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Using the particle swarm optimization algorithm to calibrate the parameters relating to the turbulent flux in the surface layer in the source region of the Yellow River

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ABSTRACT

Accurately determining the fluxes of mass and energy between land and the atmosphere is important for understanding regional climates and hydrological cycles. In numerical modeling, the parameterization of a turbulent flux is usually based on Monin-Obukhov similarity theory (MOST). According to this theory, it is necessary to simultaneously calculate the empirical similarity parameters β_m, β_h, γ_m, and γ_h, the aerodynamic roughness (z_{0m}) and the thermal roughness (z_T). However, it is difficult to solve a simultaneous set of nonlinear equations for these six parameters. In this study, a new method was introduced to solving this problem. Using measurements from Maqu Station in the source region of the Yellow River, this study employed the artificial intelligence particle swarm optimization (PSO) algorithm to calibrate the parameters relating to the turbulent flux in the surface layer. We concluded that the differences in the sensible heat and momentum fluxes between the calculations that used the calibrated parameters and the measurements were rather small and that their correlation coefficients were relatively high. The results suggested that PSO algorithm is a feasible approach which can be applied in MOST parameter estimation.

1. Introduction

The atmospheric surface layer is at the bottom of the atmospheric boundary layer. Due to the strong aerodynamic and thermal effects of the underlying surface, atmospheric motion is dominated by turbulence. The mass and energy exchanges that occur between the atmosphere and land surface via turbulent fluxes significantly impact both weather and climate (Dickinson et al., 1998; Seneviratne et al., 2006). In numerical modeling, schemes for parameterizing the turbulent surface flux enforce the balances of mass and energy between land and the atmosphere (Beljaars and Holtslag, 1991; Chen et al., 1997; Garratt and Pielke, 1989). Therefore, to improve the performance of climate models, it is important to carefully study the physical interactions between different types of land surface and the atmosphere, develop optimal schemes for parameterizing the turbulent fluxes and accurately determine the land-atmosphere fluxes of mass and energy.

In global climate models, the land-atmosphere fluxes of momentum, sensible heat and water vapor are usually calculated using the wind velocity, potential temperature and humidity gradients with the relevant bulk transfer coefficients (Dai, 2003; Niu, 2011; Zeng and Dickinson, 1998). The wind velocity, potential temperature and humidity gradients can be directly measured. Therefore, accurately determining the bulk transfer coefficients is the key to parameterizing the turbulent fluxes in numerical models. Since the Monin-Obukhov similarity theory (MOST) was proposed in the 1950s (Dyer, 1974; Monin and Obukhov, 1954), significant breakthroughs have been made in the parameterization of surface turbulent fluxes (Businger et al., 1971; Dyer, 1974). More than 20 parameterization schemes for the bulk transfer coefficients have been developed based on this theory (Abdella and McFarlane, 1996; Łobocki, 1993; Louis, 1979; Paulson, 1970), and these schemes have been widely applied in various types of numerical model. Accord-

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ing to MOST, the land-atmosphere bulk transfer coefficients can be represented as follows:

$$C_D = \frac{\kappa^2}{\left[\ln(z/z_{0m}) - \psi_m(z/L)\right]^2} \quad (1)$$

$$C_H = C_E = \frac{\kappa^2}{\left[\ln(z/z_{0m}) - \psi_m(z/L)\right]\left[\ln(z/z_T) - \psi_h(z/L)\right]} \quad (2)$$

where $C_{D,}$ C_H and C_E are the bulk transfer coefficients of momentum, sensible heat and water vapor, respectively, κ is the von Karman constant. Ψ_M and Ψ_H are the integrals of the similarity functions associated with momentum and heat. z is a reference height, L is the Obukhov length, z/L represents the atmospheric stability, z_{0m} is the aerodynamic roughness and z_T is the thermal roughness.

Many studies of the similarity functions in the above equations have been conducted (Businger et al., 1971; Dyer, 1974; Högström, 1996). Near-surface measurements with different underlying surface types were found to lead to different forms of these functions (van den Hurk and Holtslag, 1997). Sorbjan (1986) reviewed previous results and summarized the similarity functions for the momentum and sensible heat as follows, based on the status of the atmospheric stability (Sorbjan, 1986):

$$\phi_m = \begin{cases} 1 + \beta_m(\frac{z}{L})\frac{z}{L} \geq 0 \\ ^{-1/4}\frac{z}{L} < 0 \end{cases} \quad (3)$$

$$\phi_h = \begin{cases} 1 + \beta_h\frac{z}{L}\frac{z}{L} \geq 0 \\ ^{-1/2}\frac{z}{L} < 0 \end{cases} \quad (4)$$

where φ_m and φ_h are the differential expressions of the similarity functions, β_m and β_h, and γ_m and γ_h are empirical parameters that are normally regressed from measurements. In numerical models, the similarity functions obtained by Businger and Dyer have been most widely used (Dai, 2003; Niu, 2011; Oleson et al., 2010). In these functions, the empirical parameters are $\beta_m = \beta_h = 16$ and $\gamma_m = \gamma_h = 4.7$. However, these functions are not always suitable for all seasons and surface types. Numerous studies have shown that the selection of empirical parameters depends largely on the physical properties of the underlying surface, the accuracy of the measurements and the methods of the study (Högström, 1988).

The stability parameter z/L determines the atmosphere's motion and thermal status. It is usually an implicit function of C Yang et al. (2001) suggested that z/L can be represented by the bulk Richardson number and similarity functions (Yang et al., 2001). Under stable conditions, because the similarity functions are linear, an analytical solution for z/L is available. In contrast, under unstable conditions, the similarity functions are nonlinear, and z/L can be obtained via iteration or semi-analytical methods (Abdella and McFarlane, 1996; Łobocki, 1993; Louis, 1979; Paulson, 1970; Sharan and Srivastava, 2014). The atmosphere aerodynamic and thermal roughness lengths are two parameters that are important for calculating the bulk transfer coefficients. They represent the heights at which the surface wind velocity reaches zero and at which the surface temperature is equal to the atmospheric temperature. These two parameters are difficult to measure directly; therefore, they are often taken as empirical parameters in near-surface studies (Kanda et al., 2007; MacKinnon et al., 2004). Present studies suggest that the aerodynamic roughness strongly depends on the surface conditions. Therefore, in land surface models (i.e. CLM, NOAH), the underlying surface is divided into different types, and each type is assigned a different aerodynamic roughness (Oleson et al., 2010). Thermal roughness was originally considered identical to aerodynamic roughness (Louis, 1979), but further development in near-surface measurements and research have shown that thermal roughness is normally less than aerodynamic roughness (Sun, 1999; Yang et al., 2008, 2003). We can use $KB^{-1} = \ln(z_{0m}/z_T)$ to compare the two parameters. Accurately determining the aerodynamic and thermal roughnesses or KB^{-1} is critical for improving the parameterization of the turbulent flux.

From the above analysis and a combination of Eqs. (1) and (2), we can see that C_D depends on β_m, γ_m and z_{0m} and that C_H depends on β_m, β_h, γ_m, γ_h, z_{0m} and z_T. Together, these six parameters affect the bulk transfer coefficients, which can be obtained after simultaneously solving for β_m, β_h, γ_m, γ_h, z_{0m} and z_T. Determining these six parameters simultaneously requires solving a set of non-linear equations. The calculation is complex, iterative and time consuming. Previous conventional studies usually selected similarity functions, that is, assigned a value to β_m, β_h, γ_m, γ_h, and then calculated the others using the multi-layer wind velocity and potential temperature profiles under neutral conditions. Then, the bulk transfer coefficients could be calculated. This method suffered from a few pitfalls: (1) It reduced the six parameters in the original parameterization scheme to one or two parameters and did not verify the suitability of the similarity functions and the sensitivity of the calculation. (2) The six parameters were mutually related. Calculating z_{0m} or z_T using profiles of the wind velocity and the potential temperature may accurately yield one of the two bulk transfer coefficients for the momentum or sensible heat but cannot accurately yield both. (3) An accurate calculation of z_{0m} or z_T requires accurate profiles of the multi-layer wind velocity and the potential temperature. In addition, different neutral condition ranges could lead to large variations in the results. Therefore, it is necessary to investigate methods of efficiently calculating the turbulent flux parameters that avoid the caveats of the conventional approach.

The recent development of the particle swarm optimization (PSO) algorithm used in artificial intelligence provides one possible method for solving the above problem (Kennedy and Eberhart, 1995; Poli et al., 2007). This algorithm mimics animal activities such as the process birds and fish use for finding food, which essentially is a particle constrained by a certain object function solving a global or quasi-global optimal solution within a given space. Therefore, many studies have used this method to calibrate the parameters of continental hydrological models. For example, Gill et al. used a multi-objective particle swarm algorithm to estimate hydrological parameters (Gill et al., 2006). Chau et al. combined the PSO algorithm with artificial neural networks (ANNs) to predict water levels (Chau, 2006). Scheerlinck et al. used the PSO algorithm to calibrate the parameters of a simple hydrological model and found that it was easy to implement and used measurements efficiently (Scheerlinck et al., 2009).

Calibrating the turbulent flux parameters is a similar optimization process; i.e., given a different parameter space, we compare the errors between the calculated and measured values of the momentum and sensible heat fluxes within a time period, evaluate the suitability of the parameters and then obtain more accurate parameters. Hence, many optimization algorithm can be used to calibrate the turbulent flux parameters. Compared with other algorithm, the PSO algorithm has the following advantages to calibrate the surface-layer turbulent flux. (1) The particle swarm optimization is easy to implement with a set of non-linear equations to find the optimum solution. Furthermore, according to the theoretical study of PSO algorithm, it was proved that the PSO algorithm can get approximate global optimum, and has a lesser tendency of getting trapped in local minima (Schmitt and Wanka, 2015). The optimum solution is not affected by the velocity, iteration number, and initial value. (2) The ranges of turbulent fluxes related parameters have been able to obtain, but the exact values is still difficult to determine