Biogeosciences Discuss., 7, C4392–C4395, 2010
www.biogeosciences-discuss.net/7/C4392/2010/

Biogeosciences Discussions

Interactive comment on "Integrating field sampling, spatial statistics and remote sensing to map wetland vegetation in the Pantanal, Brazil" *by* J. Arieira et al.

J. Arieira et al.

juarieira@ufmt.br

Received and published: 16 December 2010

Response to the reviewer

Referee 1#

Authors: We would like to thank the referee for his/her review and the useful suggestions.

R#1: This is an interesting application of geostatistical methods to map vegetation communities. I think, however, that the title is somewhat misleading. The authors seem to be equating 'spatial statistics' with geostatistics and I suggest "geostatistics"

or more specifically 'regression kriging' be added in place of 'spatial statistics'.

Authors: In our opinion spatial statistics and geostatistics are almost synonyms. In hindsight we agree that geostatistics is maybe a better term here, also because it seems to be more widely used. Thus we changed 'spatial statistics' to 'geostatistics' in the title.

R#1: Another misused term in the paper inolves the authors' treatment of uncertainty– I think they are simply testing accuracy in the first method (cross-validation), and the simulation example they provide is not clear (has it been used in similar studies?).

Authors: In the literature, and to our knowledge, accuracy assessment and uncertainty analysis are often used as synonyms. Thus we are in the opinion that we properly use the term uncertainty here.

Monte Carlo simulation is a relatively standard method to evaluate uncertainty in model parameters and maps (Steele et al. 1998, Hunsaker et al. 2001, Papadopoulos and Yeung 2001, Johnson and Gillingham 2004, Wu and Tsang 2004, Cripps et al. 2008). Cripps et al. (2008) have used a similar approach to quantify uncertainty associated with land cover maps. Using Monte Carlo simulation, they provided maps of simulated posterior means and standard deviation of vegetation classes and discussed the results in terms of underestimated and overestimated proportions of these different classes in the map. Based on this information, the authors suggest that difficulty in discriminating vegetation classes because of similarity in vegetation structure may cause larger uncertainty in the assigned class in the map.

R#1: Also it's difficult to synthesize these results without having some kind of benchmark for comparison purposes.

Authors: The Monte Carlo simulation provides a range of possible values found at a certain location, based on the assumption that there is uncertainty in model inputs. We agree that the interpretation of the uncertainty found through Monte Carlo simulation is somewhat hampered by the very limited availability of other studies doing a similar error propagation analysis on vegetation mapping. However we hope that our study could be used as a benchmark in other studies. It should be noted, however, that the other uncertainty analysis applied here, the cross validation, does provide 'hard' evaluation data because modelled classes are compared with classes observed at measurement locations.

R#1: The authors seem to categorize this study as one type of a species distribution model (given their citing of Guisan and Zimmermann and Miller at el), but it's not really the same concept. SDM are based on relationships between environmental gradients, whereas what the authors describe is more related to image classification applications in remote sensing.

Authors: We do not fully agree with the reviewer here. We do not categorize our approach as a kind of species distribution model. We merely refer to Guisan and Zimmerman (2000) and Miller et al. (2007) because our mapping approach carries much of the framework of SDM, because predictions are made based on what predictive variables derived from satellite imagery can explain. Similar to SDM, we also combine known occurrence records with digital layers. However, we decided not to refer to digital layers as environmental variables, even though other studies show that image bands are related to environmental factors such as principal component two and wetness.

We agree that the study by Miller et al. (2007) is related to our work. They show how to incorporate spatial dependence into predictive vegetation models focusing on different statistical methods including geostatistics. They describe the potential of procedures such as universal kriging (also used in our study) for analysing the vegetation distribution. What we have done follows a similar framework.

Similarly, Guisan and Zimmerman (2000) present a review of predictive habitat distribution models showing how it is possible to use statistical techniques in vegetation modelling and the importance of remote sensing data as predictive variables.

R#1: Many of the technical methods (particularly on uncertainty) are not clear, and specific details of the technical methods should be justified (for example, why was a specific variogram model used?).

Authors: We provided a more detailed explanation of a number of methods in the revised manuscript, In particular, we improved the description of the Monte Carlo simulation procedure, the selection of the variogram model, and how we fitted the variogram model. The latter was done with the autofitVariogram function from the automap library (Hiemstra et al. 2008).

Interactive comment on Biogeosciences Discuss., 7, 6889, 2010.