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DISCUSSION PAPER

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Discussion on A high-resolution bilevel skew-*t* stochastic generator for assessing Saudi Arabia's wind energy resources

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Abstract
We provide a detailed discussion on the analysis presented by Tagle and co-authors, who suggested an approach to improve earlier models for handling non-Gaussianity in spatial wind field speed data by simplifying the model formulation to better accommodate large data sets. Our discussion focuses on the energy and socio-economic context of wind potential assessment in Saudi Arabia – an oil-rich country, statistical aspects associated with wind field forecasting, and the prediction of the wind electricity production potential from the wind field forecast.

KEYWORDS
skewed random fields, stochastic modeling, wind energy

1 | INTRODUCTION

We congratulate the authors for a very interesting article dealing with important theoretical and practical aspects of spatial statistics and analysis of large datasets. The authors suggest how to improve earlier models proposed to handle non-Gaussianity in spatial data by simplifying the model formulation to better accommodate large datasets. They proceed to indicate that this is indeed an improvement from a computational perspective by incorporating the spatial model in an uncertainty analysis of wind speed data over Saudi Arabia. They use the proposed spatial model as the foundation for the innovation distribution in a high-dimensional vector autoregressive model, and they fit this model to a very large simulated wind speed dataset using an expectation-maximization algorithm, implemented using a combination of classical numerical optimization and Markov Chain Monte Carlo methods. Finally, they use the fitted model as the foundation of stochastic generation of synthetic wind speed data in order to assess uncertainties in an analysis of wind energy potential over Saudi Arabia.

This article is welcome from several perspectives. Globally, wind is the second largest renewable energy resource, following solar energy (Lu, McElroy, & Kiviluoma, 2009), and will play a crucial role in future energy provision (Schallenberg-Rodriguez, 2013). In this regard, an important original contribution of the authors resides in the estimation of the wind electricity generation potential in an oil-rich, per capita energy-intensive country (World Bank, 2020), where the deployment of renewable energy technologies is not only at an early stage, but also has focused on solar energy to date (IRENA, 2019). The country has a complex topography and experiences a broad climatic spectrum(Hasanean & Almazroui, 2015), partly lying in the subtropical high-atmospheric pressure belt (i.e., 25–35° latitude

N/S), which is characterized by low winds. However, the region has received limited attention in climate (Hasanean & Almazroui, 2015) and wind energy potential assessment, which is attributable to a combination of environmental, geographical, socio-economic, and other factors. Until recently, the Arabian peninsula wind reserves have been considered to be limited from an economic exploitation perspective (IRENA, 2019). Studies such as the paper discussed herein, by contributing to refine wind resource estimation in less explored or challenging-to-exploit reserves, combined with advances in turbine designs for low-velocity fields, are likely to significantly contribute to further wind energy deployment globally. Although the world's sixth-largest consumer of oil (BP, 2018) and largest energy consumer in the Gulf Cooperating Council (GCC) (IRENA, 2018), Saudi Arabia only accounts for 16% of the council's installed renewable power capacity, with a national renewable power share limited to 0.2%, of which only 2% is wind (IRENA, 2018). Based on revised energy policies, it has been estimated that 25 GW of renewable power capacity could be installed in Saudi Arabia by 2030, including 3.5 GW (14%) wind, with an overall 30% of clean power generation including 16 GW of nuclear (IRENA, 2019). Such a capacity could contribute 40% of GCC regional primary energy savings by 2030 (IRENA, 2019), and up to 130 million tons of CO_2-equivalent emissions reduction as part of the country's nationally determined contribution under the United Nations Framework Convention on Climate Change (UNFCCC) (UNFCCC, 2015). In addition to domestic environmental and socio-economic benefits, renewable development is strategic in reducing domestic oil consumption to boost high-value exported hydrocarbons in the near-term energy transition. Although solar photovoltaics is currently the most economically competitive and implemented renewable power generation technology in the region (IRENA, 2019), its large-scale growth will be challenged by several factors, including power demand-supply mismatches associated with the intermittency of the resource, and consequent electric grid stability issues, unless appropriate solutions are implemented. The development of wind power at an appropriate wind/solar generation ratio could play a role in alleviating grid operational issues, thereby enabling higher solar and thus total renewable shares. The complementarity of wind and solar energy could be exploited at both national and regional level in the future, with the development of the intranational grid (IRENA, 2019). Renewable power development in Saudi Arabia would provide a prominent demonstration of the feasibility of sustainable energy transitions in currently fossil energy-based regions. Yet, the development of accurate, robust and computationally efficient methods to reliably quantify the exploitable renewable resource potential is essential to the planning and design of wind installations, considering the need to both match a spatially and temporally varying electricity demand, and to achieve specific socio-economic-environmental objectives. Typically, the basic economic goal of a wind operator is to either maximize the installation revenues, or to minimize the unit cost of wind energy production (Schallenberg-Rodriguez, 2013). Reliable assessment of the economic objective is expected to be particularly important in nontrivial-to-exploit wind fields. On the other hand, wind power forecasts will impact wind electricity pricing (Cruz, Muñoz, Zamora, & Espínola, 2011; Patel, Shandilya, & Deb, 2017). Accurate wind potential mapping is also critical to the entire energy sector, considering that sectors and technologies will strongly interact in future sustainable energy systems. Beyond the power sector, wind and solar energy can contribute to the decarbonization of critically important and difficult-to-abate sectors locally, including conventionally fueled transport (which represents 36% of Saudi Arabia's final energy consumption (IEA, 2016) and water desalination. The above context further highlights the critical importance and impact of reliable resource quantification, beyond the authors' considerations, and the need for such studies.

2 | STATISTICAL ASPECTS

At the beginning of the article, the authors claim that: "We also demonstrate in a simulation study that this simplification implies only a small loss in efficiency compared with a ground truth from a fully structured (and considerably more expensive) model, and it vastly outperforms all other models when performing inference against the same model." We apologize if we have misunderstood the article, but we are not certain that this adequately reflects what is actually done in the article. We are not sure where it is shown that the simplification of the previously suggested skew-*t* model "implies only a small loss in efficiency compared with a ground truth from a fully structured […] model." As far as we can see from the simulation study, the authors only compare two models, namely, the presented bi-resolution skew-*t* based model, and a Gaussian model, which they fit to data generated by a VAR(2) model with skew-*t* innovations similar to (but somewhat simplified compared with) the one used later in the analysis. We have not been able to understand what Gaussian model was used. The simulation study does show that use of the skew-*t* model will lead to higher wind power density estimates than in the case of a Gaussian model. Clearly, the simulation study does indicate that if the skew-*t* based model is more adequate for the dataset at hand, then an analysis using a Gaussian-based model will lead to underestimation of wind power density. Yet, we are not convinced that comparison with one model is sufficient to conclude that the suggested model "vastly outperforms all other models."

In the authors' formulation of the biresolution skew-t model, it is left implicit that the subscript r depends on s. In order to discuss the implications of this model, we find it advantageous to reformulate the model with this dependence made explicit in the notation. Let $O \subset \mathbb{R}^d$ and let $\{D_\ell\}_{\ell=1,\dots,R}$ be a partition of O, that is, by definition the collection $\{D_\ell\}_{\ell=1,\dots,R}$ covers O $\left(\cup_{\ell=1}^R D_\ell = O\right)$ and the elements of the collection $\{D_\ell\}_{\ell=1,\dots,R}$ are pairwise disjoint ($D_\ell \cap D_{\ell'} = \emptyset$ if $\ell \neq \ell'$). Define

$$r : O \to \{1, \dots, R\}$$

by

$$r(s) = \ell \quad \text{if } s \in D_\ell$$

for all $s \in O$. This is of course well-defined since $\{D_\ell\}_{\ell=1,\dots,R}$ is a partition of O. Let Σ_0 be a $R \times R$ positive definite matrix and let $U \sim \mathcal{N}_R(0, \Sigma_0)$. Let $\{Z_\ell\}_{\ell=1,\dots,R}$ be an independent collection of random variables such that $Z_r \sim \Gamma(\nu_r/2, \nu_r/2)$ where $\nu_r \in [0, \infty)$. For all $\ell = 1, \dots, R$, let C_{Ψ_ℓ} be a continuous, isotropic correlation function on $\mathbb{R}^d$ and let $(\eta_\ell(s))_{s\in O}$ be a centered Gaussian process with correlation function C_{Ψ_ℓ}. Assume that $U \perp\!\!\!\perp \{Z_\ell, \eta_\ell\}_{\ell=1,\dots,R}$ and that $\{Z_\ell, \eta_\ell\}_{\ell=1,\dots,R}$ are independent. The authors propose the following model:

$$Y(s) = \frac{\lambda_{r(s)}|U_{r(s)}| + \eta_{r(s)}(s)}{Z_{r(s)}}, \tag{1}$$

where $\lambda_\ell \in \mathbb{R}$ for each $\ell = 1, \dots, R$. This is a simplification of an earlier model provided by Tagle, Castruccio, and Genton (2020), where a more sophisticated construction, including an additional latent variable, is proposed:

$$Y(s) = \frac{\rho_{r(s)}U_{0,r(s)} + \lambda_{r(s)}|U_{1,r(s)}| + \eta_{r(s)}(s)}{Z_{r(s)}}, \tag{2}$$

where $U_0 = (U_{0,1}, \dots, U_{0,R})^T \sim \mathcal{N}_R(0, \Sigma)$, $\rho_\ell \geq 0$ for all $\ell = 1, \dots, R$ and $U_1 \sim \mathcal{N}_R(0, I)$, the rest of the variables having the same distributions as above, $U_0 \perp\!\!\!\perp \{U_{1,\ell}, Z_\ell, \eta_\ell\}_{\ell=1,\dots,R}$ and $\{U_{1,\ell}, Z_\ell, \eta_\ell\}_{\ell=1,\dots,R}$ is an independent family.

In addition, we understand that these models assume continuity of the isotropic correlation functions C_{Ψ_ℓ}, albeit this is not explicitly mentioned in the articles. Tagle et al. (2020) note that in this model Y is discontinuous on the boundaries between the regions ($\cup_{\ell=1}^R \partial D_\ell$) and if $r(s) \neq r(s')$ then $Y(s)$ and $Y(s')$ are conditionally independent given U_0. Here, discontinuity can be understood as discontinuity of the sample path, in probability, or in the mean square sense. It is obvious from the definitions that in each model the sample paths of the random field Y will locally be as regular as the sample paths of the latent Gaussian random fields. As the skew-t distribution does not necessarily have variance and since a stationary Gaussian random field with continuous correlation does not necessarily have continuous sample paths, the random field Y in the resulting model can have any combination of local continuities/discontinuities in the sample path or mean square sense (it need not even be a second-order process). However, in any case, under the assumption that $\{C_{\Psi_\ell}\}_{\ell=1,\dots,R}$ are continuous, the random field Y is locally continuous in probability, but discontinuous in probability on the boundary $\cup_{\ell=1}^R \partial D_\ell$, which indicates that this is probably the notion of discontinuity that Tagle et al. (2020) had in mind. Tagle et al. (2020) further mention that "this is arguably a suboptimal feature of the model globally [but] this can, however, be mitigated by constraining the latent process $U_{0,r}$ [$U_{0,r(s)}$] to be very smooth, by fixing the smoothness of the corresponding covariance matrix Σ_0." The model in the present article inherits these properties with the modification that in this model, if $r(s) \neq r(s')$, then $Y(s)$ and $Y(s')$ are conditionally independent given U. As such the remark by Tagle et al. (2020) applies directly to this simplified model as well.

When building a stochastic model one is often faced with finding an optimal trade-off between an adequately complex model and computational tractability. In case of massive datasets it can be necessary to select a less than ideal simpler model in order to ensure computational tractability. Large datasets imply considerable computational challenges, for example, a large amounts of memory and much central process unit (CPU) or graphics processing unit (GPU) time. For example, any model and estimation procedure that requires inversion of matrices whose dimension grows as the dimension of the dataset increases will be impractical to use for very large datasets. In particular, this applies to hierarchical models for large spatio-temporal datasets which at some stage contain a continuous Gaussian process with a strictly positive covariance function. In this regard, both models (1) and (2) are quite attractive as they allow to model longrange dependence through U_0 or U and shortrange dependence through C_{Ψ_ℓ}, while allowing for control of dimensions of the covariance matrices of the latent Gaussian variables and processes by a suitable choice of $\{D_\ell\}_{\ell=1,\dots,R}$, ensuring that neither R nor the number of data points falling in any the regions D_ℓ are prohibitively large.

Before proceeding with our discussion, let us write the generic class of models with additive structure to which both of the above models belong, and to which our comments below also apply. Both of the models above, belong to the following general class of (hierarchical) models: Let $O \subset \mathbb{R}^d$ and let $\{D_\ell\}_{\ell=1,\dots,R}$ and $r: O \to \{1, \dots, R\}$ be defined as above. Let V be a R-dimensional random vector. Let for each $\ell = 1, \dots, R$, $\{\xi_\ell(s)\}_{s\in D_\ell}$ be a random field and assume that $\{\xi_\ell\}_{\ell=1,\dots,R}$ are independent. Finally define

$$X(s) = V_{r(s)} + \xi_{r(s)}(s), \tag{3}$$

for each $s \in O$. Note that we are not assuming that $V \perp\!\!\!\perp \{\xi_\ell\}_{\ell=1,\dots,R}$, therefore this generic model includes both models above where independence does not hold due to the scaling of U_ℓ and η_ℓ with the same random variable. Assume that $\{\xi_\ell\}_{\ell=1,\dots,R}$ are all continuous in probability and that $\mathrm{P}(V_\ell + \xi_\ell(s) - V'_\ell - \xi_{\ell'}(s) = 0) < 1$ for any $\ell \neq \ell'$ and any $s \in O$. The random field X is locally continuous in probability, but discontinuous in probability on $\cup_{\ell=1}^R \partial D_\ell$ and X has locally the same sample path regularity as $\{\xi_\ell\}_{\ell=1,\dots,R}$.

When modeling many spatio-temporal physical phenomena stochastically, it seems natural to assume observations that are close to eachother to have a higher probability of being "similar" than those that are far apart. This translates into the assumption that the stochastic process used in the model is continuous in probability (in many common models the stronger assumption of sample path continuity and/or mean square continuity is made, but of course both of these assumptions imply continuity in probability.) The implied discontinuity in probability along the boundaries of the domains is therefore somewhat unnatural, and some degree of lack of fitness is to be expected at points in close proximity to the boundaries between regions if the assumption of continuity in probability is reasonable. Of course, more generally, it is always advisable to try to assess the impact of the chosen model on the conclusions of the analysis, and unnatural model assumptions, depending on the application, need not lead to less reliable conclusions. But it appears to be quite relevant in each case that this model is applied to assess the impact of the chosen partition and/or make an effort to choose a partition in such a way that the unphysicality of the model is mitigated.

Returning to the analysis and the more specific model in the article: as mentioned the supplementary material, an exploratory analysis indicates that the skew-*t* process in the proposed model can be assumed to be a second-order process. In this case the stronger statement holds that the process is continuous in the mean square sense locally but discontinuous in the mean square sense along the boundaries of the domains, and also the covariance function is discontinuous along the boundaries of the domains. The effect of the discontinuity can be seen in the plots of standard deviations, figures 7c and 8b, where the partition is in several areas quite visible. In areas close to the Red Sea the local topography is to some extent apparently picked up by the clustering algorithm, cf. figure S.5, but it would be interesting to know if a subject-matter specialist overall finds the resulting partition of the country physically reasonable.

As we understand the article, the main aim of the statistical analysis is to account for the impact of the uncertainty in the simulated wind speed data arising from imprecisions of the initial conditions. Part of an ideal solution would be to run the simulation several times with slightly varying initial conditions and/or for a long time period. However, as the simulation itself requires considerable computational resources, and as the output from several runs needed would take up a great deal of storage, Jeong, Castruccio, Crippa, and Genton (2018) suggested the use of *stochastic generators* in a similar case, that is, to use comparatively computationally cost-effective stochastic models to generate synthetic data which statistically resembles the output from repeated runs with slightly different initial conditions. In this case, the dataset consists of only a single simulation from the computationally expensive model. The authors only discuss whether the model adequately captures the variability of this single dataset (we will return to this aspect in a later part of this discussion). It seems that the model implicitly assumes that variability of the surrogate datasets will capture the uncertainties arising from variation in the initial conditions. This should happen providing that the stochastic model fits a single simulation well, and that the simulation of surrogate data incorporates uncertainties in the estimated parameters of the stochastic model. We are not sure how capturing the variability of this specific dataset indicates that the simulations based on the fitted model—even with the attempts to incorporate uncertainty in estimates—adequately captures uncertainties arising from variations in initial conditions. Jeong et al. (2018) and Tagle, Castruccio, Crippa, and Genton (2019) have studied stochastic generators for specific different models and shown that the use of stochastic generators is a viable solution. However, they studied output from different models and used different stochastic generators, so it is not clear how those results can be used to justify the analysis in the article discusses herein, where the output arises from a different model and a different stochastic generator is used. In this connection with estimation of the parameters in the stochastic model, because stochastic expectation-maximization (SEM) "is too computationally expensive for a dataset of this size" the authors use a "more practical approach" to account for uncertainties in the estimates of the stochastic model parameters. While that approach does incorporate some variability, if estimates of the parameters of the stochastic model were of scientific interest, we think that the proposed approach might not be theoretically justifiable. However, as the interest of the analysis is to generate surrogate data that adequately capture variability arising from variation in initial conditions this need not be an issue.

Returning to the question of whether the model captures the variability of the dataset: as the ultimate aim of the analysis is to determine potential wind energy lack of fit in regions where wind turbines would never be built are not of high importance. In figure 6e,f the authors compare the datasets with a synthetic dataset at two representative points with high wind speeds, that is, areas where a good fit to data is of high importance. As QQ-plots of empirical data versus empirical data can be quite variable even when the data by construction follow the same distribution, the plots do not indicate any gross distributional deviations at the two selected points. It is unclear whether the simulated wind speeds are from the fitted model or from a simulation where attempts have been made to account for uncertainties in the estimates of the parameters of the stochastic model. In any case, if the two points are indeed representative it is not completely unreasonable to believe that the stochastic model adequately captures the variability of the dataset, however, considering the scale of the dataset some more systematic way of assessing and showcasing goodness-of-fit would strengthen the claim that the model adequately captures the variability of the datasets in the regions where it matters the most.

3 | PREDICTION OF WIND ELECTRICITY PRODUCTION POTENTIAL FROM THE WIND FIELD FORECAST

The objective of the authors' study was the derivation of finely resolved statistical prediction of the wind field towards the accurate estimation of the wind electricity generation potential, in this instance for Saudi Arabia as a case study, for which results are presented. The concluded potential technical contribution of wind energy to the country's sustainable energy goals, which is likely to attract regional/global attention, and provide direction to the country's national energy strategy, could, however, be moderated from several perspectives. In general, the accurate prediction of wind power potential requires a multi-step, multi-scale approach, which would involve extending the present wind forecasting to a comprehensive wind farm siting identification, followed by detailed wind farm performance analyses, long-term validation, and detailed financial analysis (Al-Yahyai & Charabi, 2015). Although it may be considered that undertaking all key analysis steps in detail would be outside the scope of a single article, certain aspects could either be readily dealt with or deserve discussion to address further key sources of uncertainty in the predicted wind potential. The authors briefly refer to some of these aspects, with additional ones identified herein, leading to the following considerations. In general, wind potential prediction errors may be grouped in two main categories, that are associated with wind field prediction, which is the focus of the authors' work, but also those associated with electrical output prediction based on the predicted wind field (Goretti, Duffy, & Lie, 2017; Iversen, Morales, Moller, Trombe, & Madsen, 2017), to which limited consideration is given by the authors. A key finding of the authors' case study that 30%–70% of Saudi Arabia's annual electricity demand could theoretically be met by wind energy represents a significant range, the extent of which essentially results from the use of two different average stream/crosswise turbine spacings (i.e., either 10 or 17 rotor diameters). In general, aerodynamic wake effects induced by upstream turbines on the wind field of downstream turbines include reduced wind speed, and increased turbulence that results in dynamic loading. A number of analytical and computational fluid dynamics-based methods are available to represent aerodynamic wake effects induced by upstream turbines on the wind field of downstream turbines (Dhiman, Deb, & Foley, 2020). Although large turbine spacings, such as those considered by the authors, significantly reduce wake effects, the underlying fundamentals and applicability of the cited Meyers and Meneveau (2012) analysis to the conditions considered in the authors' analysis would deserve discussion. Furthermore, alternative methods could be considered to evaluate the impact of turbine configuration on wind potential.

The predicted wind power potential could be also reconsidered in the context of a series of assumptions applied. These include the following, recognized by the authors:

(i) The use of daily average air density data for the prediction of wind power density, owing to computational constraints;
(ii) The power-law exponent applied;
(iii) The need to capture the effects of complex terrain, elevated ground surface temperature, and atmospheric stability in general.

The following additional aspects could also be considered:

(iv) The use a single power-law to extrapolate near—ground wind speed to turbine hub height, irrespective of site and time. Estimation of the wind velocity at hub height is critical, considering the cubic relationship between wind speed and wind power (Schallenberg-Rodriguez, 2013). The wind profile up to hub height is significantly impacted by factors including terrain geometry and surface roughness, temperature and thus atmospheric stability. No single law can represent all conditions (Schallenberg-Rodriguez, 2013). Alternative law formulations, discussed in the literature could be considered for different local conditions.
(v) The use of single turbine type, fixed turbine power curve, and turbine placement configuration represented using an average stream/crosswise spacing. Although the turbine type may be applicable at/above the minimum power density threshold attained at the sites under analysis, different turbine rated capacities are generally selected to exploit wind power at different local conditions (Bilir, Imir, Devrim, & Albostan, 2015; Asghar & Liu, 2018). In addition, the actual power curve of a given turbine model is subject to distortion from the nominal curve based on actual conditions (Wang, Hu, Li, Foley, & Srinivasan, 2019). Also, different site conditions would result in different optimum turbine configurations based on selected optimization criteria.
(vi) The focus on maximum wind power density to identify suitable wind farm locations. Further criteria would need to be considered including other physical (e.g., wind frequency distribution, turbulence intensity), technical (e.g., supply demand matching, distance to road), and environmental factors (e.g., surrounding urban/terrain topology, potential turbine surface fouling) (Al-Yahyai & Charabi, 2015).
(vii) The effects of farm spacing would also deserve to be considered (Schallenberg-Rodriguez, 2013).

Thus, the above aspects could be examined towards a potentially more consistent alignment of wind field prediction accuracy with wind power prediction accuracy. From a wind implementation perspective, additional discussion points may include: the need for favorable economics/policies, including cost-competitiveness of wind power in comparison with other technologies, including in a context of a recent history of low crude oil prices; on a long-term basis, changes in the structure of the future power sector, and their effect on implementable wind power shares; potential local power grid transmission constraints, and role of electricity imports/exports; impacts of increasing wind power exploitation at large-scale, and climate change.

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