Author response: NIPS 2018, Paper 3656
Modeling trend in temperature volatility using generalized LASSO
August 1, 2018

We wish to thank the reviewers for their careful and well-informed comments. We are especially grateful for the literature suggestions given by reviewer 1. The Gibberd et al. (2017) and Monti et al. (2014) papers especially deserve mention in our paper, and neither was familiar to us. Both take a similar approach to ours, and while different in a number of key ways, deserve a more careful discussion than can be provided here. In particular, we should, at minimum, try their algorithms or give reasons why we cannot. However, we feel these papers provide a good launching point to discuss the main issue, mentioned by all three reviewers.

Main issue All three reviewers felt that this paper lacked sufficient novelty relative to existing literature. The novelty of our paper is best understood as an attempt to apply a slightly modified ℓ_1-trend filter to a very large and very important dataset. It is certainly true that ℓ_1 regularization is everywhere, as is trend filtering, and variance estimation under such a penalty. In that sense, our paper is not particularly new. However, we found that the size of our problem (coupled with a non-quadratic likelihood function) meant that standard methods were computationally infeasible. The time-varying networks used in Monti, Hallac et al. (2017), and Gibberd, have on the order of hundreds of time points and dozens to hundreds of nodes. Our data have (see lines 100–105) 3500 time points and 25,000 nodes. It is this massive increase in throughput which makes our methods both relevant and novel. Even building the penalty matrix (or loading the data) is relatively infeasible. This is also the reason that our simulation size is relatively paltry: to enable many replications performed quickly. Note however that Gibberd uses 10 nodes and 50 timepoints in their simulations, so our example with 35 nodes and 780 timepoints is not that out of the ordinary.

Why variance Finally, there was some confusion as to why the variance would be important here (rather than the mean). This is for a number of reasons which we tried to articulate carefully in the introduction.

1. Instrument bias in the satellite increases over time so examining the mean over time conflates that bias with any actual change in mean (though the variance is unaffected).
2. Extreme weather events (hurricanes, droughts, wildfires in California, heatwaves in Europe) are driven more strongly by increases in variance than by increases in mean.
3. Even if the global mean temperature is constant, there may still be climate change. In fact, atmospheric physics suggests that, across space, average temperatures should not change (extreme cold in one location is offset by heat in another). But if swings across space are becoming more rapid, then even with no change in mean global temperature over time, the variance is increasing, again leading to increases in extreme events.

Minor issues We will of course be careful to address typos (thank you for pointing them out!) as well as attempt to clarify points of the paper which were less precise than they should have been. And, really, thank you for your reviews.