Authors response to Anonymous Referee #1

Referee comment on "A Performance-Based Approach to Quantify Atmospheric River Flood Risk" by Corinne Bowers et al., Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2021-337-RC1, 2021

We would like to thank the reviewer for their valuable feedback and constructive comments. We have revised the manuscript accordingly and provided detailed responses to each of the comments below.

General Comments

1.1)
The authors provide a process-based probabilistic framework for predicting damages associated with ARs based on AR intensity and duration and antecedent hydrologic conditions. This is a useful tool. There are a number of technical innovations throughout the study. The 2019 Russian River case study contains several creative data sourcing and manipulation steps to overcome inherent data availability issues. The overall method has broader applications than AR damage prediction. It could be applied to any damaging hydrometeorogic events, including hurricanes and tropical storms. The AAL and loss exceedance curve calculations are compelling. A number of valuable insights are presented in the discussion section.

Response: We would like to thank the reviewer for these comments about our work and its potential applications.

1.2)
My only comment of substance is that the current ordering of sections makes the model difficult to follow as variables are introduced before being defined and the multivariate Monte Carlo integration framework is explained after presenting the series of integrals. I'd put section 2 paragraph 1 first, then 3.2 paragraph 1, then 2.1 description of pinch point variables, then 2 framework description with the equations, then 3.2 paragraph 2 explanation of Monte Carlo integration. Or something along those lines. The current ordering was difficult for me to follow although it did all make sense at the end.

Response: We acknowledge that the original ordering created unnecessary confusion and have reorganized much of Section 2 to address the reviewer's concerns. We appreciate the helpful suggestions on how to present the information in a more intuitive order. The new organization is as follows:

Section 2: Framework Description

- Law of total probability (same)
- Introduction of Eq. 1 (modified to address comments 1.8 and 1.15)
- Definition of pinch points (previously the first paragraph of Sect. 2.1)
- Definition of component models (previously the first paragraph of Sect. 2.2)
- Introduction of Eq. 2 (modified to address comment 1.15)
- Explanation of Monte Carlo integration (previously the second paragraph of Sect. 2.2)

Section 2.1: Pinch Point Variables
- Distinction between pinch points and pinch point variables (new; added to address comment 1.14)
- Detailed description of pinch point variables (same)

Section 2.2: Component Models
- General description of component models, with special attention to f(Q | PRCP, HC) (new; added to address comments 1.13 and 1.36)
- Distinction between component models and component model implementations (new; added to address comments from Reviewer 2)

We believe that this response serves to additionally resolve the concerns and questions expressed by the reviewer in comments 1.12, 1.16-1.24, 1.31, and 1.32.

1.3)
The rest of the comments are minor technical corrections / suggestions or requests for clarification. Overall this is a great contribution to the literature. I recommend accepting the manuscript after minor revisions.

Response: We would like to thank the reviewer for their recommendation, and for the time and effort put into reviewing this manuscript.

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Specific Comments / Technical Corrections

1 Introduction

1.4)
Line 26 California experiences ARs coming from a pathway called the Pineapple Express -> California often experiences ARs coming from a pathway called the Pineapple Express [not all ARs in CA are considered Pineapple Express storms]

Response: We acknowledge the reviewer's suggestion and we have removed this sentence from the manuscript.

1.5)
Line 31 $300 million -> $660 million
Data appendix S1 Top Counties lists damages for CA counties over 40 years at 26.53 billion of which AR damages were 24.86 billion in 2019 dollars. This translates into annual AR damages of 24.86/40 = 621.5 million. In 2021 dollars this is approximately $660 in 2021 dollars (e.g., https://www.minneapolisfed.org/about-us/monetary-policy/inflation-calculator)

Response: We have revised according to the reviewer's suggestion.

1.1 Disciplinary Context

1.6)
In addition to FEMA's Hazus, USACE's HEC-FIA and HEC-FDA are potential methods that can be used to convert HEC-RAS outputs to economic impacts.

Response: We acknowledge the reviewer's suggestion and have added the following sentence to Line 72.

"Other regional flood loss assessment tools include HEC-FIA (USACE, 2018) and HEC-FDA (USACE, 2014), both from the US Army Corps of Engineers; and FloodFactor (Bates et al., 2020), a commercial product from First Street Foundation."

2 Framework Description

1.7)
Line 109 total probability theorem -> law of total probability

Response: We have revised according to the reviewer's suggestion.

1.8)
Line 116 decision variable DV appears here for the first time but is described later at 165. Either move the section on pinch point variables above the introduction of DV, etc., or note that the variables are defined in detail below.

Response: We acknowledge the reviewer's comment, and we have added the following text to Line 114 to indicate that an explanation of the pinch point variable DV will be provided later in the manuscript.

"We first replace the generic variables with new variables representing pinch points, which we elaborate on later in this section. B becomes the atmospheric river event AR and A becomes the decision variable DV."

1.9)
Eq 2 consider \cdot or \times in place of asterisks.

Response: We agree with the reviewer and have switched to using \cdot throughout the manuscript.

1.10)
Eq 2 consider six integrals evenly spaced rather than two sets of three integrals.

Response: We have revised according to the reviewer's suggestion.

1.11)
Eq 2 it would perhaps make sense to include the supports over which the pinch point variables are being integrated. But perhaps it would be a distraction.

Response: We tested out the reviewer's suggestion, but felt that adding the integration supports created visual clutter and reduced the clarity of the equation. We have thus retained the integrals without explicit supports.

1.12)
Eq 2 ideally, the variables should be defined as they are introduced. Perhaps it is sufficient to note that the variables are defined below in Sect. 2.1.

Response: We have reorganized Sect. 2 as outlined in our response to comment 1.2 to address this suggestion.

1.13)
Eq 2 An explanation of why f(Q | PRCP, HC) has two conditional variables while all other elements in the chain have only one may be useful for the reader, at some point in the text.

Maybe something like: at each point in the causal chain one pinch point variable depends on the next. Flow, Q, depends on two variables precipitation, PRCP, and antecedent hydrologic conditions, HC. Could perhaps write out the whole chain in English in the paragraph below the equation. This would be easier to follow than waiting to read the text in the next section. Or else note that all variables are defined in the following section.

Response: We acknowledge the reviewer's comment, and we thank the reviewer for providing some suggested text to improve the manuscript. We have reorganized Sect. 2 as outlined in our response to comment 1.2 to provide the reader with the component model definitions before the equation. We have also added an explanation of why f(Q | PRCP, HC) has two conditional variables to the new version of Sect. 2.2. The text of this new paragraph is as follows.

"The pinch points in the framework are linked by component models, or representations of discrete physical processes. Each component model generates an expected distribution of values for the next pinch point in the sequence conditioned on the value(s) preceding it. It is important to note that, excepting the hydrologic routing model f(Q|PRCP,HC), all models are conditioned on only one variable. The hydrologic routing model differs from the others because, like the event characteristics (AR), the antecedent hydrologic conditions (HC) are framework inputs provided by the user to represent an initial system state. All other pinch point variables represent calculated variables. Conditioning on a minimal number of variables is critical to achieving the objective of modularity because it reduces the data demands at each step of the modeling process."

1.14)
Eq 2 Each pinch point variable is a scalar here?

Response: We have reorganized Sect. 2 as outlined in our response to comment 1.2 to provide the reader with the pinch point definitions before the equation. We have also added additional text to distinguish between pinch points and pinch point variables, as outlined below. The revised Sect. 2.1 includes the following paragraph (approximately Line 140 in the manuscript).

"The pinch points presented in Sect. 2 are conceptual descriptions of the intermediate system states between AR occurrence and flood loss where only a limited amount of information must be transferred to the next step. Pinch point variables are low-dimensional numerical vectors of the information at each pinch point (Garrick 1984). The following paragraphs expand upon the conceptual pinch points and introduce the specific dimensions and measurement units that are used in this paper for each pinch point variable."

1.15)
Eq 2 I'm unclear on how \lambda(AR) works and on how \lambda(DV > x) and P(DV > x | DM) work... An additional line providing some context could be helpful.

Response: We thank the reviewer for drawing attention to these elements of the PARRA framework, and we have modified the descriptions of both Eq. 1 and Eq. 2 as a result. For Eq. 1, we have removed the text from Lines 113-121 in the manuscript and replaced it with the following.

"Equation 1 modifies the statement of the law of total probability to better fit the context of natural hazard assessment.

$$\lambda(DV > x) = \int P(DV > x \mid AR) \cdot \lambda(AR)\, dAR \quad (1)$$

where $\lambda(DV > x)$ is the rate of the decision variable DV exceeding some specified threshold x, i.e., how frequently losses exceed \$x dollars; $P(DV > x \mid AR)$ is the probability of DV exceeding x conditioned on an inducing AR event; and $\lambda(AR)$ is the occurrence rate of that inducing event. The right side of the expression is integrated over all possible inducing events in the sample space. We evaluate $\lambda(DV > x)$ at a range of x values to obtain the loss exceedance curve, which is explored further in Sect. 4.2.

"We first replace the generic variables with new variables representing pinch points, which we elaborate on later in this section. B becomes the atmospheric river event AR and A becomes the decision variable DV. $P(DV > x)$ is the complement of the cumulative distribution function for DV, starting at 100% probability of exceedance for low values of x and moving to a probability of zero as x increases. $P(DV > x \mid AR)$ represents the probability of the decision variable DV exceeding some threshold value x conditioned on the inducing event AR.

"We then transform the summation into an integral and move to calculating the occurrence rate λ, which represents a continuous state variable rather than the probability P of a discrete event. Probabilities are defined with respect to predetermined time periods, and the probability of seeing an AR event in the next week, month, or year are all different quantities. Calculating the occurrence rate λ offers similar information about the underlying phenomenon of interest (AR event frequency) without imposing an arbitrary time limitation."

For Eq. 2, we have removed the text from Lines 126-131 in the manuscript and replaced it with the following.

"…where variables AR, PRCP, HC, Q, INUN, DM, and DV represent pinch points and the conditional probability expressions represent component models. The component models of the form $f(Y \mid X)$ are conditional probability density functions that describe the distribution of results from numerical analyses. The component model $P(DV > x \mid DM)$ measures the probability of pinch point DV exceeding the loss threshold x conditioned on DM. The PARRA framework is executed by starting with the outermost integration in the equation and moving inward, as each component model is conditioned on the one(s) preceding it in the model chain. This equation is also represented visually in Fig. 1."

2.1 Pinch Point Variables

1.16)
(The following comments were written as I was reading through the manuscript. They could be avoided if you are clear upfront about how the integration is Monte Carlo integration and how the pinch point variables can be vectors.)

Response: We agree with the reviewer's overall comments on the organization of Sect. 2, and we have reorganized the section as outlined in our response to comment 1.2. We believe that comments 1.17 through 1.23 have been resolved by this reorganization and by the additional understanding the reviewer has noted from comment 1.24 onward.

1.17)
I'm a little unclear on how the causal chain works with scalar variables given that the process is spatially heterogeneous. Should I think of the PARRA process running in parallel over all locations? But what about spatial correlations?

Response: Please see our response to comment 1.16.

1.18)
AR is a measure of intensity, so it could be something like peak IVT or cumulative vapor transport over some time period, the duration of the AR, say. But IVT is a vector field. So you'd need to aggregate or average over time and space to get a scalar metric of intensity.

Response: Please see our response to comment 1.16.

1.19)
PRCP as a scalar field has the same issue. You'd need to integrate over time and space to get a scalar value. Should I think of this as some metric of precipitation over the whole watershed? Or is there a way to apply PARRA with a time series of precipitation grids as inputs?

Response: Please see our response to comment 1.16.

1.20)
HC, same as AR and PRCP.

Response: Please see our response to comment 1.16.

1.21)

Q makes more sense as a single input if you're considering a single channel, although the hydrograph is a curve which captures the duration as well as the intensity of the flow above flood stage, so I'm unclear on how this enters into the formulation.

Response: Please see our response to comment 1.16.

1.22)
INUN at a given location or structure is just a scalar, but over a set of n structures is an n-dimensional vector. Here, duration of inundation may also be important, in addition to depth, in terms of generating damages.

Response: Please see our response to comment 1.16.

1.23)
I'm unclear on how DM and DV differ. DV is a metric of impact or consequence. DM is a damage measure. So, DV could be a more broad measure of impact that is perhaps related to DM through some probabilistic relationship that is modeled using the observational record?

Response: Please see our response to comment 1.16.

1.24)
Ah, the variables are discussed in more detail. AR is a vector of max IVT and duration, got it.

Response: We thank the reviewer for identifying where this portion of the manuscript achieves clarity of purpose.

1.25)
PRCP is storm-total accumulated rainfall over the watershed. Did you experiment at all with more complex formulations for precipitation? Don't tools like HEC-RAS and LisFlood take precipitation fields as inputs?

Response: We decided to present a simpler scalar representation of precipitation to streamline the model chain and keep the focus of the manuscript on the overall framework rather than the individual component model implementations. While we agree with the reviewer that both HEC-RAS and LISFLOOD have the computational capability to accept two-dimensional precipitation fields, the complexity of the precipitation pinch point variable was limited not by these dynamical models but by the statistical model chosen to represent the component model f(PRCP|AR) described in Sect. 3.2.1. We discussed some of these tradeoffs later in the manuscript, starting at Line 585, and we have added the following text to Line 150 to point readers to that discussion.

"This simplification could be modified or eliminated in future implementations of the precipitation component model, as addressed further in Sect. 5.4."

1.26)
HC watershed-average soil moisture equivalent height. There's probably some additional uncertainty introduced by averaging over the whole watershed. Upstream soil moisture may be more relevant than downstream soil moisture, for example, although these are probably highly correlated.

Response: We have modified the sentence at Line 123 to reflect that soil moisture values were averaged across only the upstream watershed, not the entire watershed. The revised sentence is as follows: *"Therefore the pinch point variable representing antecedent hydrologic conditions is a scalar value measuring the average soil moisture in the upstream watershed."*

We also acknowledge the reviewer's comment about the introduction of additional uncertainty through averaging. Because of the relatively low temporal and spatial resolution of the CPC soil moisture dataset (1 month and 0.5 degrees lat/long, respectively), we found that additional precision in averaging did not significantly affect the values calculated for the events in the historic catalog.

1.27)
Q is time series of flow at inlet. This is parameterized as a 3-vector with Q_p, t_p, and m.

Response: We appreciate the reviewer's comment.

1.28)
INUN is surface water depth at locations of interest. So this is N-dimensional.

Response: We appreciate the reviewer's comment.

1.29)
DM is a damage ratio, expected cost to repair over the total value. Assumed to be a function of water depth.

Response: We appreciate the reviewer's comment.

1.30)

DV actionable measure of impacts. So, it converts damage ratios into damages? So it requires observed building values then? What's the utility in splitting DM and DV? I think I can see it, but an explanation could be useful.

Response: We thank the reviewer for identifying the need for more information about the distinction between these two pinch point variables. We have revised the last paragraph of Sect. 2.1 and added the following additional text to Lines 166-168.

"Finally, the decision variable (DV) is some actionable measure of AR impacts. In this work we define DV as household-level monetary losses; however, DV could alternatively represent any other metric that is calculated as a function of the damage measure DM, such as the number of displaced persons or the time to full recovery."

2.2 Component Models

1.31)
This could perhaps go above the equations.

Response: We have reorganized Sect. 2 as outlined in our response to comment 1.2 to address this suggestion.

1.32)
I'd put section 2 paragraph 1 first, then 3.2 paragraph 1, then 2.1 description of pinch point variables, then 2 framework description with the equations, then 3.2 paragraph 2 explanation of Monte Carlo integration. Or something along those lines. The current ordering was difficult for me to follow.

Response: We have reorganized Sect. 2 as outlined in our response to comment 1.2 to address this suggestion.

3 Case Study: Sonoma County

1.33)
Line 185 The spatially repetitive, locally severe flooding seen in Sonoma County is a signature characteristic of ARs. <- I'm not sure if I agree with this statement; I suggest removing it. The statement suggests that ARs tend to reoccur at the same locations and always generate locally severe flooding. Some ARs generate multi-basin flooding, like the 1862 event. Some locations affected by ARs flood (relatively) infrequently.

Response: We agree with the reviewer and have removed this sentence from the manuscript.

3.2.1 Precipitation Component Model

1.34)
Line 238 mixture model 90% with WLS standard errors, 10% with distribution fit to largest 10% of events. I'm familiar with WLS but not with this approach. More detail on this method, or a reference, would be helpful.

Response: We have adopted a Gaussian mixture model to represent the non-normal residuals in both the precipitation and streamflow regressions. We used mixture models where the regression coefficients are held constant and only the errors are allowed to vary, and we further restricted the errors to be represented by a mixture of zero-mean Gaussian distributions such that only the differences were the error variances. We chose the Gaussian mixture model because it is semi-parametric, meaning it is more flexible than other parametric distributions that could be used for non-normal errors, and because mixture models are often applied when we believe that there are latent variables or that observations may be coming from different populations (i.e., precipitation stemming from different climatological drivers). We have added citations to Line 240 referencing related work by Bartolucci and Scaccia (2005) and Soffritti and Galimberti (2011) for more information on this method.

3.2.2 Precipitation 2019 Case Study

1.35)
Line 271 We note that Sonoma County is not guaranteed to see any impacts -> We note that, according to the simulated distribution, Sonoma County... (or, according to the distribution simulated from the observational record, etc.)

Response: We have revised Line 271 according to the reviewer's suggestion. The new sentence reads: *"Our simulation results indicate that Sonoma County is not guaranteed to see any impacts…"*

3.3.2 Hydrologic Conditions 2019 Case Study

1.36)
Line 289 it is interesting that soil moisture is an "input" here and not simulated, just as AR IVT and duration are "inputs." This is explicitly captured in the flow chart and in the Eq 2 multiple integral. It might be worth emphasizing this in the description of the flow chart, for example.

Response: We appreciate the reviewer's suggestion. We have highlighted the fact that soil moisture is an input rather than a calculated variable in the new version of Sect. 2.2, as outlined in our response to comment 1.2. The text of this new paragraph is included as part of our response to comment 1.13. We have also modified the caption of Fig. 1 as follows:

"Figure 1: PARRA framework flowchart. Graphical depiction of the PARRA framework, as presented mathematically in Eq. 2. White boxes represent component models. Arrows represent pinch points: an arrow pointing towards a box indicates a required component model input, and an arrow coming out of a box indicates a component model output. The background colors broadly represent existing research domains."

We would additionally like to note that this comment from the reviewer brought a numerical error to our attention in the calculation of soil moisture, which has affected both the estimate of losses for the 2019 event and the overall AAL for the study area. We have included the updated results as part of our response to comment 1.49.

1.37)
Line 291 why is observed precipitation used as an input here? Shouldn't the full precipitation distribution, derived from the input AR intensity and duration, enter here? What am I missing?

Response: We thank the reviewer for noting that this sentence created confusion. The observed precipitation and soil moisture are used as input for the streamflow component model in Sect. 3.4 because this section focuses on model-by-model calibration and comparison. To resolve confusion for future readers, we removed the sentence referenced by the reviewer and added a new sentence to Line 326 to improve clarity. The introduction to Sect. 3.4.2 now reads as follows:

"Given the 2019 observed precipitation and antecedent soil moisture, we generated 1,000 Monte Carlo realizations from the streamflow model and compared the predicted streamflow hydrograph from the calibrated component model implementation to the observed hydrograph from the February 2019 event. Using observed data as input rather than the simulated distributions from Sects. 3.2 and 3.3 allows us to examine the fit and uncertainty associated with this specific step of the model chain in isolation."

3.4.1 Flow Component Model

1.38)
Line 310 - what data were you using here? The observational precipitation record? Fed into the runoff calculation? So, you have how many observations to fit the mixture OLS model?

Response: The OLS regression referenced by the reviewer predicts the peak streamflow value Q_p as a function of precipitation and runoff. The coefficients of the regression were fit based on observed precipitation and runoff values from the historic catalog of 382 events. Based on the reviewer's questions presented here we have chosen to shorten the discussion of the runoff calculation, because we felt it was drawing attention away from the main point of the section. The full calculation process is still available through the supplemental code release. We have replaced the text from Lines 302-309 with the following sentence:

"Runoff, the portion of precipitation that flows over the ground surface rather than contributing to evapotranspiration or infiltration, was calculated for each event in the historic catalog using the empirical curve number method (NRCS, 2004, Chapter 10)."

3.4.2 Flow 2019 Case Study

1.39)
Fig 5 b - any speculation on the early streamflow peak in the 2019 event? It doesn't seem to be captured within the 90% PI. A horizontal line indicating flood stage could also be informative in this figure.

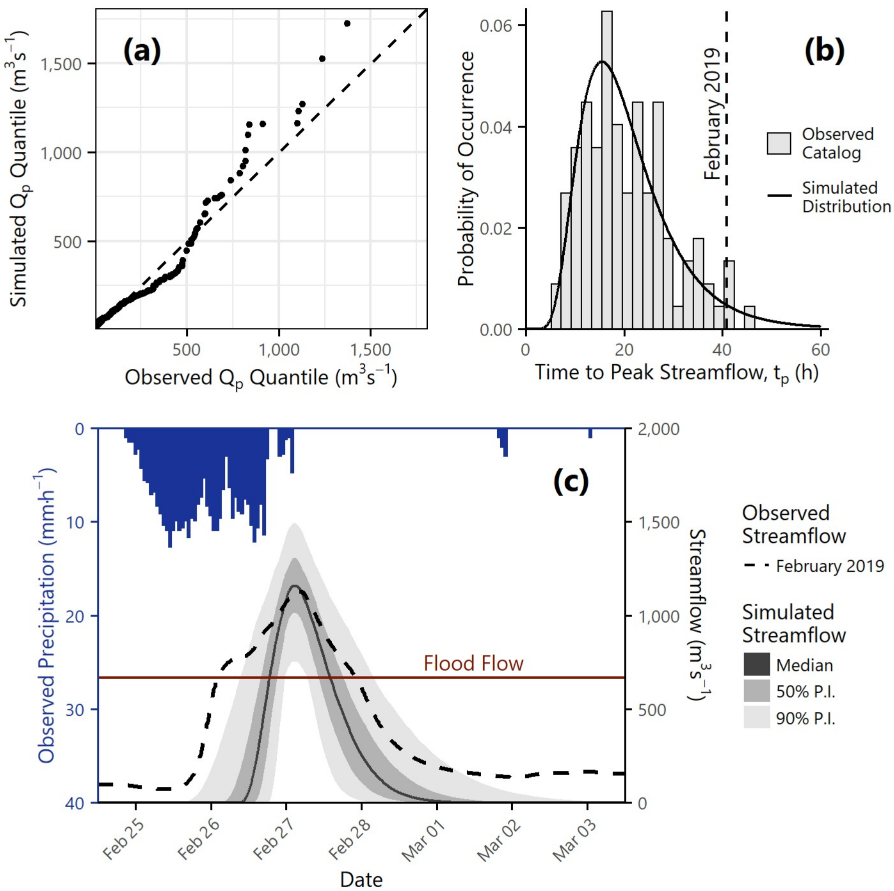
Response: We acknowledge that the early streamflow peak seen in Fig. 5(b) requires more contextualization. We have added a hyetograph of observed precipitation to the figure as shown below. We have also added additional commentary on both the early peak and the new hyetograph. The new text starts at Line 332 and reads as follows.

"The complex shape of the observed streamflow timeseries in Fig. 5(b) is a function of the unique watershed response as well as the spatial and temporal heterogeneity of the input precipitation. By contrast, the simulated distribution is based on the unit hydrograph method, which assumes that the precipitation distribution is uniform and that all runoff enters the channel at a single location. This limits our ability to capture certain kinds of behavior, such as the early peak seen in the observed streamflow timeseries in Fig. 5(b). The early peak could be due to catchment processes that cause a lagged tributary response, input from direct surface runoff, spatial variation in precipitation intensity and duration, or any number of other mechanisms. We include the observed hyetograph to the top of the plot in Fig. 5(b) to show just one aspect of the natural variability that affects the observed timeseries.

"Despite the simplification imposed by the unit hydrograph method, many metrics of interest are reasonably well characterized by the simulated timeseries. The observed peak streamflow (1,130 m^3s^{-1}) is at the 43rd percentile and the observed floodwave duration (81 h) is at the 63rd percentile of the respective simulated distributions. Recall from Sect. 3.2 that the observed precipitation was notably high conditioned on the observed atmospheric conditions. We now

note that while the observed streamflow may have been high for a Category 3 event, it was in the middle of the simulated distribution conditioned on the observed precipitation. Therefore we conclude that the hydrologic routing was likely not one of the physical processes contributing to the "extremeness" of the 2019 event."

Additionally, we appreciated the reviewer's suggestion to add a line indicating the flood stage. We have added one to the revised version of Fig. 5 below.



Revised streamflow figure.

3.5.1 Inundation Component Model

1.40)
Line 344 100 year peak flow -> 100-year peak flow, etc. (make this change throughout the manuscript)

Response: We have made the change from "100 year" to "100-year" throughout the manuscript according to the reviewer's suggestion.

1.41)
Line 367 how many buildings were there in your domain? What year were the building footprints taken from?

Response: We have added the following sentence to Line 385 to answer the reviewer's question: *"We used building footprints from 2019 SonomaVegMap LIDAR data and building parcel information from the 2021 Sonoma County Clerk Recorder Assessor to identify 41,000 homes within the study area."*

Citations for both of these datasets can be found in the "Code and data availability statement" at the end of the manuscript, which starts at Line 641.

3.5.2 Inundation 2019 Case Study

1.42)
Figure 7 in the Data Type legend it appears that Observed is dashed and Simulated in solid. Making this more clear would be helpful.

Response: We have revised Figure 7 according to the reviewer's suggestion.

3.6.2 Damage Measure 2019 Case Study

1.43)
RESA tagging is a fascinating approach.

Response: We would like to thank the reviewer for their comment.

3.7.1 Decision Variable Component Model

1.44)
Interesting approach to estimating property values from tax assessments adjusted using ACS correction factors.

Response: We would like to thank the reviewer for their comment.

3.7.2 Decision Variable 2019 Case Study

1.45)
Line 451 missing comma after i.e.

Response: We have revised according to the reviewer's suggestion.

1.46)
Figure 9 b - it would be useful to have a high-resolution version of this figure in the appendix, or in a data appendix.

Response: Figure 9b is available in high resolution as part of the supplemental code release mentioned on Line 622; specifically, it is part of the markdown file named lossexceedance.Rmd that reproduces Figures 9 and 10. Based on the reviewer's comment, we will additionally add a spreadsheet with the values shown in Figure 9b to our next Github code release.

4 Results

1.47)
Eq 6 - consider \cdot or \times in place of asterisk, or no multiplication symbol at all. Same comment throughout equations.

Response: We agree with the reviewer and have switched to using \cdot throughout the manuscript.

4.1 AAL

1.48)
Line 487 You could note that $156m is likely to be an overestimate given that the county-wide penetration rates are lower than the penetration rates for properties at risk.

Response: We agree with the reviewer that the $156M reported in the manuscript at a county level is likely an overestimate. Upon revisiting the available data, we found we were able to revise the calculation of the NFIP AAL and estimate both the insurance penetration rate at the census tract level rather than the county level. The revised NFIP AAL is $121M. We have revised the description on Lines 483-487 and modified every instance of the word "county" to "census tract" within this paragraph to reflect the change in the calculation process. This is a far more targeted geographical area and is therefore likely to represent insurance penetration rates (and consequently flood risk) relatively well, and we thank the reviewer for highlighting this opportunity to improve our estimate.

1.49)
Line 487 What is the uncertainty around the $163m estimate?

Response: Due to the numerical error mentioned in our response to comment 1.36, the soil moisture component model was incorrectly oversampling from the high (wet) end of the soil moisture distribution. In addition, although the manuscript stated that soil moisture was an input based on observed data rather than a simulated value, the PARRA simulation results reported in Figs. 9 and 10 were based on calculations that were using simulated soil moisture values. Correcting this error increased the expected losses for the 2019 event (because the "observed" soil moisture for this event was very high relative to others in the record) and lowered the overall AAL (because the simulated realizations were rebalanced to include more events with dry antecedent conditions). We have edited the manuscript accordingly, and we thank the reviewer for their comment that led to us finding this inconsistency.

As a result of these changes the mean expected AAL in the study area has been revised to $111M, and through Monte Carlo simulation we have estimated a 90% confidence interval to span from $93M to $133M. Based on the reviewer's question we have added the following text to Line 482.

"The mean AAL estimated from the stochastic record for AR-induced flood losses to residential structures is $111 million, with 90% confidence that it lies between $93 and $133 million."

5 Discussion

1.50)
There are many valuable insights in the discussion section.

Response: We would like to thank the reviewer for their comment.