and a peak in the beginning of spring. Fig. 1 shows mean and standard deviations of reference evapotranspiration for the region under study. Interannual variability is rather small. For instance, mean values for reference evapotranspiration in the month of January (the month that exhibits the highest intensities) are around 6.8 mm day^{-1} with a coefficient of variation of only 3%. Previous work (Meza, 2005) has shown a significant ENSO footprint in the evaporation regime of the Maipo basin (central Chile), but the greater differences among ENSO phases are observed in winter and fall seasons.

Meteorological data

We collected daily data for the period 2004–2007. MM5 outputs were provided by the department of geophysics (Universidad de Chile). Each time the model is run it provides forecast for meteorological conditions up to 144 h ahead. To ensure we would work with the data with a minimum of uncertainty, we only used the values that represent the period from 0 to 24 h in the future, selecting the variables that are equivalent to the surface records.

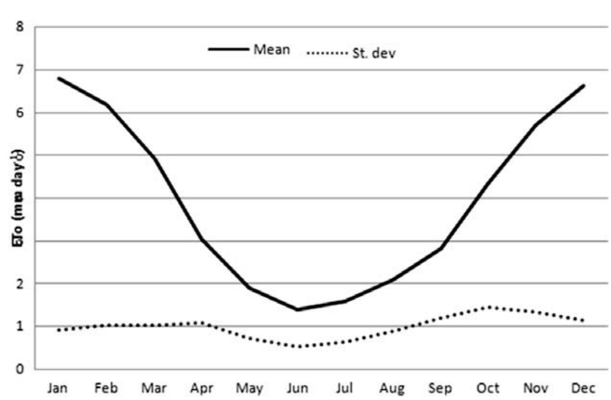

Fig. 1. Seasonal variation of reference evapotranspiration in central Chile.

Surface weather information was collected form different sources. One of them is a network of automatic weather stations called AGROCLIMA, the other sources were the Directorate General of Waters (DGA) and the Chilean National Weather Service (DMC). Within the existing network of meteorological stations in the basin, only five (Pudahuel, Los Panguiles, Talagante, Quinta Normal and Pirque) recorded the meteorological variables needed to calculate reference evapotranspiration according to Penman–Monteith formula. Two stations (Quinta Normal and Pirque) had also data from class A pan evaporation, allowing us to have an alternative estimate of reference evapotranspiration. Fig. 2 shows the geographic distribution of weather stations (control points) and MM5 grid points within the Maipo basin.

We removed outliers and inconsistent data from both series (i.e. MM5 forecasts and weather observations). We used the series from 2004 to 2006 to fit the coefficients of a MOS for each location and left the year 2007 as an independent validation data set.

Since grid points of MM5 forecasts do not coincide with the sites of observation we interpolate values from the closest four grid points using a three dimensional inverse distance algorithm. Although MM5 can give information in 29 sigma coordinate levels, we only used surface values as proxy for meteorological data. The variables used were: surface pressure, precipitation, temperature, shortwave radiation, longwave radiation, wind speed, latent heat flux and specific humidity.

MOS equations

In this case, we develop specific MOS equations for each station and applied this procedure for raw outputs of MM5 model (i.e. maximum temperature, minimum temperature, mean temperature, specific humidity, daily sum of shortwave radiation, and daily mean wind speed) as well as the estimation of ETo using latent heat data from MM5.

Since MM5 variables and observed meteorological data show marked seasonality, we fit a Fourier series to each variable and remove the seasonality, working only with anomalies. In this way we reduced the probability of choosing a predictor that shows high correlation only because it varies over time following a similar mode of the predictand. The general Fourier series equation is:

$$F_{W,t} = b_0 + b_1 \cdot \sin\left(\frac{2 \cdot \pi \cdot t}{365}\right) + b_2 \cdot \cos\left(\frac{2 \cdot \pi \cdot t}{365}\right) \quad (6)$$

$F_{W,t}$ corresponds to the value of the Fourier series for variable W in time t (1, ..., 365), b_0 is the annual mean of the variable, b_1 and b_2 are the coefficients associated to the first harmonic.

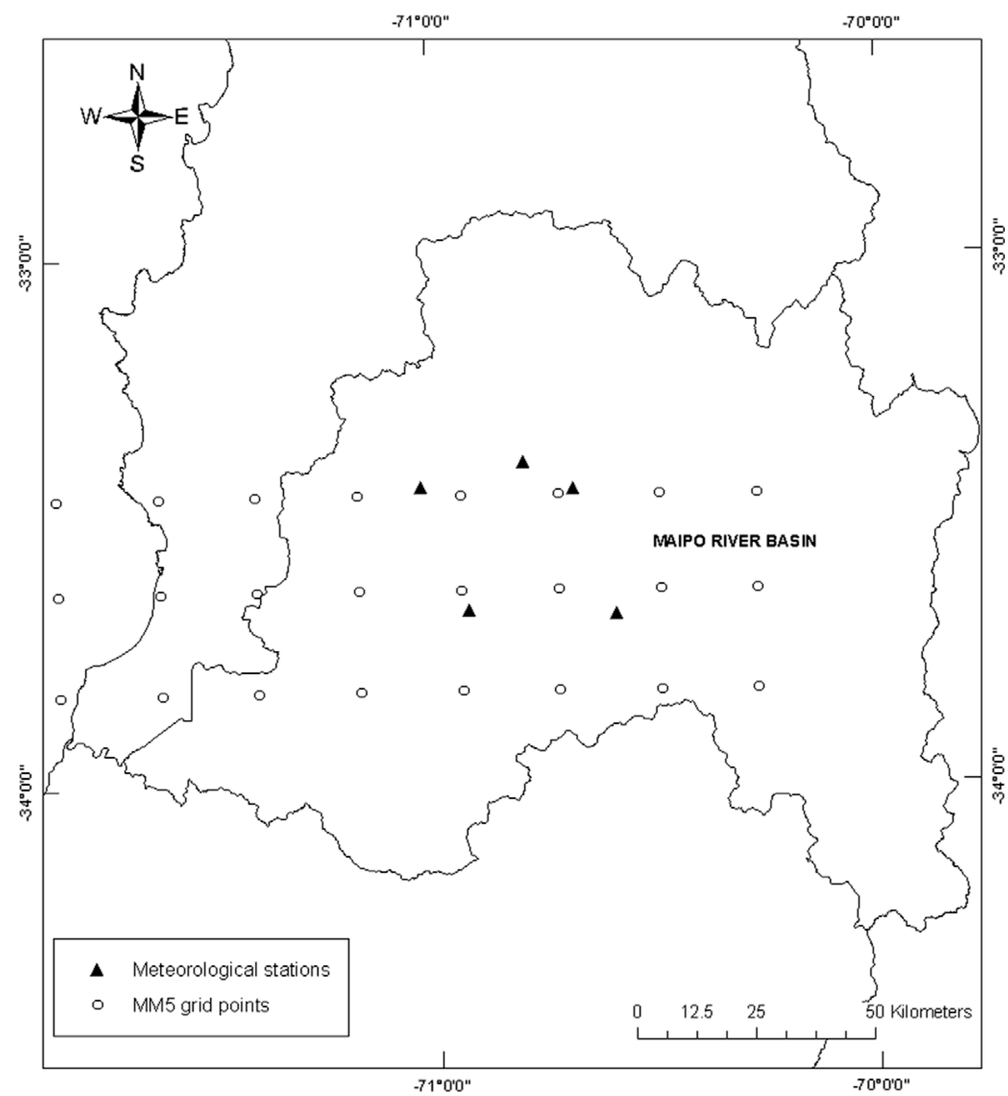

Fig. 2. Geographic distribution of meteorological stations and MM5 grid point.

Once seasonality is being removed we used a stepwise fit procedure included in Matlab to select the predictors for each variable and location. Thus the general MOS equation is:

$$(Y_t - F_{Y,t}) = a_0 + a_1 \cdot (X_{1t} - F_{X1,t}) + a_2 \cdot (X_{2t} - F_{X2,t}) + \cdots + a_n \cdot (X_{nt} - F_{Xn,t}) \quad (7)$$

Here, Y represents the predictand, and X_i ($i = 1, \ldots, n$) the selected MM5 predictors.

The performance of MOS equations for individual meteorological variables (i.e. temperature, relative humidity, wind speed and solar radiation) is discussed in Silva et al. (2009).

Comparison of results

Since the objective is to evaluate the use of MM5 forecasts to estimate reference evapotranspiration we compare three different methods. Method 1 corresponds to direct use of latent heat fluxes obtain from MM5. Dividing this value by the latent heat of vaporization (λ) one obtains an estimate of evapotranspiration. Method 2 corresponds to the calculation of ETo by means of Penman–Monteith equation, using raw data from MM5 (without MOS). Method 3 calculates ETo using Penman–Monteith equation, but in this opportunity the formula is fed with MOS-corrected MM5 outputs.

To compare the accuracy of the estimates from all methods, in each station we calculated Penman–Monteith reference evapotranspiration using observed weather data, and in two of them we calculated reference evapotranspiration using class A evaporation pan.

We computed root mean square error, maximum absolute deviance and the coefficient of determination between observed and predicted values of reference evapotranspiration. We also conducted a *T*-test for observed and predicted values with the null hypothesis that there are no differences between the two data sets. This procedure has been used in similar studies (Jacovides and Kontoyiannis, 1995), but in this case is necessary to apply a variance inflation factor (Wilks, 1995) since observed and predicted data show significant autocorrelation coefficients.

Table 1
Fourier series coefficients (b_0, b_1, b_2) and summary statistics of goodness of fit for reference evapotranspiration (PM-ETo and A-ETo) and MM5 variables.

	b_0	b_1	b_2	R^2	RMSE
Pudahuel					
PM-ETo (mm)	2.39	−0.03	1.55	0.68	0.67
Maximum temperature (°C)	24.46	1.22	7.39	0.77	2.67
Minimum temperature (°C)	8.02	1.53	5.08	0.66	2.54
Solar radiation (MJ m^{-2})	16.73	−1.42	9.04	0.89	2.03
Wind (m s^{-1})	2.94	−0.03	−0.24	0.03	0.89
Pressure (kPa)	94.56	−0.10	−0.11	0.16	0.24
Quinta Normal					
PM-ETo (mm)	2.80	−0.02	1.97	0.75	0.75
A-ETo (mm)	3.32	0.59	2.86	0.63	1.44
Maximum temperature (°C)	24.23	2.45	7.35	0.79	2.70
Minimum temperature (°C)	7.65	2.67	4.43	0.66	2.63
Solar radiation (MJ m^{-2})	16.52	−1.07	9.34	0.88	2.09
Wind (m s^{-1})	2.80	0.01	−0.72	0.20	0.89
Pressure (kPa)	94.13	−0.05	−0.23	0.29	0.23
Los Panguiles					
PM-ETo (mm)	4.41	0.37	1.05	0.31	1.15
Maximum temperature (°C)	23.64	1.21	7.32	0.78	0.78
Minimum temperature (°C)	8.53	1.56	4.92	0.67	2.50
Solar radiation (MJ m^{-2})	16.68	−1.51	9.15	0.88	2.12
Wind (m s^{-1})	2.77	−0.11	−0.07	0.01	0.81
Pressure (kPa)	94.90	−0.08	−0.15	0.26	0.20
Pirque					
PM-ETo (mm)	3.19	−0.17	1.52	0.49	0.96
A-ETo (mm)	3.88	0.71	3.04	0.71	1.27
Maximum temperature (°C)	23.05	1.69	6.45	0.78	2.29
Minimum temperature (°C)	7.64	1.82	4.32	0.65	2.26
Solar radiation (MJ m^{-2})	16.40	−0.91	9.34	0.87	2.22
Wind (m s^{-1})	3.21	−0.02	−0.84	0.43	0.60
Pressure (kPa)	92.10	−0.05	−0.10	0.17	0.16
Talagante					
PM-ETo (mm)	2.37	−0.14	1.34	0.60	0.68
Maximum temperature (°C)	23.53	1.12	7.41	0.77	2.71
Minimum temperature (°C)	8.60	1.57	4.91	0.65	2.59
Solar radiation (MJ m^{-2})	16.54	−1.51	9.25	0.88	2.22
Wind (m s^{-1})	2.85	−0.06	−0.18	0.01	1.00
Pressure (kPa)	94.89	−0.07	−0.14	0.23	0.21

Results and discussion

Seasonal variation

One of the most important sources of variability in almost all variables (i.e. calculated ETo and MM5 forecast data) corresponds to seasonality. Table 1 shows the results of a single harmonic Fourier series fit to the data to model the behavior of each variable throughout the year. Even tough the analyses of variance were statistically significant in all cases; wind speed and pressure did not show seasonal variations that can be represented using sinusoidal functions. In those cases the anomalies were comparatively larger than in the case of temperature and solar radiation. In the case of reference evapotranspiration, the use of Fourier series allowed us to capture up to 75% of the variability. The strong seasonality observed is a consequence of the characteristic pattern of variation of temperature, relative humidity, and clear skies found in semi-arid and Mediterranean regions.

MOS procedures

MOS data contains a number of different predictors that can be used to obtain the best representation of real weather data. We performed a MOS procedure using stepwise regression to choose only the ones that achieve better results in terms of variance explained. Table 2 shows an example of selected predictors for maximum and minimum temperature.

Even tough some predictors may have no direct connection with the meteorological variable from the biophysical standpoint, the main advantage of this method is that usually the bias is removed and variance of the error is reduced. Table 3 shows a comparison of goodness of fit indices for selected variables, with and without MOS. It is clear that MOS procedures outperform raw MM5 data in the ability to represent daily surface weather observations. A complete evaluation of the use of MOS-corrected MM5 data as proxy for daily weather variables is presented in Silva et al. (2009).

Estimation of ETo

Daily data from 2004 to 2006 was used to calibrate MOS equations and later on used to calculate reference evapotranspiration using Eq. (2). Note that reference evapotranspiration shows a very strong seasonal behavior. Even though the harmonic analysis carried out here does not represent a forecast method by itself, given the proportion of the variance captured by the Fourier series, we have considered it as a baseline for comparison, so a good method to assess reference evapotranspiration must not only outperform the others, but also show improvements over simple seasonal models such as the ones obtained using Fourier series.

Table 4 shows a comparison between methods in terms of their ability to represent reference evapotranspiration. Except for the case of class A evaporation Pan at Pirque, maximum absolute deviation was substantially reduced in all cases where ETo is estimated

Table 2
List of MOS predictors used to represent maximum and minimum temperature at each location.

	Location				
	Pudahuel	Quinta Normal	Los Panguiles	Pirque	Talagante
Maximum temperature					
MM5 total solar radiation			x		
MM5 maximum solar radiation				x	
MM5 maximum temperature	x	X	x	x	x
MM5 maximum wind speed	x	X		x	
MM5 maximum specific humidity			x	x	x
MM5 minimum specific humidity		X			
MM5 mean specific humidity				x	
Minimum temperature					
MM5 total solar radiation		X			
MM5 maximum solar radiation				x	
MM5 minimum temperature	x		x	x	x
MM5 mean temperature		X		x	
MM5 surface pressure		X		x	
MM5 maximum wind Speed	x				x
MM5 maximum specific humidity		X			
MM5 minimum specific humidity			x		
MM5 mean specific humidity		X		x	

Table 3
Comparison of goodness of fit indicators for some selected variables, with and without MOS.[a]

Location	Without MOS					With MOS				
	R^2	RMSE	n	m	MAD	R^2	RMSE	n	m	MAD
Maximum temperature										
Pirque	0.74	2.90	−0.85	1.02	13.70	0.79	2.64	0.00	1.01	12.52
Talagante	0.63	3.69	2.09	0.85	13.20	0.69	3.38	0.03	1.00	8.80
Quinta Normal	0.80	2.86	−1.37	0.99	12.60	0.84	2.59	0.00	1.00	8.87
Minimum temperature										
Pirque	0.48	2.49	0.59	0.63	10.30	0.74	1.76	0.00	1.00	5.89
Talagante	0.46	2.59	3.18	0.55	11.50	0.57	2.31	0.00	1.00	6.75
Quinta Normal	0.63	2.41	3.85	0.70	10.40	0.84	1.60	0.00	1.00	6.33
Mean temperature										
Pirque	0.85	1.57	1.45	0.84	10.11	0.88	1.41	0.00	1.00	7.35
Talagante	0.75	2.05	3.58	0.71	10.74	0.84	1.65	0.00	1.00	5.20
Quinta Normal	0.83	1.98	3.13	0.85	6.45	0.90	1.51	0.00	1.00	4.90

[a] R^2 is the determination coefficient, RMSE corresponds to root mean square error, MAD corresponds to the maximum absolute deviation and m and n are the slope and intercept of the observed vs. predicted regression, respectively.

Table 4
Comparison between methods[a] to estimate reference evapotranspiration from MM5 outputs. Bold values of RMSE represent cases where the null hypothesis of a *T*-test for autocorrelated data is not rejected at the 5% significance level.

	MAD (mm)			RMSE (mm)			R^2			
	M1	M2	M3	M1	M2	M3	M1	M2	M3	FS
Pudahuel	2.77	4.34	2.68	0.78	0.99	**0.63**	0.57	0.30	0.71	0.68
Quinta Normal	3.97	4.20	2.07	0.96	0.99	**0.66**	0.52	0.48	0.77	0.75
Quinta Normal (pan)	5.66	5.23	3.19	1.21	1.16	0.98	0.44	0.49	0.63	0.63
Los Panguiles	8.71	7.86	5.13	1.34	1.54	**1.22**	0.21	−0.06	0.35	0.31
Pirque	6.42	6.47	5.00	1.39	**1.51**	**1.17**	0.38	0.27	0.56	0.49
Pirque (pan)	3.57	3.46	3.81	1.00	1.13	**0.92**	0.67	0.59	0.73	0.71
Talagante	3.89	4.70	2.34	0.74	1.15	0.65	0.52	−0.15	0.63	0.60

[a] M1 estimates ETo using latent heat flux, M2 uses raw MM5 variables, and M3 uses MOS-corrected MM5 variables. FS corresponds to a single harmonic Fourier series, representing seasonal variation.

with MOS-corrected MM5 data. Root mean squared error also shows important reductions, ranging from 10% to 20%, and consequently the percentage of the observed variance that is explained by the estimates increases.

As in the case of routine meteorological data (i.e. precipitation, temperature and wind speed), the estimation of ETo using raw MM5 values do not produce satisfactory results. In some cases the coefficient of determination gives values that are even smaller than zero. This result implies that either original variables used or the estimates of ETo must be statistically corrected to achieve some degree of predictability.

It is interesting to note that estimates of ETo using latent heat fluxes from MM5 (Method 1) provide results that are better than the ones obtained using the set of meteorological variables

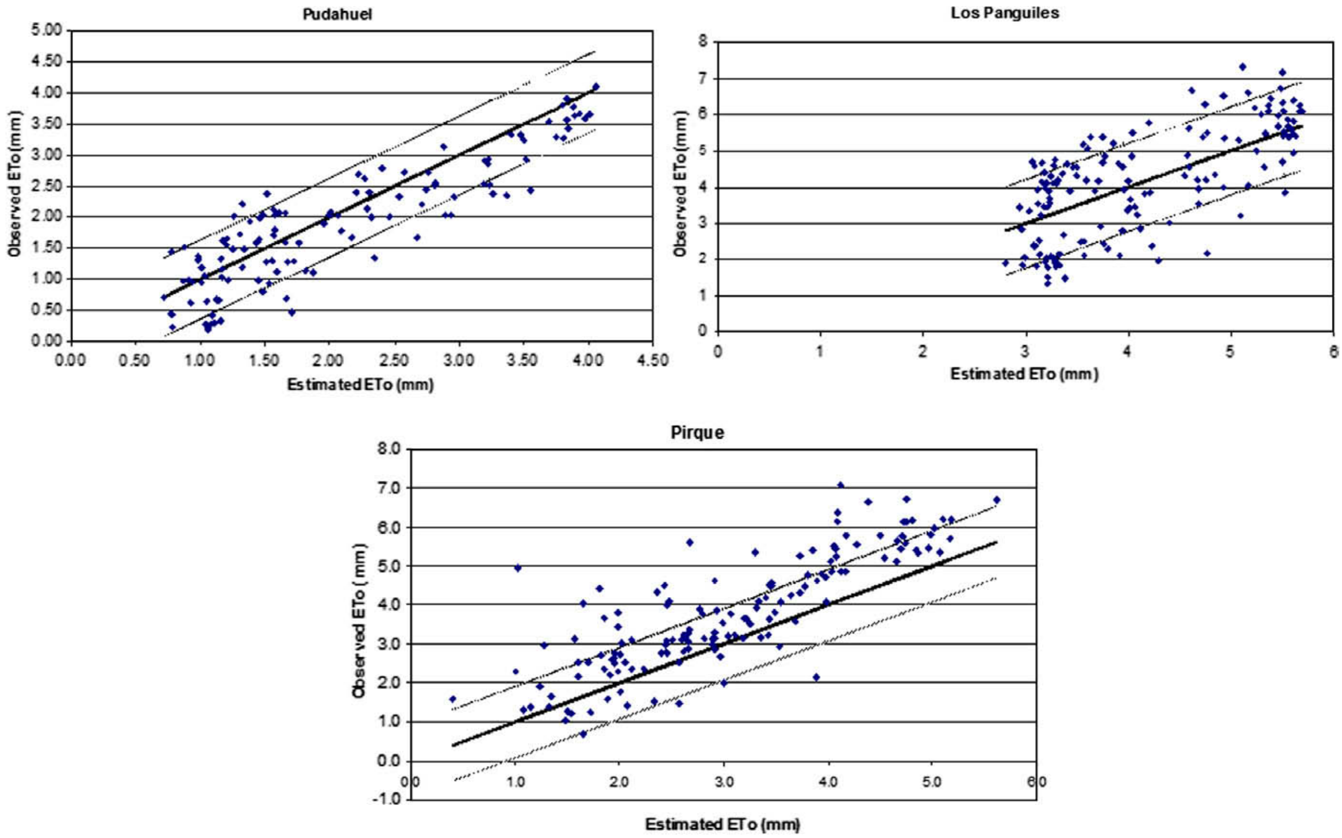

Fig. 3. Comparison between observed and predicted values of ETo for three locations in the year 2007.

forecasted. Perhaps a better representation of the terrain (i.e. type of vegetation and surface roughness) will allow MM5 model to improve the estimation of energy fluxes and water vapor fluxes.

The estimation of ETo using MOS-corrected MM5 data is the only method that gives better results than simple statistical models developed to represent seasonal variations. Increments in the percentage of the variance explained range from 2% up to 7%.

Although all methods show some interesting indicators of performance, it is necessary to assess in a more formal manner, their ability to predict reference evapotranspiration. This is done using a *T*-test for autocorrelated data (i.e. correlation between simultaneous observations in time). With the sole exception of MOS-corrected MM5 data (Method 3), in the majority of the cases the test showed values that suggest strong evidence against the null hypothesis (Ho is rejected at 5%), indicating that Methods 1 and 2 are not adequate to predict reference evapotranspiration.

Since the method based on MOS corrected data was the one that produced better results, we applied it to see whether it will be able to estimate correctly reference evapotranspiration observed during 2007. Since the coefficients associated to the predictors of each meteorological variable were obtained with a different sample, some differences appear. For instance, the slope of the regression line between observed and predicted values is 0.86 for Quinta Normal station and it is statistically different from 1. In the case of Pirque the regression between observed and predicted values shows a bias of 0.5 mm which is also statistically significant. Fig. 3 shows the comparison between observed and predicted values using MOS-corrected MM5 data for the location of Pudahuel, Los Panguiles and Pirque. Dotted lines represent confidence intervals of plus and minus 1 standard deviation. The majority of the observations fall within those intervals. The problem of bias detected in Pirque can be clearly appreciated in the figure. As in most of the statistical forecasting methods, one can expect that these problems can be reduced using larger sample sets that allow us to improve the estimates of the coefficients involved in the stepwise regression.

Conclusions

Evapotranspiration is one of the most important meteorological variables for assessing crop water requirements and irrigation needs. In several places of the world, the existing network of meteorological stations is insufficient to capture the spatial heterogeneity of this variable. In addition to that, some satiations do not record all necessary variables to produce estimates of evapotranspiration.

The objective of this work was to investigate the potential use of mesoscale model MM5 as proxy for surface meteorological variables to produce estimates of reference evapotranspiration.

Results showed that MM5 raw data does not produce good results in terms of evapotranspiration. MM5 estimates of latent heat flux are considerably better for those purposes.

MOS-corrected MM5 data improve the quality of the information and allow us to generate estimates of ETo that are more accurate that the ones obtained using raw data, and also outperform simple statistical models that represent seasonal variations of this variable.

Even though there is an important limitation in the use of MOS-corrected MM5 data, because of the need of larger data sets to calibrate the equations, the fact that MM5 grid points have higher spatial resolution opens promising avenues to use this information as proxy for surface weather variables and provide with estimates of evapotranspiration in regions where there are no meteorological stations.

Acknowledgements

This work was carried out with the aid of a Grant from the Inter-American Institute for Global Change Research (IAI) SGP-HD #003 which is supported by the US National Science Foundation (Grant GEO-0642841) and with the aid of FONDECYT throughout Grant 1060544.

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