

Interactive comment on “Improving terrestrial CO₂ flux diagnosis using spatial structure in land surface model residuals” by T. W. Hilton et al.

Anonymous Referee #4

Received and published: 17 July 2012

This study used NEE observation from 65 NA eddy-covariance towers to estimate the parameter set for a simple diagnostic terrestrial ecosystem model, VPRM. On this basis, it calculated the differences between tower NEE (data) and VPRM-simulated NEE (model), and further attempted to quantify the spatial structure existing in the data-model residuals by the means of semivariogram. The main findings of the study, as claimed by the authors, are: 1) the estimated VPRM parameter values do not clearly separate from each other by plant function type (PFTs); 2) the “range” of the spatial semivariogram of the VPRM-data residuals is about 1000 km. However, I found the methods and the results presented in the current paper are not convincing. My main concerns are as follows:

- 1) The first part of the analysis, the parameter fitting of VPRM, is relative straightfor-

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ward. The finding that the estimated parameters have similar values among different PFTs is possibly valid and as mentioned by the paper, has been reported by previous studies. However, statements such as “our results suggest that may not be the most useful predictor of a land area’s carbon cycle dynamics, that alternative partitioning schemes may be more skillful (P14, Line 446-448)” seem to exaggerate the implication of this finding. This is because VPRM is a highly simplified model and many important processes (e.g., carbon pools) are not included in its formulation. For instance, a forest/non-forest mask can be very useful in mapping biomass distributions from remote sensing. Therefore, the close values of lamda (λ) may only indicate that the light-use efficiency of green leaves is similar among PFTs. Also, some VPRM parameters are by definition not PFT-related. For instance, the β parameter of VPRM represents a base respiration rate that is not affected by climate but mostly by site disturbance history.

- 2) Though the concept of semivariogram is clearly explained in the paper, its application in the analysis is quite confusing. First and most important, it is unclear that whether the 65 sites are enough to render a robust estimate of the semivariogram. This is particular true considering that quite many of the sites are co-located, which further reduced the number of free samples (Fig. 1). Second, though the authors tried to test the above question by Monte-Carlo simulations and AIC tests (P11, 2-3 paragraphs), the results seem biased towards the “pure nugget” model as only ~7% of the data generated with underling exponential model are correctly classified as “exponential” by the AIC test. This suggests that either 1) the spatial sampling process has significant impacts on the tests; 2) the estimated spatial parameters (range, sill, and nugget) have a very large uncertainty or simply not reliable. This problem is clearly illustrated by Fig. 5 (see below).

- 3) Fig. 5. Because all the pseudo-data are generated with parameters estimated from the VPRM-NEE residuals, one would expect that the Monte-Carlo simulated samples well encompass the original VPRM-NEE residuals. However, this is not the case shown

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here (in the right panel). The seemingly agreement in the left-panel can be misleading because it is a statistical principle not to compare data with subjectively selected data.

4) Table 3, Fig. 6-7. The estimated values of “range” vary dramatically at interannual basis. For instance, the first row in Table 3 shows that the range is only 4km in 2003 but is over 3500km and 1500km in 2002 and 2004, respectively. Similar large interannual variability is found in many other rows as well. Such variability can hardly be interpreted in a physically meaningful way. In addition, Fig. 6-7 are also rather confusing.

5) Fig. 4. It is hard to compare these plots because the residuals have different standard deviations. For instance, the “all sites” plots have higher semivariance because they have fewer parameters and thus less “fit” with the data. It may be better to normalize the plots by their own standard deviations.

Interactive comment on Biogeosciences Discuss., 9, 7073, 2012.