1 Manu's Ideas

Let us tie in financial instruments as well as structural design – financial instruments are probably better suited for our argument and also this is an active area whereas infrastructure stories are kind of not moving – but should cover both. Most importantly let us put the climate adaptation or climate risk mitigation spin on it since that is the most pertinent case – so in the intro we should develop that idea

I think we need to have the focus on illustrating that for sequential decisions on offers or purchases of insurance like instruments or on the construction of infrastructure one needs to consider the risk as a function of estimation uncertainty of the quantile (N for stationary, and $N-p$ for non-stationary – where $N-p$ is the effective degrees of freedom) as well as the uncertainty associated with the time period of length M.

Where, the process is stationary and sequential decisions are considered, we explore whether the choice of the design quantile or the trigger for insurance like instruments depends on N and M in addition to the cost and loss parameters.

For the nonstationary case, the projection of the risk on the period of length M based on the estimation using a period of length M also depends on the form of the underlying nonstationarity and the degree to which the "prediction" is likely to be successful. This is a more interesting and realistic case, since directional information as to the risk to be faced in the M period may depend on the duration M and the uncertainty may also correspondingly change. Thus, exploring how the optimal quantile level or trigger for design changes under such conditions is of interest. Here, we consider the identification and assessment of these uncertainties for various combinations of M, N, quantile or trigger level, and form of nonstationarity. For simplicity, we consider a monotonic trend in the location and scale prameters, as well as a periodic trend in the location and scale parameters of the underlying climate extreme process, and consider varying signal to noise ratios for these parameters. Models that are properly specified, i.e., period to estimate periodic trends, and linear for linear trends are considered. Since our intention is to help develop intuition as to how these cases may influence decision making, we consider only these idealized cases, and do not consider model mis-specification for now.

The fair price for the premium is $p \times \kappa$, where κ is the coverage and $p = p(X > X^*)$. So if $p = 0.01$ and coverage = 1×10^9 USD and $M = 1$ year then this would be $0.01 \times 1e9$. If M were 10 years and you got paid per event then one would need to compute the payoff probability for 1 or more events (complement of 0 events) over that time corresponding to annual $p = 0.01$. Or to simplify we could make the example to be a payoff on the 1st event and no further events (though if we want to illustrate time clustering with time changing probabilities, the 1 or more game is attractive) Now we can derive the fair premium for the $M = m$ game However, there is a risk premium associated with the policy that prices the uncertainty in p – since x_T the trigger is specified in the contract and is not uncertain. This risk premium is proportional to the $V(p)$ or more generally related to the uncertainty distribution of p.

Now we come to the N side – and the $V(p|N, M)$ will depend on the underlying model for the process, the estimation scheme and M and N, so under the assumption of these things we can derive the risk premium and help illustrate how it changes by condition and hence identify a tradeoff point for dynamic vs static risk given these parameters and M/P position during decision making.

The insurance example is a way to illustrate the general principle. If we are designing infrastructure we are faced with the same uncertainty on p. However, to properly analyse it we need detailed information on losses that we may incur and costs. These are themselves highly uncertain and would need to be assessed but the underlying principle that the risk due to the uncertainty and bias in p has to be assessed is not any different and the parametric insurance example is then used to get the concept across – this is how one should present it. Of course as discussed separately, it is not just N and

M but the static and dynamic risk considerations which imply predictive uncertainty and bias as well and this is why we demonstrate these ideas via simulation

building blocks

1. static risk, stationary process implications of M and N = basically my old paper provides V
2. static risk, non-stationary process (drift and periodic terms, estimation using full N or partial, most recent N – as some people recommend and Vogel argues recent N is better in his forthcoming paper) illustrate via simulation for different signal to noise ratio of nonstationary terms and M and N
3. dynamic risk, i.e. updating and sequential decisions, nonstationary, M and N considerations – ok this is the last case

So for AGU if you can even wrap up 1 and 2 and then by end of year paper with all 3 I think we are good for the 1st paper. We need enough to motivate the real options paper which is then introduced as the decision making framework considering multiple options.

Let us frame this more precisely in the context of climate change adaptation by giving examples 1) consider a place where under IPCC scenarios there is a wide variation in the projected probability distributions when all scenarios are considered and this uncertainty increases as one looks out into the future. 2) We have regime like behavior that varies stoachastically – could be quasi-periodic or modeled using HMM etc and in this case, essentially we have a structured long-memory process with shifts in all parameters with time, but the underlying dynamics may be stationary. Now from a decision making perspective, one could either design and build a project that gives us protection through the year 2100 considering both types of nonstationarities, or consider a sequence of projects every M years that incrementally add (or not) protection. How does the uncertainty and hence risk for these decisions manifest depending on the design level p, the duration M, and the uncertainty associated with the estimation of the f(Qp(t)) given a methodology used for prediction – e..g the model chain using gcms and such and models fitted to a historical data length m. WHat is the implication for choices of p and M under different models for stationarity and uncertainty using some simple loss and cost functions. How could financial risk mitigation instruments be used in conjunction with structural design to identify a robust, adaptive climate risk mitigation strategy with sequential decisions that are informed by updated estimates of risk.

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2 Extra Lit Review

The first element of the model is the distribution function. Although Bulletin 17-B (IACWD, 1982) mandates the use of the log-Pearson type III (LP3) model of annual-maximum floods in the United States, annual-maximum floods are also modeled three-parameter distributions such as the generalized extreme value distribution and two-parameter models such as the lognormal (LN2) (Vogel and Wilson, 1996). Alternatively, peaks-over-threshold floods are typically modeled with the Generalized Pareto distribution (Jain, 2001; Silva et al., 2016). Many other approaches have been utilized in the literature, as the choice of model is generally made for practical rather than theoretical reasons (Kidson and Richards, 2016).

The second element is an approach for estimating the parameters of the model. Popular approaches include the delta, bootstrap, and profile likelihood approahces (Obeysekera and Salas, 2014). More recently Bayesian approaches have gained popularity due to their ability to fully quantify uncertainty. Another advantage of Bayesian approaches is the straightforward approach to integrating data from multiple data sources (i.e. Bracken et al., 2016; Lima et al., 2016; Steinschneider and Lall, 2015; Sun et al., 2014), filling a key need identified in previous literature reviews (Merz et al., 2014; Merz and Blöschl, 2008).

Finally, FFA requires a parameterization of the time evolution of the model parameters. Under assumptions of stationarity used in classical flood frequency analysis, this quantity is assumed constant in time: $p(Q(t)) \equiv p(Q)$. One approach to nonstationary FFA is to parameterize the distribution of Q as a linear, logarithmic, or polynomial function of time itself (Obeysekera and Salas, 2014; Serinaldi and Kilsby, 2015; Strupczewski et al., 2001; Vogel et al., 2011). A problem with these time-varying parameters is that the different forms of the trends might be almost indistinguishable for the observational period, but lead to different future behavior at the end of the project operation period (Rootzén and Katz, 2013; Serinaldi and Kilsby, 2015). Additionally, as these statistical approaches condition on more variables, the number of parameters estimated increases, leading to problems of high uncertainty and overfitting (Serinaldi and Kilsby, 2015). Some studies address this problem by using null hypothesis significance testing (NHST) to detect nonstationarity and fitting time-varying parameters only if nonstationarity is rejected (i.e. Luke et al., 2017; Obeysekera and Salas, 2014). This approach, however, translates poorly to decision-making settings (Rosner et al., 2014; Vogel et al., 2013). This is in line with recent criticims in the statistics literature of the use of NHST in situations where the null hypothesis, such as that the flood time series is fully stationary, is implausible (Gelman, 2016; Gelman and Carlin, 2014; McShane et al., 2017). [1]

An alternative approach to purely statistical fits of $Q(t)$ is to numerically simulate the physical processes that lead to floods. Typically this is done through a long model chain emcompassing: (1) emission scenario (2) general circulation model (GCM) (3) downscaling (4) hydrological catchment model; and (5) flood frequency analysis. Typically bias correction is applied at several steps of this chain, which can complicate interpretability of results. While this approach allows for estimates of flooding at high spatial and temporal resolution, results are sensitive to the choice of a model at each step of this chain and uncertainty propagation is difficult to characterize (Dankers and Feyen, 2009; Dittes et al., 2017; Ott et al., 2013). Ideally, one could run large ensembles of models that capture the full distribution of uncertainty in each step of the model chain and use ane exhaustive set

[1] Manu: introduce idea that nonstationarity in terms of all parameters of these models may exist and be monotinic – important to link to mechanism – or quasi-periodic. Use appropriate refs. Then introduce the literature htat has tried to make estimates in these settings.

of physical parameterizations, but in practice the computational cost of such an approach is prohibitively expensive. Further, there is a need for theory for combining model results which are not idependent and identically distributed, complicating the task of flood frequency analysis. More recently, studies have attempted to shorten the model chain by modeling $Q(X(t))$, where X is a set of climate state variables from a GCM run (Delgado et al., 2014; Griffis and Stedinger, 2007; Hall et al., 2014; Silva et al., 2016; Villarini et al., 2010, 2009). Though this approach does not resolve the difficulties of GCM bias and herding[2], by "shortening" the model chain it allows for a more interpretable characterization of $p(Q(t))$ and reduces uncertainty associated with subsequent steps.

1. High government indebtedness levels in many if not most emerging-market countries no longer allow public-debtd riven delivery as a scalable alternative to build urgently needed infrastructure (World Economic Forum, 2016).

2. In specific cases, investors' risk appetite and the risk level of infrastructure projects can be bridged through credit and project guarantees, insurance and other credit-enhancement schemes, also known as Risk Mitigation instruments (World Economic Forum, 2016).

3. The sustainable management of water resources requires a long-term perspective. Yet looking to the future reveals a host of major uncertainties, with respect to pressures from climate change, demographic change, land-use changes and other socio-economic drivers (Hall et al., 2012).

4. Despite widespread interest in index insurance for industries such as agriculture (Clarke and Grenham, 2013) and navigation (Meyer et al., 2016), there has been little exploration of financial instruments for hydroclimate risks beyond a year or two.

5. The insurability of risks depends on a number of factors, including: (1) mutuality (that a large pool of risk can be created); (2) quantifiable loss; (3) randomness of the insured event; and (4) economic viability (that the premium is sufficient to cover losses and affordable to the policyholders). (Wolfrom, 2016).

[2] there must be a better way to say this – I mean it in the Nate Silver sense

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