



A PARAMETRIC STUDY FOR FIREFLY ALGORITHM BY SOLVING AN INVERSE PROBLEM FOR PRECIPITATION FIELD ESTIMATION

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Abstract. *In this paper we consider the parameter estimation problem of weighting the ensemble of convective parameterizations implemented in the Brazilian developments on the Regional Atmospheric Modeling System (BRAMS). The inverse problem is applied to BRAMS precipitation simulations over South America for December 2004. The forward problem is addressed by BRAMS, and the ensemble of convective parameterizations are expressed by several methodologies used to parameterize convection. The inverse problem is formulated as an optimization problem applying the metaheuristic Firefly algorithm (FA) to retrieve the weights of the ensemble members. The FA algorithm represents the patterns of short and rhythmic flashes emitted by fireflies in order to attract other individuals. The flashing light is formulated in such a way that it is associated with the objective function. The precipitation data estimated by the Tropical Rainfall Measuring Mission (TRMM) satellite was used as the observed data. The quadratic difference between the model and the observed data was used as the objective function to determine the best combination of the ensemble members to reproduce the TRMM measurements. Sensitivity analysis was used to test the FA algorithm parameters to adjust the algorithm to retrieve precipitation observations. The tested parameters were the initial attractiveness and the gamma parameter, which characterizes the variation of the attractiveness and is very important in determining the speed of convergence of the method. The results showed a high sensitivity to the gamma parameter variation, and the largest values resulted in the best combinations of weights, resulting in a retrieved precipitation field closest to the observations.*

Keywords. *Cloud parameterization, inverse problem, firefly optimization, BRAMS*

1 INTRODUCTION

Clouds processes operate on scales smaller than model resolutions, with a strong effect at resolvable scales (Cotton and Anthes, 1989). Due to the low horizontal resolution, a model cannot resolve many of the processes associated with clouds and their interaction with the environment. Several physical processes and parameters cannot be explicitly predicted in full detail on the model grid points (or wave numbers for spectral models), but their effects on the resolvable variables in the model are crucial for correct forecasting. These effects are known as subgrid-scale processes. Important vertical redistribution of heat and moisture by convection occurs among the grid boxes of a model (Cooperative Program for Operational Meteorology and COMET, 2011). Subgrid-scale variations in convection have an effect on moisture and heating in some of the model grid boxes. Therefore, these effects are important for representing meteorological phenomena at scales ranging from mesoscale to large scale. For example, according to Lin and Neelin (2002), for global numerical models, it is necessary to determine the area averaged precipitation rates for each grid box, and some places will get more precipitation than the average. The uncertainty in the convective heating and drying rates creates an uncertainty at the larger scales (Jones and Randall, 2011). Therefore, it is important to determine, as well as possible, the effects of subgrid-scale processes associated with convection in the atmosphere.

In order to represent the subgrid processes associated with clouds and interactions with the environment, the model must include a parameterization in the moisture and heat prediction equations. The key problem of numerical prediction is trying to predict, with incomplete information, the effects of subgrid-scale processes with information from the grid scale. In this sense, cumulus parameterization is one of the most difficult problems in weather and climate prediction. Computational limitations require running numerical models with low spatial resolution, making it impossible to fully computationally resolve convective processes. A cumulus parameterization is an attempt to account for the net effect of an ensemble of clouds on the scale of the atmospheric model (Arakawa and Schubert, 1974). A statistical approach is used to assume their solution, which always introduces errors, providing an additional source of uncertainty to the stochastic nature of the atmosphere. The goal of cumulus parameterization is to determine changes in the simulated large-scale environment due to the collective influence of multiple cumulus clouds (Jones and Randall, 2011).

Each parameterization method must derive information about the processes from the meteorological variables, considering a set of assumptions. Several schemes have been developed to represent the convection process (Yanai et al., 1973; Arakawa and Schubert, 1974; Kuo, 1974; Grell and Dévényi, 2002). These parameterizations differ mainly in their closure assumptions and description of the interaction between the environment and the convection. Closure refers to the link between the assumptions in the parameterization and the forecast variables, and it closes the loop between the

parameterization and forecast equations. These differences in the parameterization are a consequence of the uncertainties in the understanding of the physical and dynamical processes of the convection, particularly with respect to how to express the interaction between the larger flow and the convective clouds in parameterized terms (Bao et al., 2011).

Using these parameterizations separately in a single model framework provides a way to take advantage of the above mentioned uncertainties in the generation of ensemble predictions (Bao et al., 2011). Grell and Dévényi (2002), hereafter GD, developed a deterministic scheme for the convective cloud processes. It is based on an assumed "quasi-equilibrium" balance between large scale (resolved) forcings and the net large-scale effects of unresolved convective cloud processes (Arakawa and Schubert, 1974). The scheme expands the convective parameterization of Grell (1993) to include several assumptions of classical closures and parameters commonly used in convective parameterizations. The ensemble of closures consists of disturbances around the classical closures of Grell (1993); Arakawa and Schubert (1974); Kain and Fritsch (1993), low-level Omega (Frank and Cohen, 1987), and moisture convergence (Kuo, 1974). The GD parameterization scheme has been developed to provide more freedom to users to choose one or more assumptions, and closures within the extensive existing options. However, the approach is strongly based on the scheme of Arakawa and Schubert (1974) and Grell (1993).

The GD ensemble has 16 closure members, which are allowed to interact with 22 members (variations in several parameters), giving a total of 13824 ensemble members. GD used these members to determine the ensemble average, see Grell and Dévényi (2002). As a result, the precipitation forecast can be combined in several ways, generating a numerical representation of precipitation and atmospheric heating and moistening rates. These assumptions, from several considerations of convection initiation and development, represent a natural span of uncertainties in convective parameterizations (Bao et al., 2011).

The ensemble members are chosen to allow a large spread in terms of accumulated convective rainfall (Bao et al., 2011). However, the influence of each member of the GD ensemble for a given place must be quantified. In order to address this problem, an inverse problem methodology is applied for parameter estimation. The inverse problem is formulated as an optimization problem for retrieving the weights of the GD convective parameterization ensemble, and it is solved using the Firefly algorithm (FA). The forward problem is computed by the Brazilian developments on the Regional Atmospheric Modeling System (BRAMS) (Freitas et al., 2007).

The parameter estimation consists of minimizing an objective function using the model parameter adjustment. The objective function is a measure of the distance between the experimental data and the model forecasts, the root mean square deviation of the model prediction and the experiment.

The inverse analysis is applied to precipitation simulations over South America using BRAMS (Freitas et al., 2007). The goal is to find the weights for each ensemble member in the GD convective parameterization implemented in the BRAMS model.

2 THE FIREFLY ALGORITHM

The Firefly (FA) algorithm was proposed by Yang (2008), and it is based on the bioluminescence process which characterizes fireflies. The reason for using the FA algorithm is because we already have obtained satisfactory preliminary results with this methodology employed on this important application Luz et al. (2009); dos Santos et al. (2010a,b,c). In addition, a new version for the FA is under development. Therefore, the goal here is to evaluate the robustness of the standard FA.

According to Yang (2008), scientists do not yet have complete knowledge about the function of the flashing lights of fireflies. However, there are at least two important functions associated with the flashes: (a) attracting mating partners and (b) attracting potential prey.

In order to implement the algorithm based on the flashes of fireflies, Yang (2008) used the following three idealized rules: the fireflies are unisex, so one firefly will be attracted to all other fireflies regardless of their sex; (ii) the attractiveness is proportional to their brightness, so, for any two flashes, the less bright one will move towards the brighter one. The attractiveness is proportional to the brightness, and they both decrease as their distance increases. If there is no brighter firefly, it will move randomly; (iii) the brightness of a firefly is affected or determined by the landscape of the objective function.

The attractiveness is determined by the emitted light intensity, and it is a function of its evaluation. There are two important pieces of information for determining the FA: the light intensity variation, and the attractiveness formulation. For simplicity, the attractiveness is determined by its brightness, which in turn is associated with the objective function.

For a simple case, the brightness (I) in a particular location is a function of its position x as follows:

$$I(x) \propto f(x), \quad (1)$$

and the attractiveness (β) is relative to the firefly position from which the more attractive firefly is observed. Thus, I will depend on the distance r_{ij} between the firefly i attracted by the brightness of the firefly j . Moreover, the light intensity decreases with increasing distance from its source and depends on the propagation medium, so the attractiveness varies with the degree of absorption. With that, the objective function is the inverse of the light intensity.

The light intensity is assumed to be $[I(r)]$ and it varies according to the inverse square distance r ,

$$I(r) = \frac{I_f}{r^2}, \quad (2)$$

where I_f is the light intensity at the source. For a given medium with a fixed light absorption coefficient γ , the light

intensity varies with r as follows:

$$I = I_0 e^{-\gamma r}, \quad (3)$$

where I_0 is the original light intensity. Combining the inverse square law and the absorption, we have:

$$I(r) = I_0 e^{-\gamma r^2}, \quad (4)$$

which can be approximated as

$$I(r) = \frac{I_0}{1 + \gamma r^2}. \quad (5)$$

The attractiveness β is proportional to the light intensity seen by adjacent fireflies as follows:

$$\beta = \beta_0 e^{-\gamma r^2}, \quad (6)$$

where β_0 is the attractiveness at $r = 0$. This function can be approximated by:

$$\beta(r) = \frac{\beta_0}{1 + \gamma r^2}. \quad (7)$$

The distance between any two fireflies i and j at x_i e x_j , respectively, is the Cartesian distance

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^d (x_{i,k} - x_{j,k})^2}, \quad (8)$$

where $x_{i,k}$ is the k th component of the spatial coordinate x_i of i th firefly.

The movement of a firefly i attracted to another more attractive (brighter) firefly j is determined by:

$$x_i = x_i + \beta_0 e^{-\gamma r_{ij}^2} (x_j - x_i) + \alpha \left(rand - \frac{1}{2} \right), \quad (9)$$

where α is the randomization parameter and $rand$ is a random number generator uniformly distributed in $[0, 1]$.

The second term in the rhs of Eq. 9 is due to the attraction while the third term is the randomization. This term is associated with the randomization of the movement of a firefly i toward a firefly j . Without this term, the fireflies would possibly be attracted to a firefly that is not necessarily the brightest. The solution would be restricted to a local minima, directly toward the best solution in the local search space. With the randomization term, the search over small deviations makes it possible to escape from local minima, having a higher chance of finding the global minimum of the function.

The γ parameter characterizes the attractiveness variation and its value is crucially important in determining the speed of convergence and how the FA behaves. In theory, $\gamma \in [0, \infty)$, but in practice and in most applications, $\gamma = O(1)$ typically varies from 0.1 to 10.

3 THE BRAMS MODEL

The BRAMS model (Freitas et al., 2007) is a joint project of several Brazilian institutes, including the Center for Weather Prediction and Climate Studies (CPTEC) of the National Institute for Space Research (INPE), and is funded by FINEP (The Brazilian Funding Agency). BRAMS is based on the Regional Atmospheric Modeling System (RAMS) (Walko et al., 2000), with several new functionalities and parameterizations. The BRAMS model is a numerical model developed to simulate atmospheric circulations at many scales. It solves the fully compressible non-hydrostatic equations described by Tripoli and Cotton (1982). The BRAMS model has a set of physical parameterizations appropriate for simulating processes such as surface-air exchange, turbulence, convection, radiation and cloud microphysics (Freitas et al., 2007). The BRAMS model includes, among others, an ensemble version of a deep and shallow cumulus scheme based on the mass flux approach (Grell and Dévényi, 2002).

The convective parameterization trigger function uses the turbulence kinetic energy (TKE) of the RAMS Planetary Boundary Layer (PBL) parameterization to modulate the maximum distance that air parcels can rise from their source level and, based on that, to determine if a grid column will be able to sustain convection (Freitas et al., 2007). The trigger function is modified using the parameter `cap_max`, which represents the maximum distance the air parcel can rise and trigger the convective portion of a column if it can reach the condensation level and, subsequently, free convection. `cap_max` is modified with three values to be used in the ensemble. Operationally, the model can be performed with 144 members, where 16 members are variations in five popular closure assumptions, such as Arakawa and Schubert (1974), moisture convergence (Kuo, 1974), low-level Omega (Frank and Cohen, 1987), Kain and Fritsch (1993) and Grell (1993), hereafter AS, MC, LO, KF and GR, respectively, 3 members are variations in the trigger function and 3 members are variations of the precipitation efficiency. These members are combined in order to obtain an ensemble mean realization closure (hereafter ENS), or the user can use only one closure option, choosing among the five available options.

4 EXPERIMENTAL DESIGN

The BRAMS model version 4.2 was used to simulate precipitation over South America from 02 to 13 December 2004. The model was performed for a forecast length of 24 hours, once a day, from 01 December 2004 until 12 December at 12:00 UTC, with a restart every 24 hours. The following configuration was used: the GD convective parameterization scheme, a model grid with 25 km horizontal resolution covering South America and a 100 meter vertical resolution in the first level. The vertical resolution varied telescopically with higher resolution at the surface with a ratio of 1.1 up to a maximum vertical resolution of 950 m, with the top of the model at approximately 19 km (a total of 40 vertical levels). As initial and boundary conditions, we used the CPTEC/INPE Atmospheric General Circulation Model (AGCM) analysis with T126L28 resolution, where T126 is the rhomboidal truncation at wave number 126, and L28 is the number of model vertical levels.

Six different model simulations were performed, generating six precipitation fields, each one using a single closure option. One of the runs was performed using the ENS option. This precipitation field was used as the control experiment, which was compared with the results obtained with the FA algorithm.

For the experimental data, precipitation information from CPTEC/INPE was used. The experimental precipitation data is calculated by a technique called MERGE (Rozante et al., 2010), combining data from the Tropical Rainfall Measuring Mission (TRMM) satellite precipitation estimates (Huffman et al., 2006) with surface observations over the South American continent. Although TRMM is highly valuable for numerical model evaluation, the MERGE technique is used to correct of TRMM precipitation estimation problems, because systematic errors are verified in particular in the eastern portion of Northeast Brazil (precipitation is underestimated due to formation of warm clouds, Huffman et al. (2006)).

4.1 Solving the inverse problem: weight estimation

The inverse solution is obtained by identifying the optimum weight values associated with each member of the ensemble in the GD parameterization. The weight set is the unknown vector of parameters denoted by \vec{W}^T . The objective function consists of the square of the difference between observations and predictions.

The precipitation fields were computed from the model (P_M , a linear combination of five precipitation outputs using five parameterization closures) and one observed precipitation field or MERGE data (P_O). The estimator P is a random variable that minimizes the Euclidian norm square of $P_M - P_O$, i.e., P minimizes

$$J(\vec{P}) = |P_M(\vec{W}^T) - P_O|^2 = [P_M^{\vec{W}} - P_O]^T [P_M^{\vec{W}} - P_O] = \sum_{i=1}^{w_i} [P_M(\vec{W}^T) - P_O]^2, \quad (10)$$

$$P_M = \sum_i w_i P_i, \quad (11)$$

where $\vec{W}^T \equiv [w_i, i = 1, \dots, N_w]^T$, P_i ($i = 1, 2, \dots, N_w$) and N_w denotes the dimension of the parameter vector, as well as the dimension of the ensemble, i.e., the different precipitation parameterization closures. For GD parameterization closures, we have $\vec{W}^T = [w_{GR}, w_{MC}, w_{LO}, w_{AS}, w_{KF}]^T$, and the subscripts *GR*, *MC*, *LO*, *AS* and *KF* denote the classical closures assumed in the parameterization (see Section 3).

The FA algorithm was used to solve the optimization problem. Each firefly represents a candidate solution (in the vector with five components, each component is associated with a single closure), and the brightest firefly identifies the best weight set for the five closures.

The parameters used in the FA algorithm are: the number of fireflies (n), β_0 , α and the number of generations (G), i.e., the number of iterations used in the FA code. The parameters α , β_0 , γ were tested with respect to the variations in the weight results. Each parameter was tested, and when one was tested, the other one was fixed. Later, the number of fireflies used was modified, to verify the impact of the number of fireflies on the representation of the best solution for solving the inverse problem. As a result, a table was generated with different results obtained with the variation of all parameters. Table 1 summarizes the information about initial and final values, as well as the rate of variation of each parameter.

Table 1: Experimental tests with the FA algorithm parameters.

Parameter	initial value	final value	increment
α	0.01	0.1	0.01
β	0.1	1.0	0.1
γ	1.0	10.0	1.0
n	5	50	5
G	10	100	10

The sensitivity of the algorithm with respect to the chosen parameters was tested, allowing the choice of the best parameters to be used together to solve the proposed inverse problem.

The weights estimation was performed in two different ways. First, each weight was obtained for the entire domain, i.e., only one weight was computed for weighting all grid points. So, the FA parameters were tested according to Table 1.

The results were analyzed using the RMS index, defined as follows:

$$REQM(\theta) = \frac{1}{N} \sum_{n=1}^N \left[\frac{1}{I \cdot J} \sum_{i=1}^I \sum_{j=1}^J (\theta_{i,j,n}^P - \theta_{i,j,n}^O)^2 \right]^{1/2} \quad (12)$$

where θ is a given variable, I and J are the total number of model grid points in the horizontal and the superscripts P and O are the forecasts (or the new precipitation field) and observations, respectively.

The mean RMS from 02-13 December was computed for each value of the parameters in Table 1.

With the best values for the parameters, a new experiment was performed, and then the unknown vector was computed at each grid point over South America.

4.2 Precipitation retrieval

The set of weights at each grid point was determined and they were used to retrieve the precipitation fields for the period of 02-13 December (2004). For each day, the set of weights was used; however, to simplify the analysis, the mean field for the period was computed. Finally, the retrieved precipitation was compared with the BRAMS model precipitation computed with the ENS closure. A simple difference was computed to compare both fields.

5 RESULTS

According to climatological records (not shown), during December, precipitation is of the order of 100 mm in Southern Brazil, and 250 mm to 300 mm over Central Brazil. The observed accumulated precipitation during 02 to 13 December and the average precipitation for this period are shown in Figure 1. The accumulated precipitation was of the order of 200 mm over several places over Southern and Central Brazil, as well as over the latitude belt of 10°N (Figure 1(a)). The average precipitation (Figure 1(b)) indicates that higher values are seen over the tropical region at 10°N, with precipitation higher than 20 mm. Over most of Southern and Central Brazil, precipitation is the order of 5 mm to 20 mm in some places.

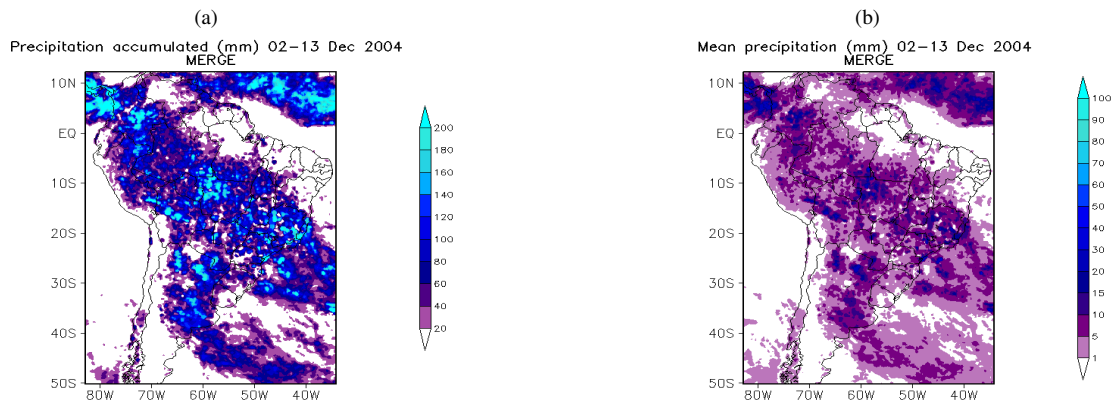


Figure 1: Observed observed precipitation during 02 to 13 December and the average precipitation for the same period (mm) from the MERGE data.

The average precipitation from simulations is shown in Figure 2. When the AS and KF closures are used (Figure 2(a) and 2(c), respectively), it can be seen that the average accumulated precipitation during 24h of simulation is larger than when the other closures are used. A simple average of the results with different precipitation parameterizations (ENS closure, Figure 2(f)) basically represents the contribution from the AS and KF schemes (Figures 2(a), 2(c)), because other schemes have very low estimated precipitation (Figures 2(b), 2(d), 2(e)).

Figure 3 shows the variation of RMS with the variation of α (top), β_0 (middle) and γ (bottom) parameters. In general, for increasing α the RMS values increase. The best value of α was obtained in the first iteration, with a value of 0.1. The variation in β_0 showed that between values of 0.2 and 0.5, the RMS decreased, with a minimum at 0.5. However, for values greater than 0.5, an increased RMS was observed. The γ parameter showed different behavior, i.e., a decrease was observed in the RMS with an increase in this parameter, with a minimum at 10. Among all computed values of RMS using the variation of all FA parameters, the best results were found for the following parameters: $\alpha = 0.1$, $\beta_0 = 0.5$ and $\gamma = 10$. These values were used as fixed parameters to compute the vector of weights for each model grid point.

The distribution of the weights with variation in the FA parameters can be seen in Figure 4. The weights are predominantly positive, with some variability of the weights according to increasing parameters. Their values were found mainly between the interval of -0.2 to 1, but with one minimum value verified in the analysis of the α parameter of the order of -2. The weights are the same when the RMS is at a minimum for all parameters. In other words, when α , β_0 and γ are, respectively, 0.1, 0.5 and 10, the vector of weights is $\vec{W}^T = [w_{GR}, w_{MC}, w_{LO}, w_{AS}, w_{KF}]^T = \{0.82, 0.80, 0.61, 0.41, -0.19\}$. This is in accordance with the results shown in Figure 2. The closures with large precipitation (i.e., AS and KF) have small weights, and those with lower precipitation (i.e., GR, LO and MC) have larger weights.

The retrieved precipitation is shown in Figure 5. Comparing the retrieved mean precipitation for the considered period with the control experiment (Figure 2(f)), a gain by using the proposed methodology is verified. The retrieved mean

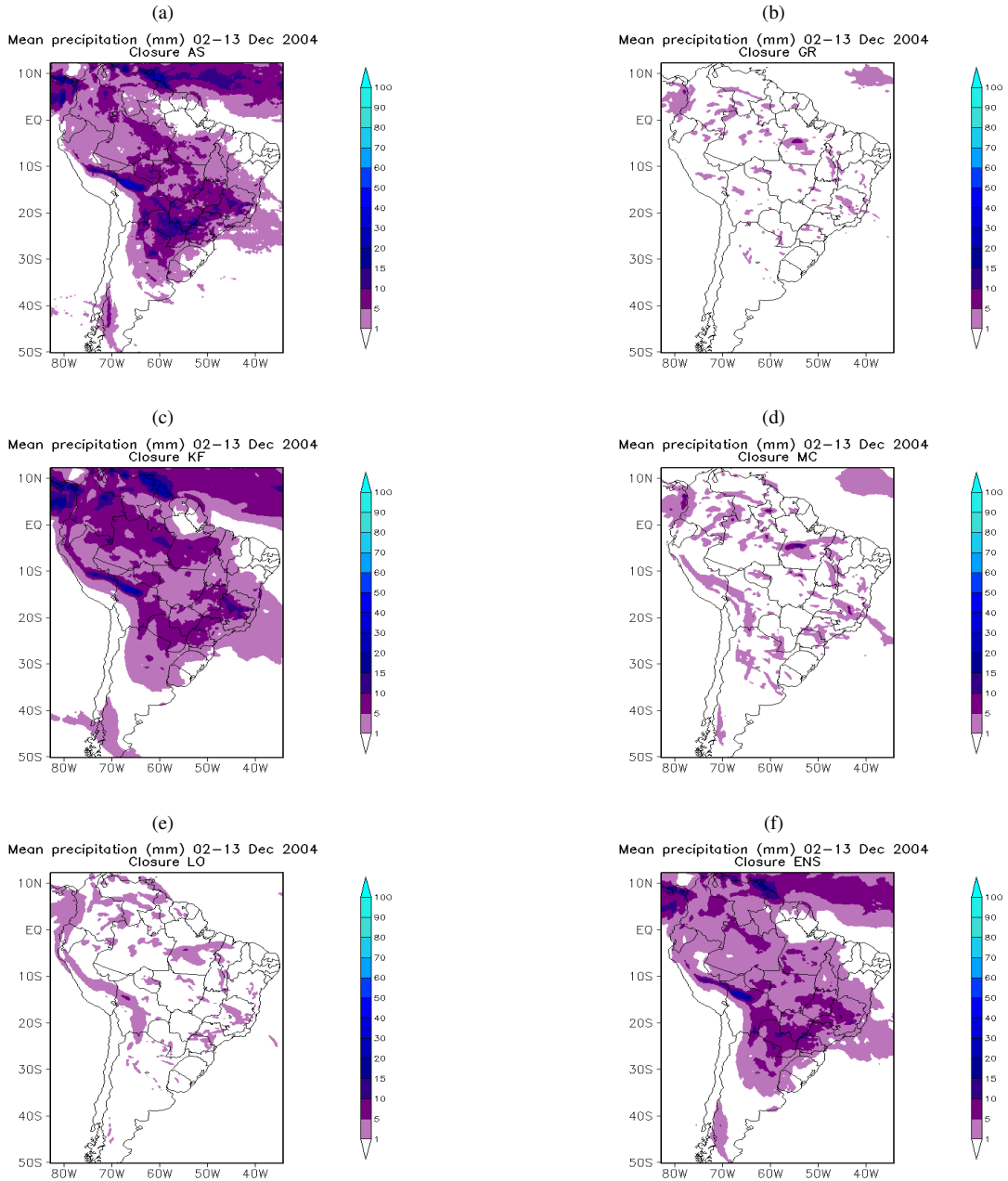


Figure 2: Mean accumulated precipitation (mm) in simulations to 24h using the following closures: a) AS; b) GR; c) KF; d) MC; e) LO; f) ENS.

precipitation shows less precipitation over tropical regions compared with the control experiment. This pattern is better identified using the difference between the retrieved mean precipitation and MERGE data (Figure 5(c)) and the difference between the control experiment and MERGE data (Figure 5(b)). In the Figures, shaded red areas are associated with overestimation of the models and shaded blue areas are associated with underestimation of the models. The retrieved mean precipitation overestimates and underestimates less than the control experiment. Over central Brazil and east of the Andes Cordillera, the overestimation of the retrieved field is of the order of 5 mm while the overestimation of the control experiment is of the order of 10 mm to 15 mm.

6 CONCLUDING DISCUSSION

The computational methodology to identify the weights for the ensemble representation of precipitation was described. The inverse problem was solved by the Firefly optimization algorithm. A numerical experiment was designed to identify the best parameters to be employed to the Firefly algorithm with focus on the application to the retrieval of model precipitation fields. It is difficult to find a general procedure to identify the best parameters for the most of metaheuristic algorithms (Lukasik and Zak, 2011).

The best performance for the Firefly algorithm was obtained (considering the range selected for the firefly parameters to our application) with the values: $\alpha = 0.1$, $\beta_0 = 0.5$, $\gamma = 10$.

The resulting RMS always increases when the value of α increases, for fixed values for β_0 and γ . On the other hand,

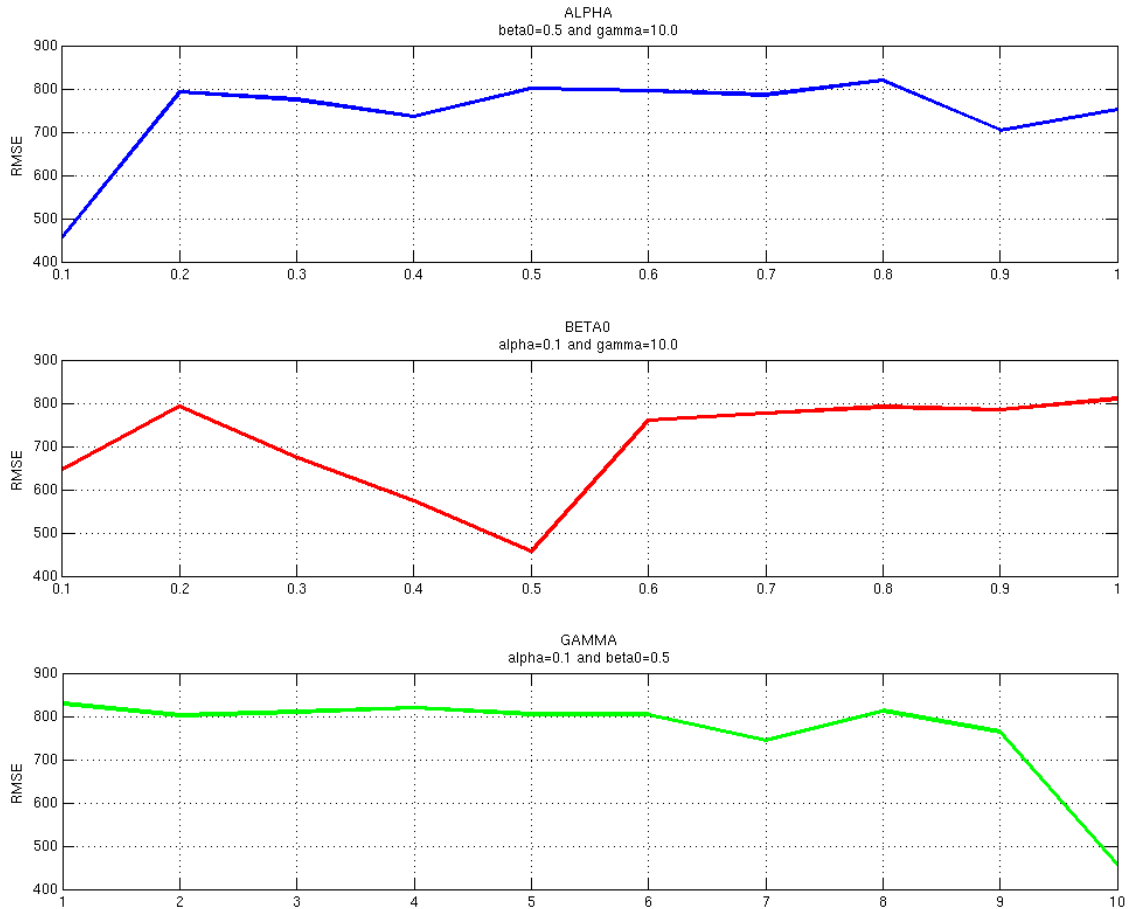


Figure 3: Root mean square error (RMS) of the mean precipitation (mm) over South America.

when α and γ are fixed and β_0 is variable, the RMS decreases between values of 0.2 and 0.5, with a minimum at 0.5. The γ variation indicated a decrease of RMS when γ increases. As a final result, using the best parameters, it was possible to improve the BRAMS model precipitation fields using the weights for weighting the precipitation fields computed with each closure. It is a first step to include the weight vector in the BRAMS model for weighting the GD parameterization ensemble.

Despite the uncertainties associated with different results for variations on the Firefly parameters, the results agreed with the comments expressed by Lukasik and Zak (2011). According to Lukasik and Zak (2011), although most heuristic algorithms face the problem of inconclusive parameter settings, his results showed the opposite, determining the best parameters evaluated using the FA algorithm. This is an indication that the performance of the Firefly algorithm is similar, even when dealing with different inverse problems.

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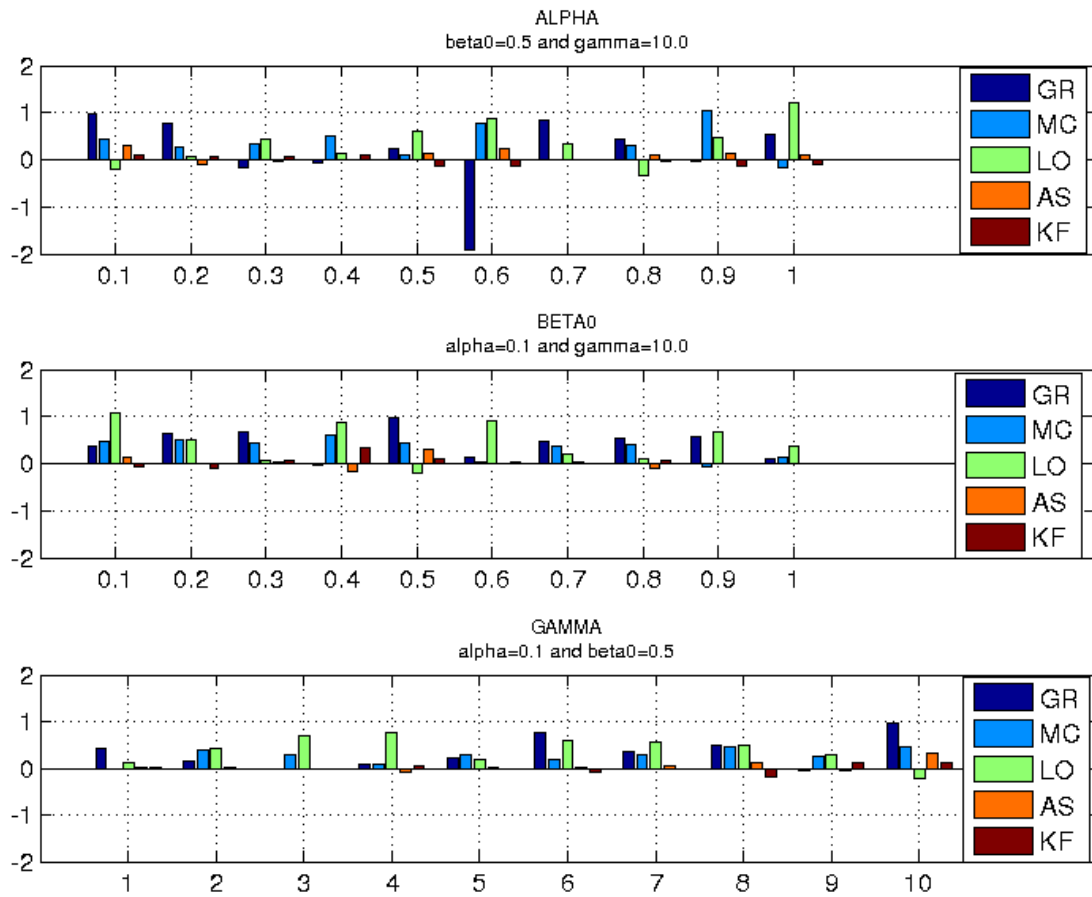


Figure 4: Distribution of the weights according to variations in the FA parameters. The dark blue, light blue, green, orange and brown bars represent, respectively, the variations of the weights for the closure members of GR, MC, LO, AS and KF.

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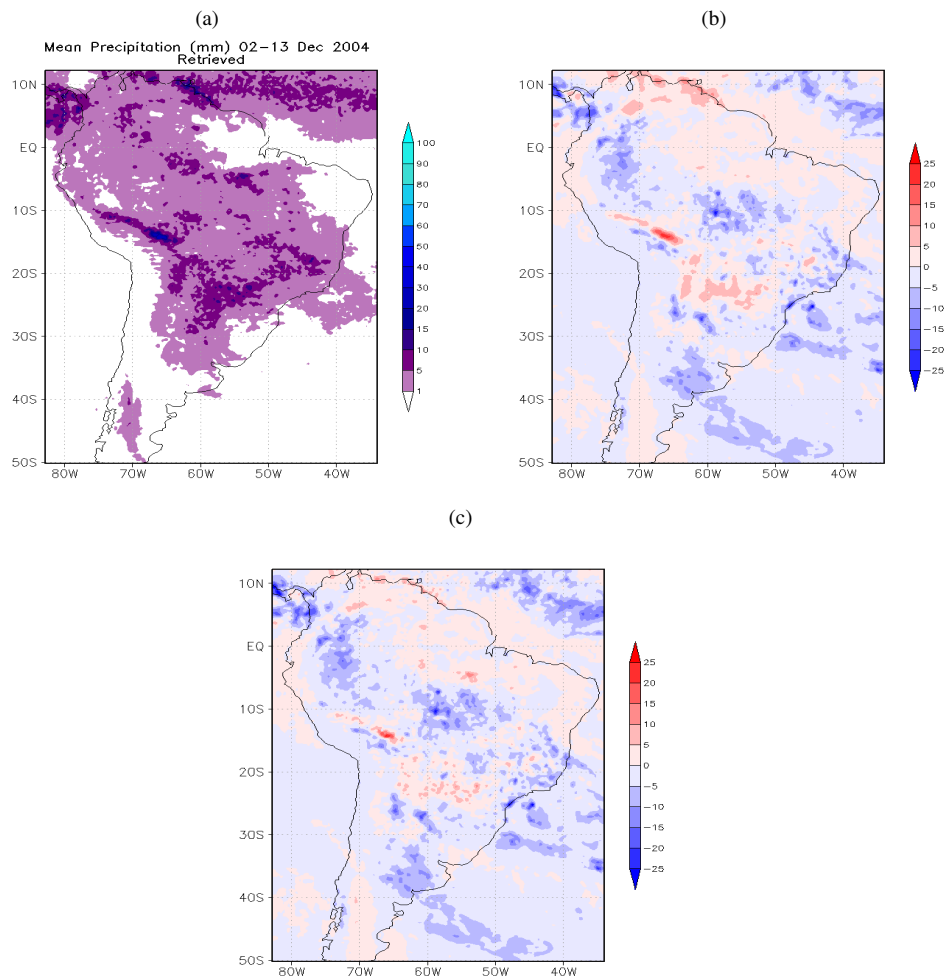


Figure 5: a) Mean retrieved precipitation (mm) on 02-13 Dec 2004; b) difference between the control experiment (ENS) and MERGE (mm) and c) difference between the retrieved precipitation and MERGE. Both differences are the mean during the considered period.

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