Atmos. Meas. Tech. Discuss., 8, C1184–C1187, 2015
www.atmos-meas-tech-discuss.net/8/C1184/2015/

Atmospheric Measurement Techniques Discussions

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8, C1184–C1187, 2015

Interactive Comment

Interactive comment on "Spatial mapping of ground-based observations of total ozone" *by* K.-L. Chang et al.

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Received and published: 19 May 2015

The paper compares the standard covariance-based approach to spatial modelling with the SPDE-based approach for an application to ozone mapping.

The article is generally well-written although some of the technical descriptions are confusing. For example, the authors claim to be comparing kriging with the SPDE approach but, as also stated in the article, kriging is the procedure for computing a predictor of a random field at some unobserved location whereas the SPDE approach is a method for specifying flexible and computationally efficient statistical models. If the field is Gaussian, the kriging predictor coincides with the conditional mean of the field given the data. Problems such as high computational cost or the difficulty of introducing non-stationarity are typically effects of using a covariance-based model when computing the kriging predictor, and are not caused by the fact that we are computing a conditional mean. Thus, saying that kriging is compared with the SPDE approach is a bit misleading, when the comparison is between using a covariance-based model, a stationary Matérn field, and a non-stationary SPDE-based model for ozone mapping.

Further, the motivation for using the Matérn covariance function (page 3971) is incorrect: It is obviously not the "most advanced" covariance function, and saying that it always outperforms all other covariance functions is just wrong. See for instance Bolin and Lindgren (2011) or Jun and Stein (2008) for examples where other covariance models outperform the Matérn model, even for Ozone data similar to the data studied in the article.

If I understand the comparison correctly, a polynomial regression basis is used for the mean of the Gaussian field in the "kriging approach" whereas the random field is assumed to have mean zero in the SPDE approach. If this is the case, it is difficult to know if the differences in the results are caused by using the SPDE approach instead of the covariance-based approach or if they are caused by the different assumptions on the mean value structure. Furthermore, the SPDE-based model is estimated using INLA, which is a Bayesian approach, and the parameter uncertainty is therefore taken into account in the predictions. Unless the covariance-based model is also estimated in a Bayesian context, which I assume is not the case, it is again difficult to know if the differences in the results are caused by using different models or by using different estimation and prediction methods. Computing a frequentist kriging estimator $E(X(s)|\text{data, parameters})$ or a Bayesian estimator $E(X(s)|\text{ data})$ can lead to quite different results, especially if one is also interested in the standard errors of the estimators. Thus, as I see it there are three possible reasons for the differences in the results:

1. Bayesian versus frequentist models and methods.

2. Non-stationarity in the mean versus non-stationarity in the covariance structure.

AMTD

8, C1184–C1187, 2015

3. A covariance-based model using chordal distance versus a SPDE-based model using great circle distance on the sphere.

Clarifying to what extent each of these three factors contribute to the differences in the results is in my opinion crucial for the article.

Some further minor comments:

1. Are the results in the article obtained for ozone data modeled in linear or transformed scale? Gaussian models typically fit well to the natural logarithm of TCO data, but not to the data in linear scale.
2. Page 2971, row 22: A covariance-based model is easy to use on manifolds if it is embedded in $\mathbb{R}^d$. One can then simply use a covariance function on $\mathbb{R}^d$ restricted to the manifold, as pointed out in the article on page 3973. The advantage with the SPDE approach is that it will use the correct distance metric on the manifold.
3. Page 3970, row 16: Not all statistical models assume that the unknown process is Gaussian. Even the SPDE approach can be made non-Gaussian, see Bolin (2014) or Wallin and Bolin (2015), and this could be of interest for ozone mapping.
4. Page 3973, row 24: What value of α was used for the SPDE approach? If $\nu = 20$ was used for the kriging approach, this is quite different from $\nu = 1$ which would correspond to the standard choice in INLA. If the same value of ν would be used for both models, how much do the results change?
5. Page 3984, row 17: The parameters κ and τ need to be positive in order to have a well-defined model, but assuming that they are positive does not solve the identifiability issues if a non-stationary mean is used.

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8, C1184–C1187, 2015

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Interactive comment on Atmos. Meas. Tech. Discuss., 8, 3967, 2015.