Reviewer's Comment on
Variability and Predictability of a reduced-order land atmosphere coupled model
by Anupama K Xavier, Jonathan Demaeyer, and Stéphane Vannitsem

General. This paper presents a coupled land-atmosphere model that is applied to midlatitude atmospheric variability and predictability. The model itself is formulated in a flexible Python framework called qgs (Demaeyer et al., *J. Open Source Software*, 2020) that adds surface features, oceanic or terrestrial, to a two-layer quasi-geostrophic model in a periodic beta-channel. It seems to be the first application of qgs to coupling with a land surface. The Vannitsem group in Brussels has earned already quite a reputation with its modular arbitrary-order ocean-atmosphere model (MAOOAM: De Cruz et al., *Geoscientific Model Development*, 2016) that has been used worldwide for nonlinear studies of the climate in several configurations and on different time scales.

The present paper examines the effects of the surface features on the number and stability of distinct atmospheric midlatitude regimes, including zonal, blocking and transient ones. The key tools are the backward Lyapunov spectrum and the associated vectors, abbreviated as BLVs, which are studied as a function of the coupling coefficients between the atmosphere and the ground, namely those that scale the momentum and heat exchanges. The model has a fairly low order, with a total of 30 spectral variables, ten each for the barotropic and baroclinic components of the atmosphere, and ten more for the ground temperature field. Despite this low order, the spatial features of the blocking and zonal regimes in model simulations are rather realistic; see Appendix B.

The most interesting finding of the paper, to my mind, is the greater predictability of zonal flows, when this regime coexists with the blocked one for the same parameter values. This finding seems to contradict both the prevalence of zonal flows over blocked ones in observations and the widely held belief in the community that it is blocked flows that are stabler. More on this in the first major comment below.

Overall, the paper should be accepted and published pretty much in the present form. Two major comments follow and addressing them is recommended.

Major Comments.

1. Given the importance of the finding on the relative predictability of the blocked and zonal regimes, I would suggest giving a bit of history on it. Overall, the review on low-frequency variability (LFV) of the midlatitude atmosphere in the paper's introduction is quite careful and complete. But the authors might wish to emphasize the fact that Legras & Ghil (*JAS*, 1985) were the first to find the greater stability and hence predictability of zonal flows in their 25-variable barotropic model on the sphere. This result was followed in the experimental paper of Weeks et al. (*Science*, 1997), using a barotropic rotating annulus, by a study of the variability and persistence of the laboratory blocked flow that essentially confirmed the findings of Legras & Ghil (1985); see especially Fig. 5 in Weeks et al. (1997). So did the Lucarini & Gritsun (*Clim. Dyn.*, 2020) paper, which used the three-layer quasi-geostrophic model of Marshall & Molteni (*JAS*, 1993) and the methodology of unstable periodic orbits

(UPOs). The fact that Lucarini & Gritsun (2020) used a baroclinic model removes the doubts about the greater stability of zonal flows being exclusively due to the barotropic character of the Legras & Ghil (1985) model and of the Weeks et al. (1997) apparatus.

It would be of particular interest if the authors of the present paper could take a closer look at baroclinic vs. barotropic effects in their model, with respect to this question of the relative stability and persistence of blocked vs. zonal flows, when the two types of regimes coexist. See also the discussion in Ghil & Lucarini (*Rev. Mod. Phys.*, 2020, p. 035002-36).

2. The authors refer to using a "machine learning algorithm called Gaussian Mixture Clustering (GMC)," which is described in Appendix A. While machine learning and AI are all the rage these days, I'd be curious to know how this algorithm differs from the one that was used on observational data by Smyth et al. (*JAS*, 1999).

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