Rebuttal for NHESS Discussion Manuscript

Towards predictive data-driven simulations of wildfire spread – Part I: Reduced-cost Ensemble Kalman Filter based on a Polynomial Chaos surrogate model for parameter estimation by M.C. Rochoux et al.

We thank the Reviewer for its frank reply; we appreciate his/her positive and constructive comments to improve the overall quality of the paper. Further explanations to the two main issues raised by the Reviewer are given below. We hope that these explanations are sufficiently detailed and clear to convince the Reviewer that the ensemble Kalman filter we used in the present study is correct and consistent with the literature in parameter estimation problems.

(1) "level-set method?

a. "c=0.5 does not even exist at the initial time"

► As explained in Section 2.2.2, the prognostic variable of the FIREFLY simulator is the two-dimensional progress variable c = c(*x*,*y*,*t*); the location of the simulated fire front is *a posteriori* defined as the contour line c_{fr} = 0.5. This implies that FIREFLY requires a two-dimensional field c = c(*x*,*y*,*t-1*) to initialize any assimilation cycle [t-1,t]. Note that this initial condition is constructed in FIREFLY such that the transition between c = 0 (unburnt area) and c = 1 (burnt area) is smooth; a tangent hyperbolic function is used to describe this transition. Still, this transition remains thin over all the model time-integration (a few mesh step sizes, with a step size Δx = Δy = 1 m for all synthetic cases). We propose to add a comment on this initialization, in Section 2.2.2 for the model and in Section 3.1.2 after Eq. (23) for the model restart after analysis, in order to clarify this aspect.

b. "At first sight, it looks really unclear whether this approximation should converge to the solution of the propagation problem."

► Model diagnostics have been developed to ensure the correct numerical behavior of the FIREFLY front-tracking simulator. These diagnostics were not given in the paper since it is already rich in concepts. Still, these diagnostics were reported in a previous publication demonstrating the feasibility of an extended Kalman filter for wildfire spread forecasting (see Rochoux et al. 2013a). Furthermore, they are described in full detail and illustrated in a series of tests for different fire configurations (with/without wind, spatially-uniform/-distributed vegetation) in the Ph.D. thesis of the first author (see Section 6.4. in Rochoux, 2014). To summarize, these model diagnostics were derived from the Kolmogorov-Petrovsky-Piskounov

(KPP) analysis and were extended to heterogeneous fuel. These diagnostics check that the rate of change of the progress variable c matches the average rate of fire spread (average meaning *average along the fireline*) and also that the rate of spread at the head of the fire is consistent with the Rothermel's 0-D formulation. In addition, they also verify that the front thickness, estimated as the average inverse of the maximum gradient of c, remains small and relatively constant over time. In all tests performed to date, these diagnostics have demonstrated the correct numerical behavior of FIREFLY consistently with the physics of the fire spread problem. This aspect is already mentioned in Section 2.2.2. The authors propose to emphasize the discussion and show the convergence of the solver by adding 2 examples of model performance, for a uniform case on the one hand, for a wind-aided case with randomly-distributed vegetation on the other hand.

(2) "filter?"

a. "There is a need for justification of the filter. The algorithm should retain some optimality property to be a filter. "

► First, let us summarize some important results about parameter estimation that are reported in the literature.

Most parameter estimation techniques use an augmented state vector, which includes the control parameters in addition of the state vector. Still, it is not the only option. For instance, Pétron et al. (2002)[1] and Peters et al. (2005)[2] successfully performed a stand-alone parameter estimation strategy within the framework of atmospheric chemistry, the estimation targets are the species surface fluxes that can be considered as input parameters with regards to the atmospheric dynamical model (Peters et al., 2007)[3]. Furthermore, it has been shown in the literature (Moradkhani et al. 2005, Ruiz et al. 2013a[3], Yang and DelSole 2009[4], Koyama and Watanabe 2010[5], Evensen 2008[6], Dechant and Moradkhani 2012[7]) that the augmented state problem can be divided into two independent problems: one for the control state variable(s) and the other for the control parameters. Thus, the parameter estimation and state estimation approaches are performed sequentially and not instantaneously. Stated differently, the Kalman update equation is applied twice and independently:

(1) for the control parameters similarly to the work proposed by the authors or by Durand et al. (2008);

(2) for the state variables similarly to a classical state estimation approach.

That is why the authors believe that the reference due to Moradkhani et al. (2005) is still relevant in the context of the present study. Currently, the two steps are performed separately in the series of two papers proposed by the authors. Future plans include the extension of the algorithm to a dual or joint parameter-state estimation approach. Which is the most accurate and time-efficient approach between these 2 possibilities requires some further evaluations as highlighted in references by Ruiz et al. 2013a[3] or Bocquet and Sakov, 2013[8].

Koyama and Watanabe (2010)[5] demonstrated that spatial localization is not necessary for the estimation of global parameters (i.e., spatially-uniform parameters).

Even though the true control parameters are varying over time, they are usually assumed to be constant during the model integration. Thus, parameter values only change when moving to the next assimilation cycle (Ruiz et al. 2013a[3]). When performing an ensemble Kalman smoother (Bocquet and Sakov 2013[8]; Evensen and van Leeuwen 2000[9]; Hunt et al. 2004[10]), the correction on the control parameters is performed on a time-window that includes several observation times. In the study presented by the authors, the assimilation is performed at each observation time; the latter corresponds to an ensemble Kalman filter (Evensen 2003[11]).

These aspects highlight that parameter estimation can be successfully performed using an ensemble Kalman filter, even though the control vector does not include the state vector but only the control parameters (it corresponds to one step of a dual state-estimation approach with global parameters). Note that the control parameters are spatially-uniform in the present study and are therefore global. Note also that the control parameters are assumed constant over each assimilation cycle (one cycle corresponding here to a forecast and an analysis at a single observation time); subsequently, they are modified only when moving to the next assimilation cycle. Thus, the filtering algorithm proposed by the authors seems consistent with the literature.

► From a mathematical viewpoint, the Kalman update equation can be applied to any quantity of interest, the state vector, the augmented state vector or the stand-alone control parameters. The type of control variables is independent of the filter optimality issue. From this perspective, the authors believe that the filter equation formulation used in this study does not need a specific justification.

► To clarify these issues raised by the legitimate questions of the Reviewer, the authors propose to add a detailed comment in Section 3.1. (p. 3312), to provide a more extensive literature review on these aspects, to explicitly state that we are not in a case of augmented state vector and to justify this current choice of a stand-alone parameter estimation.

b. "The observation operator depends on the front position (at t-1). Hence it is different from one member of the ensemble to the other. This is a fairly unusual setting […] consequence that the observation error and the parameter error are strongly correlated, which breaks a classical assumption for Kalman filtering".

► It is important to recall that for parameter estimation (stand-alone or dual), the observation operator always includes the integration of the forward model (to obtain the model state that is induced by a particular set of control parameters over the assimilation cycle) on top of a selection operator (that describes the interrelation between the model state and the model counterparts of the observations). Thus, it is not a novelty for parameter estimation that the observation operator depends on the model state at the previous analysis time.

The definition of the observation operator is given in Section 3.1.1 (p. 3306-3307). It is true that the selection operator H_t is time-dependent in the present study since the observation is dynamically-evolving: the selection procedure depends on the location and on the topology of the fire front at a given time. The authors propose to add in Section 3.1.1 a comment on this aspect that is specific to a tracking problem. Similar setting is used in Chen and Snyder (2007)[12], where the observation operator provides the time-evolving vortex location for hurricane tracking.

As in the references by Ruiz et al. (2013a)[3] or by Peters et al. (2005)[2], the uncertainty in the optimal parameters is assumed to be constant in time in the study proposed by the authors. The error standard deviation used in the random walk model (there is no physical model for the evolution of the parameters as it is common in parameter estimation problems) remains constant over all assimilation cycles (see Eq. 23, p. 3310). In Peters et al. (2005)[2], p. 6., it is said that *In absence of a suitable dynamical model we couple forecasted CO2 fluxes to analyze CO2 fluxes through a simple form of persistence forecasting M = I, where I is the identity matrix. This means that we assume the background CO2 fluxes for one time step to equal the once optimized fluxes of the previous time step.* In this case presented by Peters et al. (2005)[2], they chose to specify the mean background for a given assimilation cycle using the mean of the analyzed fluxes obtained at the previous assimilation cycle. Then, they generated the ensemble of background surface fluxes by applying a standard deviation to this mean background. This technique is very similar to that used by the authors in the present study and the present filter can therefore be viewed as a *3d variational technique which also lacks the dynamic coupling between analyzed and background covariances* (Peters et al. 2005[2]). The authors propose to add a comment along with references (Peters et al. 2005[2], Ruiz et al. 2013b[13]) in Section 3.1.2., p. 3310, near to Eq. (23) to explain in more details the choice of the random walk model, which is a common feature in parameter estimation problems. Also, a comment will be added to clearly state that the forecast members of the ensemble are generated based on perturbations in the control parameters and starting from the same initial condition (i.e., the two-dimensional progress variable field associated with the mean analysis estimate obtained during the previous assimilation cycle similarly to Peters et al. 2005[2]).

In this context, the authors do not understand how the observation error and the error in the control parameters could be strongly correlated; they are convinced that this assumption of the ensemble Kalman filter remains valid in the present study.

c. **"The reader may be under the impression that the algorithm was simply written by the analogy with a proper ensemble filter, without any mathematical justification."**

▶ The questions asked by the Reviewer were legitimate and helped us to clarify the proposed methodology.

- A parameter estimation approach can be considered by itself as an estimation problem and does not need to be combined with a state estimation approach to obtain an optimal ensemble Kalman filter;
- In a parameter estimation approach, the observation operator includes the forward model integration over the assimilation cycle; this does not degrade the quality of the filter since the parameters are assumed global (i.e., spatially-uniform), constant over the assimilation cycle and their errors are assumed constant over the whole assimilation experiment.
- In an ensemble Kalman filter, there is also a need for an evolution model for the parameters between the assimilation cycles. As no dynamical model usually exists to describe the time-varying behavior of the parameters, two techniques are reported in the literature: (1) inflation; or (2) random walk model (Ruiz et al. 2013b[13]). In the present study, the authors chose to rely on a random walk model.

As mentioned above, additional references and comments will be included in the text to clarify the distinction with a state estimation approach (proposed in Part II of this series of two papers), in particular with regards to the definition of the classical variables for data assimilation, as well as to convince the readers that the proposed algorithm is a proper ensemble Kalman filter adapted for parameter estimation problems related to coherent features tracking.

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