Responses to Reviewer 1 Comments

General comment 1
The authors provide a comparative review of three alternative approaches for assessing the local compound flooding probability. They implement the approaches for studying compound flooding in the estuary of the Swan River in Western Australia. Such an application provides a basis for discussing the advantages and limitations of the three approaches. Overall, I did find the study very interesting and timely. I recommend revising the manuscript based on my comments prior to publishing the manuscript.

Response:
Thank you for your overall positive comments on our paper. Please find responses to your detailed comments below.

General comment 2
In general, I found the introduction pleasant to read, but I would recommend improving the presentation of the methodology, especially of Method 3. In fact, I found it particularly difficult to understand some components of Method 3.

Response:
This section on method 3 has been revised: a brief introduction has been added at the beginning to outline all of the steps involved; and the description of each step is also revised to include details of how each step is carried out (e.g. in relation to the case study used). Please also see detailed responses on relevant comments below.

General comment 3
The discussion of the advantages and limitations include a part regarding the limitations/advantages that the approaches have for assessing the climate change effect on compound flooding probability. The idea of discussing this topic is certainly interesting, but it requires some revision in my view. For example, the authors mainly refer to the possibility of including changes in the dependence between the drivers through method 3, but it is not discussed the relevance of the change in the marginal distributions, which is fundamental. In particular, I understand that the authors state that method 2 is difficult to be considered for assessing climate change as it requires time series of storm tide and precipitation for the future. This would be an issue also for method 3, despite the fact that they claim that method 3 can consider climate change effects easily. See comments related on this topic below.

Response:
We agree with the reviewer that changes in the marginal distributions as a result of climate change are of fundamental importance, and have ensured that this is clearly articulated in the manuscript.

However we maintain that there are several key advantages of using method 3 that make it much easier to apply for climate change applications in practice compared to method 2.

Of these, the most important is that the nature of the decomposition between the marginal and joint distribution in method 3 means that it is relatively straight forward to capitalise on existing information and agreed approaches (including those embedded in flood risk estimation manuals that are available in various countries around the world) that allow uplift of the 'marginal distributions'. For example in Australia, there is guidance on increasing Intensity-Duration-Frequency curves (which characterise the marginal distribution of rainfall) by 5% per degree (range 2%-10%) (Ball et al. 2019) as a result of climate change. Similar approaches to uplift factors exist in many other parts of the world. In relation to sea level rise and storm surge, one could also elect to increase the marginal distributions by 'factors' representing changes in those components. The capacity to align with standard flood estimation approaches (e.g. the Australian Rainfall and Runoff and the UK flood guidance) is more than a pragmatic advantage, as it also enables seamless interface between estuarine floods and upstream flood risk estimates, since both would be driven by the same changes to IDF curves (the same example could be used for transitioning between estuarine and coastal floods).

A secondary benefit is that, under certain conditions, the method capitalises on existing hydrodynamic model runs rather than requiring these to be repeated, since it would be possible to use changes in both the marginal and joint distribution to recalculate the probabilities of the simulated flood levels (in other words, the simulated water levels would stay the same, but the exceedance probabilities ascribed to those levels would change).

This is contrasted to method 2, which would require the full joint timeseries of the boundary conditions (e.g. sub-daily time series of wind and pressure needed as a boundary condition to storm surge, plus rainfall needed for inland catchment processes) and thus is a much more involved problem. Indeed, to our knowledge, we are not aware of any examples where this has been achieved in practice or published in the literature. Of course it could be argued that one can just apply similar scaling factors to historical time series; however in the case of rainfall, it's well known that the averages will change in a very different way to the extremes, so this scaling would be difficult in practice. As a result, solving this is a much more challenging problem and unlikely to be practically viable except for very research-heavy applications.

The following discussions (and additional references) have been added to improve clarity:

> "A range of multivariate approaches have been applied to compound flood estimation problems, including Vine copula (Bevacqua et al., 2017), standard copulas (Muñoz et al., 2020), unit Fréchet transformations (Zheng et al., 2014), regression type models (Serafin et al., 2019) and conditional exceedance models (Jane et al., 2020). The use of copulas or equivalent formulations (e.g. unit Fréchet transformations) enables the factorisation of multivariate distributions into a set of marginal distributions and a dependence structure (i.e. a joint probability distribution). This joint probability distribution captures the defining features of the variables of interest and their interaction. "
>
> "…,it becomes easier to incorporate the effects of future changes. This is particularly the case if one is able to assume that the dependencies between variables are either not greatly affected by climate change or that changes in dependencies produce second-order effects on flood probability compared to changes in the marginal distributions. Under these conditions, the method can capitalise on published information on uplift factors to changes

in the key marginal distributions (e.g. scaling factors for IDF curves, or for peak ocean levels), which are becoming increasingly commonly available as part of engineering flood guidance in many parts of the world (Wasko et al, in press). A further advantage is that under the assumption that the relative timing of different flood drivers is not considered (see discussion in the paragraph below), the flood surface produced using hydrodynamic models will not change under climate change; rather it is how the flood surface is converted into flood probability based on the dependence model that will change. Indeed, by separating the flood estimation problem into the two components indicated above, it could be possible under certain conditions to estimate the impact of future changes such as climate change on estuarine flooding without additional hydrodynamic simulations, simply by re-calculating the probabilities of the flood drivers and their dependence structure under changed future conditions."

In addition, the following changes have been made to section 2.4 to improve clarity:

- The 'two steps' in this section has been change to 'two components' to differentiate form the steps required when implementing each method.
- Component 2 is revised to "the estimation of the flood magnitude (i.e. water levels) for each combination of boundary conditions, using what is often referred to as a 'structure variable' or 'boundary function'."

Specific comment 1

L47, I would cite the paper from Wahl at the end of the sentence (already mentioned in the manuscript).

Response:

The reference has been added.

Specific comment 2

L64, please, consider merging this sentence with the last sentence of the previous paragraph (on the same topic).

Response:

Thank you for this suggestion. The first sentence is on the joint impact of different flood drivers. The second one is on the impact of future climate conditions on the joint impact of different flood drivers. Therefore, we felt it best that these be kept as distinct ideas.

Specific comment 3

L76 I suggest that produce an inverse barometric effect and on-shore winds, which in turn leads to storm surges and waves

Response:
Thank you for the suggestion. It is changed to “that produce on-shore winds and an inverse barometric effect, which in turn leads to storm surges and waves”.

Specific comment 4
L78 water -> oceanic water level (to make clear you are referring to the sea component only in this sentence).

Response:
It has been revised as suggested.

Specific comment 5
L116, typology

Response:
Thank you for the observation. It has been corrected.

Specific comment 6
L128 “and considered here” after identified

Response:
Thank you for the suggestion. It has been added.

Specific comment 7
L 129-130, Consider using "compound flood" here and elsewhere when referring to the compound flooding water level, such to make clear that you are referring to the resulting water level from the two drivers. For example, in the caption of Fig 2. I can certainly say that this would have made my reading easier.

Response:
Added, as suggested.

Specific comment 8

L 146 “numerical” is fine here? In method 2 you may not need a numeric model (i.e., hydrodynamical model) rather use an e.g., statistical model (personally, I do not see that as numerical). I see that in your case you use numerical modelling, but this part of the manuscript appear of a more general nature.

Response:

The wording has been changed to “numerical or statistical modelling”.

Specific comment 9

L 166 Similarly to the above, doesn't dynamically refer to something that is not statistical? Anyway, I would modify, to make clear that such modelling can also be purely statistical.

Response:

“Numerical modelling” is not referred here, so no changes are made.

Specific comment 10

L 159 Consider adding Approach 1,2,3, also earlier on, to give a better orientation to the reader.

Response:

Added at the beginning of section 2.1.

Specific comment 11

L 174, do you mean 30 years of data to estimate the 1-in-100 years return level? Anyway, you may want to qualify "estimate", anything can be estimated, but would that estimate be too uncertain or not?

Response:

Yes this is correct. The sentence has been revised to “to ensure sufficient accuracy in flood estimates, with a typical rule-of-thumb being the requirement of at least 30 years to estimate flood levels corresponding to probabilities up to the 1% annual exceedance probability (Ball et al., 2019)”.

In addition, a statement on the uncertainty of the results obtained using this method is added in the results section:

“The confidence intervals become increasingly wide with increasing return period, and it is important to note that return periods have been calculated based on only 22 years of historical water level data.”

Specific comment 12

L 185, During a discussion among colleagues, it was hypothesised that this may be related to the fact that often there is interest in measuring either the sea level or the river discharge and therefore no stations are collocated at the interface between the two. What do you think about this? Discuss it if you think that this is relevant. I guess that this appears also discussed/hypothesised in Paprotny et al. ("Compound flood potential in Europe").

Response:

Thank you for this suggestion, the following comment has been added.

"The lack of gauges within estuaries are likely to be at least in part due to the fact that there has historically been greater interest in measuring either the sea level or the river discharge and therefore there is less interest to place stations at the interface between the two (Paprotny et al., 2018)."

Specific comment 13

L 188, please, make it clear that you are referring to the need of transforming flow into the water level

Response:

The sentence has been revised to

"…, which can be problematic in estuarine regions where flows can be bidirectional and water levels are influenced by both upstream and downstream processes."

Specific comment 14

L 205, Do you have a reference? Not sure if this was given earlier.

Response:

The following references have been added:

Boughton, W. and Droop, O.: Continuous simulation for design flood estimation—a review, Environmental Modelling & Software, 18, 309-318, 2003.

Sopelana, J., Cea, L., and Ruano, S.: A continuous simulation approach for the estimation of extreme flood inundation in coastal river reaches affected by meso- and macrotides, Natural Hazards, 93, 1337-1358, 2018.

Specific comment 15

L 227, “Although…”. Consider moving this to the beginning of the next paragraph. In general, regarding sections 2.2-2.4, 230-241, I believe that the reader would benefit from finding dome additional references to works where similar approaches have been used. In my view, this can help, especially in a work like that aims at reviewing available methods.

Response:

Thank you for this suggestion. The paragraph has been revised as suggested. The following references have been added.

Hasan, H. H., Mohd Razali, S. F., Ahmad Zaki, A. Z., and Mohamad Hamzah, F.: Integrated Hydrological-Hydraulic Model for Flood Simulation in Tropical Urban Catchment, Sustainability, 11, 2019.

Heavens, N. G., Ward, D. S. & Natalie, M. M. 4: Studying and Projecting Climate Change with Earth System Models., Nature Education Knowledge, 4, 4, 2013, 4(5):

Zaehle, S., Prentice, C., and Cornell, S.: The evaluation of Earth System Models: discussion summary, Procedia Environmental Sciences, 6, 216-221, 2011.

Specific comment 16

L230-241, I find this part a bit too strong in the statements. Hydrodynamical modelling works based on oceanic and streamflow input that is available from climate models. I see that there are uncertainties and that storm tide and river flow need to be obtained based on computationally expensive modelling. But some data are available out there that can be helpful to assess the climate change impact on compound flooding even with Approach 2. I would suggest discussing this topic more.

Response:

I agree that this is a topic that different people may feel differently and worth discussion. The authors believe that by extending modelling boundary the model will generally become more complex and additional errors will be introduced. It is important to recognise this challenge when considering extending model boundaries. However, it is also important to recognise that some datasets already exist as boundary conditions, which are helpful to assess the climate change impact on compound flooding even with Approach 2. This section has been revised in the manuscript:

“Widening the modelling chain to explicitly represent an ever-increasing set of time-varying processes is certainly an attractive means to explicitly address non-stationarity of key flood generating processes. This is especially the case considering that some datasets from climate models already exist as boundary conditions for hydrodynamical modelling runs (e.g. Kanamitsu et al. (2002) and Naughton (2016)), which are helpful to assess climate change impact on compound flooding with Approach 2. However, it is important to recognise that widening the modelling chain can also lead to evermore complex models, with greater possibility of inducing biases and other forms of modelling errors into the results (Zaehle et al., 2011).”

Specific comment 17

L252, Isn't it what you produce the value of the structural variable rather than the variable itself? You use a "function" to convert a given bivariate event into a water level.

Response:

It is correct that the second component of this method is to produce the water levels. This statement is revised to:

"2) the estimation of the flood magnitude (i.e. water levels) for each combination of boundary conditions, using what is often referred to as a 'structure variable' or 'boundary function'."

Specific comment 18

L 262, "condition." Please, provide a reference, where this method is described

Response:

The following reference is added.

Ball, J., Babister, M., Nathan, R., Weeks, W., Weinmann, E., Retallick, M., and Testoni, I. (Eds.): Australian Rainfall and Runoff: A Guide to Flood Estimation, Commonwealth of Australia, 2019.

Specific comment 19

L 266, how to select the design events? Multiple pairs in the bivariate space can have the same probability to occur, i.e. return period. Therefore the selection is not as easy as in the univariate case. This is discussed in the paper of Moftakhari et al. (2019). A brief discussion (2/3 sentences) on these issues is welcome.

Response:

It is true that multiple pairs of drivers in the bivariate space can have the same probability to occur. However, this is expected and not considered an issue. In fact the method is design to deal with this, as on the flood surface (e.g. Figure 8), the estimated flood contour highlights how the same flood level can occur for different combinations of both flood drivers. The key of flood event selection is to have flood drivers with a return period much longer than that of estimated flood levels, as pointed out in section 5.3.

The discussion on the selection of flood events is now included in the second paragraph of revised section 4.3.

"In the first step, compound flood events caused by different flood drivers, such as storm tide and river discharge (i.e. combinations of boundary conditions with different return periods) need to be selected for simulation. Flood levels generated from these flood events will be interpolated to form flood surfaces or response surfaces with different flood magnitudes. The DVM only requires the simulation of a limited number of 'flood events' (often on a regular grid, e.g. 10 by 10 flood events generated from combinations of flood drivers with different return levels) to produce a reasonable cover of the bivariate probability surface formed by two flood drivers (Zheng et al., 2015a; Zheng et al., 2014). In this study, both historical and synthetic flood events on an irregular grid are used to ensure flood events from drivers with significantly longer return period than the estimated flood required are included. This is recommended in order to have reasonable confidence in the estimates (Zheng et al., 2014)."

Specific comment 20

L 268, please, clarify this sentence.

Response:

The following explanation has been added:

"This is particularly the case if one is able to assume that the dependencies between variables are either not greatly affected by climate change or that changes in dependencies produce second-order effects on flood probability compared to changes in the marginal distributions. Under these conditions, the method can capitalise on published information on uplift factors to changes in the key marginal distributions (e.g. scaling factors for IDF curves, or for peak ocean levels), which are becoming increasingly commonly available as part of engineering flood guidance in many parts of the world (Wasko et al, in press). A further advantage is that under the assumption that the relative timing of different flood drivers is not considered (see discussion in the paragraph below), the flood surface produced using hydrodynamic models will not change under climate change; rather it is how the flood surface is converted into flood probability based on the dependence model that will change."

Specific comment 21

L 298 "Due to...complexity", Or is it that none has rally tried to develop one?

Response:

This is correct. There is currently no hydrological model exist for the entire catchment, mainly due to the size and complexity of the catchment.

Specific comment 22

L368, Authors tend to oppose GPD and GEV as alternative approaches. Do you expect any differences in terms of uncertainties? Also, you use the GPD to estimate return periods/level. Shouldn't you also provide an equation for that?

Response:

The difference in the estimation outcomes from GPD vs GEV is out of the scope of this paper. The equation for the GPD is included in section 4.1.

Specific comment 23

L 390, Please, refer explicitly to the fact that extreme H may also be driven by non-extreme conditions of either of the drivers, therefore this should be taken into account when defining the threshold for Q and T.

Response:

The following additional comment has been added in the revised manuscript.

“For example, extreme water levels H may also be driven by non-extreme conditions of either of the flood drivers.”

Specific comment 24

L 390, It is not clear to me why you need to account for the low water level periods through the resampling approach, given that you will fit the GPD only to the extremes. I understand that is necessary to be aware of the time in between the peaks to estimate the return periods, but why simulating it?

Response:

One important reason that flood data during low water level periods are also ‘simulated’ using the resampling approach is because the actual threshold values that will be used to fit the GPD is not known a priori. The resampling approach will provide a reasonable transition of flood levels between ‘flood periods’ and ‘low water level periods’ compared to just using zero values and makes sure reasonable flood level estimates will be used for flood probability estimation.

Specific comment 25

L412, Are you simulating also a fraction only of the low water level and then using such a short simulation to fill a longer part of the time series? Please, explain better.

Response:

This is correct. The following comments is added:

“In other words, only a fraction of the low water level periods is simulated and resampling with replacement is used to fill in flood data across the entire low water level periods.”

Specific comment 26

L 426, This is shorter than then 31years, which correspond to about 271560hours. I would highlight this explicitly as it is relevant as you implicitly suggest.

Response:

Thank you for this suggestion. The following comment is added:

“…, which is approximately 10% the entire 31 year period under consideration.”

Specific comment 27

L 436, "conditions", refer to variables to guide the reader (storm tide and river discharge)

Response:

Thank you for the suggestion. The following wording has been added:

"i.e. flood drivers, such as storm tide and river discharge"

Specific comment 28

L437, Introduce the "grid" or make it clear what the grid is here in this context.

Response:

The following wording has been added to improve clarity:

"e.g. 10 by 10 flood events generated from combinations of flood drivers with different return levels"

Specific comment 29

L 442, "250 years", what return period? The univariate of the individual drivers? This is unclear. Also, you may need to clarify what type of data are you using for the boundary conditions. You seem to have 22 years of data of storm tide only, how did you estimate the 250 year return period without massive uncertainties?

Response:

The return period has been changed to "1 in 250 years". As indicated in the sentence, the return period refers to that of flood drivers (i.e. univariate).

As described in both section 2.4 and section 4.3, Method 3 under Approach 3 is event based and no continuous flood data are used. There are in total 28 flood events are used. These events have univariate flood drivers with return periods up to 1 in 250 years, in order to estimate compound flood levels up to 1 in 100 year return period. A summary of these flood events is provided in the supporting material. The locations of these 28 event in the flood surfaces are indicated by the black dots in Figure 28.

The 22 years of data are observed water level data at a tide gauge near location Sw10. They are used for Method 1 only. Additional comment has been added in section 5.1 on results from Method 1 to emphasise this.

"The confidence intervals become increasingly wide with increasing return period, and it is important to note that return periods have been calculated based on only 22 years of historical water level data."

Specific comment 30

L 445, The dependence between the drivers within the 28 events? Please, clarify.

Response:

The dependence here refers to the dependence between the flood drivers, which are not estimated using the 28 flood events. The dependence structure between the flood divers can be estimated using observed or simulated data. In this study, it was estimated using observed flood driver data. The following comment has been added to improve clarity.

“For the case study, the dependence between flood drivers are estimated using observed data of storm tide and river discharge.”

Specific comment 31

L458, I see that you use MIKE21 for Methods 1 and MIKE FLOOD for method 3. Can this be responsible for the differences in the results based on the two methods? Please, discuss.

Response:

Sorry for the confusion. MIKE21 is one module in MIKEFLOOD. The same hydrodynamic model is used for Method 2 and Method 3. MIKEFLOOD has been changed to MIKE21 in the manuscript, except in Acknowledgements, where MIKEFLOOD license is mentioned.

Specific comment 32

L 459, step 1 was not introduced formally.

Response:

Section 4.3 on Method 3 has been revised to improve clarity. The writing in this section has been changed.

Specific comment 33

L460, this small paragraph is not clear to me. Please, explain better for people who are not familiar with the method.

Response:

This is the final step of estimating flood probability by integrating the generated flood surface in step 3 and estimated dependence model in step 2 using an integration method. The details of the integration method are out of the scope of this paper. A reference has been provided for readers who are interested in the details. In addition, this paragraph has been rewritten to improve clarity.

“In the fourth and final step, the probability of different compound flood levels simulated in Step 3 can be derived based on the bivariate dependence model developed in Step 2 using the bivariate integration method introduced by Zheng (2015a). More details of this integration method can be found in Zheng et al. (2015b).”

Specific comment 34

472, In the methods, please mention how you retrieved the uncertainties in the estimate (based on the uncertainties in the fitted parameters).

Response:

The following phrase has been added to improve clarity.

"…(estimated using a bootstrap method)"

Specific comment 35

488, I suggest highlighting that this location was used in Method 1 (so to allow for a comparison).

Response:

Thank you for the suggestion. "(i.e. this is where the results of Method 1 and Method 2 can be directly compared)" has been added.

Specific comment 36

L 498, Aren't you also for Method 2 using the MRL plot applied to the H water level? Please specify if not done already and include a discussion on this within this sentence (one may expect that MRL to define a thresholds such result in similar uncertainties at all locations.

Response:

It is correct that MRL plots are used in Method 2. This part of discussion is still under Method 2.

Specific comment 37

L 509, Why do you use the values maximising the dependence? Understanding when the dependence is maximised provides interesting information on the physical system, however, the dependence values that are relevant from a point of view of the impact is that between the variables at the same time. In fact, the storm tide and the river flow interact at the same time in the real world.

Response:

This is because in Method 3 the information on the temporal dynamics (i.e. relative timing) of storm surges and astronomical tides is discarded and only the peaks of flood drivers are considered via the use of a static tail water level, as discussed in section 2.4. This is one of the limitations of Approach 3 and thus, Method 3. The following statement has been added to improve clarity:

"This is because in this method the information on the temporal dynamics of storm surges and astronomical tides is discarded and only the only the peaks of flood drivers and their joint dependence are considered, as discussed in section 2.4."

Specific comment 38

Fig 8, The 2D simulations receive as input time series of T and Q, therefore a question arises: which is the value of the time series that you consider as that to be reported on the x and y axes?

The plots, e.g., panel c, suggests that for a given 10 year return level of Q, when T becomes larger (from 0 to 1-year return period), H decreases. This is physically inconsistent. Such inconsistent behaviours seem to occur in the range of T AND Q below 1-year return levels. Do you have an explanation for that? If the explanation is convincing, one would then consider not showing values in this bivariate range (up to 1-year return level for both variables).

Response:

This variation is potentially caused by the interpolation method used. Additional discussion has been added in the revised manuscript to explain this.

"It can also be observed in **Figure 8** that there are some variations in estimates of flood levels with very short return periods (e.g. return periods of 1 in 1 year or below), with the increase in one flood driver leading to decreased compound flood levels. Careful inspection of the results shows that this feature does not apply to any of the simulated data points, in the sense that simulation points with larger values of the boundary conditions always yield larger flood levels. Rather, the 'inflection' only occurs in a sparsely sampled region of the plot, and is thus suggestive of the limitations of using a log-linear interpolation scheme in this region. This therefore highlights the importance of carefully considering the sampling scheme as part of the analysis."

Specific comment 39

L 524, How do you estimate the case of complete dependence/independent variables? I understand that you get the water level based on 2d simulation with input T and Q observed time series. If they were not time series, I could see the concept of independence, but in this context, I find it unclear. This comment is related to that on the general explanation of method 3.

Response:

The case of complete dependence/independence can be estimated by using different alpha values representing complete dependence (i.e. alpha = 0) and complete impendence (i.e. alpha = 1). This is discussed in section 4.3. Additional reference to section 4.3 has been added here to improve clarity.

Specific comment 40

L 550 I would reverse the sentence, highlighting the result based on method 2 and 3 compared to 1, the observation-based method. Hence, "2 and 3 lead to lower estimates than 1…"

Response:
Thank you for this suggestion. As this part focuses on results of Method 1, the way the results are discussed is not changed.

Specific comment 41
L 565 can the comparison be affected also by the difference model type used in method 2 and 3?

Response:
The same model is used for Method 2 and Method 3. See response to Specific Comment 31 above.

Specific comment 42
Table 2,

Disadvantages for method 2, "Difficult to assess future conditions…": Why isn't this the case also for case 3?

The advantage for method 3 about future conditions: This does not seem to me as simple as stated. Please discuss. By the way, also changes in the marginals should be included, which appears to be the most relevant for future changes and at least the change for which we have the highest confidence (the confidence on the changes in the dependence is small). I would suggest discussing this taking into account the following papers (at least):

– About changes in the dependence: Wahl et al. (Nature Climate Change)highlights a

change in the dependence in the past, Bevacque et al (https://eartharxiv.org/repository/view/293/) highlights the changes in the dependence are uncertain, and Ganguli and Merz (https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019GL084220) also discuss changes in the dependence for the past.

– Moftakhari et al.,(PNAS) and Bevacque et al (above) about projected changes in the marginals (i.e. Storm surge, precipitation, and sea level rise).

Response:
For response to the comment on advantages of Method 3, please refer to response to General Comment 3 above.

In addition, the end of discussion on Approach 2 in section 6 has been revised to:

"Although, these high-resolution and temporally consistent data are at present not widely available under future climate scenarios, they can potentially be developed in the future allowing Approach 2 to be used to assess compound flood probability under future changes."

The following paper has been added in the revised manuscript.

Ganguli, P. and Merz, B.: Trends in Compound Flooding in Northwestern Europe During 1901–2014, Geophysical Research Letters, 46, 10810-10820, 2019.

The Bevacque et al. paper (https://eartharxiv.org/repository/view/293/) is not peer reviewed yet and is therefore not included.

Specific comment 43

L 590 “stationarity”, add “in the estuarine characteristics”. You are referring not to the meteorological conditions here, so make it clear, please.

Response:

Thank you for this suggestion. It has been changed.

Specific comment 44

L598 Could you clarify/discuss why should accounting for the dependence explicitly be an advantage (compared to method 1)? Thanks.

Response:

By accounting for dependence implicitly, the method has one less variables to estimate, which simplifies the estimation process and reduces chance of introducing additional error/uncertainty.

Specific comment 45

L602, Personally, I would add something along this line. “incorporated in the modelling framework”, add: “through considering the most recent bathymetry characteristic of the estuary when interested in the present-day estimate of the flooding probability”.

Response:

There are multiple ways long-term driver data can be incorporated. The authors believe that it is better to leave it open rather than suggesting a specific way how the data are incorporated. For example, in order to address future changes, future projections of changes in the estuarine regions need to be used. Therefore, no changes have been made here.

Specific comment 46

L 609, There is high-resolution data of sea level (storm surge/waves) and precipitation available, though I understand that especially for sea level, these are rare and in general can be uncertain. There are climate models. How can they be used to solve the issue? The fact that data is not widely available at high resolution does not mean, I think, that this is something to negatively judge this method given that I am not sure about what would a better alternative be.

Response:
The statement referred to is “These high-resolution and temporally consistent data are at present not widely available under future climate scenarios.”

This statements here simply points out the fact the high resolution data required for this method may not be readily available. There is no judging of this method involved.

Specific comment 47
L612, “updating”, Are you referring to update with respect to changes due to climate change? If not, please discuss the climate change issue, as this is done in the other two cases. If yes, please clarify. In addition, I do not understand how you would estimate the changes in the dependence. Do not we have the same issue as in method 2? Also, we have the problem that we need to estimate changes in the marginals, not only in the dependence. See comments above regarding this topic too.

Response:
The dependence model includes the marginal distributions for individual flood drivers and the dependence structure, and can be estimated under future conditions, considering but not limited to climate change. The advantage of method 3 is that the hydrodynamic runs required to produce the flood surface will not need to be repeated. For detailed response, please refer to response to General Comment 3.

Specific comment 48
L649, See comment above about climate change. This needs to be discussed carefully.

Response:
See response to Specific Comment 47 and General Comment 3 above.

Specific comment 49
L 655, “Implementation of each approach available” -> “approaches available”

Response:
This sentence emphasis that there are multiple implementations of each approach available. Therefore, it has not been changed.

Responses to Reviewer 2 Comments

General comment 1

Since half of the manuscript is a review of the methods used in previous studies more references to previous applications of the discussed approaches would be desirable. Please see the specific comments for some examples of where this is the case.

Response:

Thank you very much for this suggestion. Relevant references have been added at various locations. Please see responses to specific comments below.

General comment 2

In the introduction, the two physical processes causing estuarine flooding are described in detail, however, a discussion regarding the possible mechanisms enhancing estuarine water levels due to the interaction of the two processes is missing.

Response:

The discussion of the interaction of the two process and its impact on compound flood is included in the paragraph after Figure 1.

General comment 3

Section 2.4 would benefit from a similar brief discussion on the methods of selecting multivariate extremes perhaps a summary of Zheng et al. (2014). Also, the multivariate statistical methods used to estimate the probability of compound flood events e.g. regression type models (Serafin et al. 2019), standard copulas (Muñoz et al. 2020), Vine copula (Bevacqua et al. 2017) and conditional exceedance models (Jane et al. 2020) should so be discussed or at least listed. The selection of design events i.e. the issues with choosing hazard scenarios and the use of meta models to increase the efficiency of the numerical models also warrant a mention.

Response:

The method by Zheng et al (2014) is introduced in section 4.3. A discussion including the references recommend above has been added in the revised manuscript. The following additional references have been added.

Jane, R., Cadavid, L., Obeysekera, J. &Wahl, T. 2020. Multivariate statistical modelling of the drivers of compound flood events in South Florida. Natural Hazards and Earth System Sciences, 20(10), 2681-2699.

Muñoz, D. F., Moftakhari, H., & Moradkhani, H. (2020). Compound effects of flood drivers and wetland elevation correction on coastal flood hazard assessment. Water Resources Research, 56,

Serafin, K. A., Ruggiero, P., Parker, K., &Hill, D. F. (2019) What's streamflow got to do with it? A probabilistic simulation of the competing oceanographic and fluvial processes driving extreme along-river water levels, Nat. Hazards Earth Syst. Sci., 19, 1415–1431, https://doi.org/10.5194/nhess-19-1415-2019

General comment 4

The description of the method in Section 4.3 could be improved a lot. For instance, the link between the DVM grid and probability model is not clear to me.

Response:

This section has been revised to improve clarity.

Specific comment 1

Line 45: Wahl et al. (2015) analyzed the temporal variation in the dependence between precipitation and surge in the USA. Consider adding as a reference at the end of this sentence.

Response:

Thank you for this suggestion. This reference has been added at the end of this sentence.

Specific comment 2

Line 48: This sentence is rather strong given that there are locations with gauges in the 'joint probably zone' and the results of a univariate probability analysis maybe satisfactory. Consider removing "if ever".

Response:

"If ever" is removed as suggested.

Specific comment 3

Line 90: Please consider referencing one of the many studies that have demonstrated this (see Santiago-Collazo et al. 2019).

Response:

The following references have been added.

Santiago-Collazo, F. L., Bilskie, M. V., & Hagen, S. C. (2019). A comprehensive review of compound inundation models in low-gradient coastal watersheds. Environmental Modelling & Software, 119, 166-181.
Bilskie, M. V. and Hagen, S. C.: Defining Flood Zone Transitions in Low-Gradient Coastal Regions, Geophysical Research Letters, 45, 2761-2770, 2018.

Ikeuchi, H., Hirabayashi, Y., Yamazaki, D., Muis, S., Ward, P. J., Winsemius, H. C., Verlaan, M., and Kanae, S.: Compound simulation of fluvial floods and storm surges in a global coupled river-coast flood model: Model development and its application to 2007 Cyclone Sidr in Bangladesh, Journal of Advances in Modeling Earth Systems, 9, 1847-1862, 2017.

Specific comment 4

Figure 2: This caption is the only place the word ‘pathway’ mentioned. Since pathway 1 concerns approach 2 and pathway 2 approach 3 consider changing the label numbers to 2 and 3 and mentioning in the caption that approach 1 just uses observational data.

Response:

The pathways are related to how the dependence is estimated, e.g. via a univariate or multivariate frequency analysis, rather than the type of data being used - observed or simulated. Pathway 1 concerns both Approach 1 and Approach 2, where observed and simulated data are used respectively. Therefore, the type of data is not mentioned in the caption of this figure.

Specific comment 5

Line 319: Does this not vary with distance along the channel? As stated later in the manuscript: “The region downstream of Sw10 is mainly storm tide dominated; the region upstream Sw16 (near the Perth 320 Airport) is mainly flow dominated; and the region between Sw10 and Sw16 has significant joint impact from both tail water levels at Fremantle and upstream flow, and therefore is referred to as the ‘joint probability zone’.”

Response:

This does vary with the distance of the channel. However, it is also affected by the topography of area. As shown in Figure 4, there is a very narrow section of the channel right downstream of location Sw10, which has reduced the impact of the tide in regions upstream. In addition, this classification is not absolute. As can be seen in results that even at location Sw19, there will be some impact of the tide for small flood events. Therefore, in this section it is stated that “The region downstream of Sw10 is ***mainly*** storm tide dominated; the region upstream Sw16 (near the Perth Airport) is ***mainly*** flow dominated, …”

Specific comment 6

Line 206: Should add some examples here.

Response:

The following references have been added:

Boughton, W. and Droop, O.: Continuous simulation for design flood estimation—a review, Environmental Modelling & Software, 18, 309-318, 2003.

Sopelana, J., Cea, L., and Ruano, S.: A continuous simulation approach for the estimation of extreme flood inundation in coastal river reaches affected by meso- and macrotides, Natural Hazards, 93, 1337-1358, 2018.

Specific comment 7

Line 244: I think the aim is to derive a series of multivariate ‘design events’ rather than ‘translating the boundary conditions into a series of multivariate ‘design events’.

Response:

This sentence refers to how the dependence is estimated. This sentence has been revised to:

"…, because of the emphasis on deriving a series of multivariate 'design events' for further simulation through a modelling chain."

Specific comment 8

Line 245: "These approaches are the multivariate analogy of applying IFD curves for delineating design rainfall 'events' with pre-defined probabilities, which are then converted into streamflow events of an equivalent probability." It is the streamflow event that corresponds to (or is associated with) the rainfall event with the predetermined probability not the streamflow events of an equivalent probability.

Response:

This is correct. The sentence has been revised as suggested.

Specific comment 9

Line 249: Rephrase. I do not believe that "conversion" is the correct term here. The multivariate distribution describes the probability of the continuous boundary conditions.

Response:

The statement has been revised to

"1) the estimation of a multivariate (commonly bivariate) probability distribution function based on the continuous boundary conditions."

Specific comment 10

Line 249: Also, sometimes called a "response function"! Not all the events will result in a flood. Would "flood magnitude" be more accurately termed "water level"?

Response:

"Flood magnitude" has been changed to "water level" as suggested.

Specific comment 11

Line 255: "The use of copulas or equivalent formulations (e.g. unit Fréchet transformations) enables the factorisation of multivariate distributions into a set of marginal distributions that capture the defining features of the variables of interest, together with a joint probability distribution that describes their interaction." 42 word sentence!! The joint distribution typically includes the marginal distribution and the dependence structure.

Response:

Thank you for this suggestion. The original sentence has been changed to:

"The use of copulas or equivalent formulations (e.g. unit Fréchet transformations) enables the factorisation of multivariate distributions into a set of marginal distributions and a dependence structure (i.e. a joint probability distribution). This joint probability distribution captures the defining features of the variables of interest and their interaction."

Specific comment 12

Line 268: Second, because the drivers of estuarine flooding are factorised through the multivariate distribution, it becomes easier to incorporate the effects of climate change while preserving key dependencies between variables." This and the advantage discussed in the next sentence requires the assumption that the dependencies between the variables is stationary which should be stated. Also, "separating" maybe an easier term for readers to grasp than "factorizing" here and elsewhere.

Response:

Thank you for this suggestion. This section has been revised to improve clarity:

"Second, because the drivers of estuarine flooding are factorised through the multivariate distribution, it becomes easier to incorporate the effects of future changes. This is particularly the case if one is able to assume that the dependencies between variables are either not greatly affected by climate change or that changes in dependencies produce second-order effects on flood probability compared to changes in the marginal distributions. "

Specific comment 13

Line 272: The downscaling approach in Bevacqua et al. (2017) which related the water level in a 'joint probability zone' to the meteorological forcing's as a way of accounting for climate change may be of interest.

Response:

Thank you for this suggestion. This reference has been added.

Specific comment 14

Line 283: This sentence is very long and discusses two related but distinct issues. Please divide into two sentences.

Response:

This sentence has been broken into two sentences.

Specific comment 15

Line 284: Consider adding MacPherson et al. (2019) here as another method of accounting for the temporal shape of surge peaks in stochastic modelling and Environment Agency (2019) for an example where a single shape is derived to represent the largest surge peaks at a site.

Response:

The two references have been added.

Specific comment 16

Line 287: I suggest adding a reference to a review of the numerical models used to study compound flooding by Santiago-Collazo et al. (2019) here.

Response:

This reference has been added.

Specific comment 17

Line 296: Typo. Missing an "of" after "range".

Response:

Thank you for this observation. This has been corrected.

Specific comment 18

Lines 299: Grammar could be improved at the end of the sentence which starts on this line. Figure 3: Caption needs improving e.g. need to state what the colors of the points denote. Also, it is not clear why the Swan-Avon basin is split into two sections.

Response:

The sentence has been changed to:

"However, there are a few stream flow gauges near the outlet of the catchment but outside of the zone of tidal influence. These gauges include the Walyunga stream gauge and the Great Northern Highway stream gauge and are shown in Figure 3."

The caption is also revised as suggested.

Specific comment 19

Line 309: If URS is an acronym it needs to be defined.

Response:

It is a name, not an acronym.

Specific comment 20

Line 321: Also commonly referred as the 'transition zone' which could be added here.

Response:

This has been added as suggested.

Specific comment 21

Line 331: Poor grammar. The term “good quality” is not defined, and it should be made clearer the numbers at the end of the sentence refer to water levels. Is the data missing randomly throughout the series or is there a pattern e.g. missing values only occur during storms? This should be explored.

Response:

The data are missing or wrong when the gauge is out of order. It is not related to storms. The sentence has been revised:

“This leads to about 22 years of data with no missing or erroneous values, and with water levels ranging from 0.06 m to 1.92 m.”

Specific comment 22

Line 369: Is the Mrl plot method the approach used to find the GPD threshold in the other approaches listed?

Response:

Yes. As mentioned at the end of section 4.2 no Method 2, “the same GPD-based frequency analysis described under Method 1 is used …”.

Specific comment 23

Line 379: “One advantage of using the peak-over-threshold model for Approach 2 is that censoring can be used to improve the efficiency of full continuous simulation using a 2D hydrodynamic model, as only values above certain high thresholds are fully accounted for.” I am a little confused here as the explanation in the introduction implies all of the water levels will be simulated when applying this approach. I appreciate the censoring is a good idea.

Response:

Thank you for this comment. Censored continuous simulation is used here because the GPD based frequency analysis is used and values below the threshold value does not need to be fully simulated. This also makes Method 2 feasible in terms of computational time.

Specific comment 24

Line 387: “By selecting all of the time periods when at least one of the boundary conditions is above the pre-determined threshold, this approach aims to simulate all water levels H above a specified high threshold value.” Moderately high values of both boundary conditions could produce high water levels above a specified highwater level threshold, but these will not be accounted for in the suggested approach.

Response:

It depends on what is considered moderate, i.e. the threshold values used for both drivers and the final threshold value determined for water level H. This is also why a buffer time of 12 hours was used – partially to account for flood drivers with moderate values. Based on preliminary analysis conducted, all water levels values above the determinised threshold value are simulated.

This point has been added in the revised manuscript to improve clarity.

“The use of a time buffer accounts for the travelling time of water in the hydrodynamic model, and further ensures that the periods when flood level H are above the suitable GPD threshold value (e.g. generated by combination of moderate flood driver levels) will be fully simulated.”

Specific comment 25

Line 412: “a random sample of simulation period (e.g. 1,000 hours)” Is this a continuous 1,000 hour period?

Response:

Not exactly. It includes a few different continuous periods that are in the low water level period.

Specific comment 26

Line 441: “In total, 28 flood events with flood drivers”, why 28 events?

Response:

There are in total 15 historical events available. However, most of them cover case when one of the flood driver is extreme. In order to have a symmetric response surface, an additional 13 events were generated using scaled up historical flood driver data – they are like design events. The selection os events is discussed in section 4.3. A summary of these events is provided in the supporting material.

Specific comment 27

Line 459: “Finally, flood levels at the locations of interest (Step 3) are superimposed onto the bivariate dependence model 460 (Step 2) to estimate associated return periods.” Not clear.

Response:

This section has been changed to:

“In the fourth and final step, the probability of different compound flood levels simulated in Step 3 can be derived based on the bivariate dependence model developed in Step 2 using the bivariate integration method introduced by Zheng (2015a). More details of this integration method can be found in Zheng et al. (2015b).”

Specific comment 28

Line 524: How are the independence and full dependence return periods calculated? Once added consider rearraigning some text so that Figure 9 is discussed in the same paragraph in which it is introduced.

Response:

The case of complete dependence/independence can be estimated by using different alpha values representing complete dependence (i.e. alpha = 0) and complete impendence (i.e. alpha = 1). This is discussed in section 4.3. Additional reference to section 4.3 has been added to improve clarity.

Specific comment 29

Line 531: Results reported in this paragraph are similar to those in Moftakhari et al. (2019) and Serafin et al. (2019) and probably elsewhere which could be cited here.

Response:

These references have been added.

Specific comment 30

Line 551-554: "This is very likely due to the systematic difference between the observed flood level data (with a maximum value of 1.92 m within the 22 years' data) and flood levels simulated using the MIKE21 model (with a maximum level of 1.86 m within the 31 years' analysis period) at this location." Interesting, is this due to a shortcoming of the MIKE21 model or the (short) distance between the two locations?

Response:

This could be a combination of both. The following comment has been added to improve clarity:

"In addition, the (short) distance between the tide gauge and the modelling location Sw10 could also be a contributing factor to this difference."

Specific comment 31

Line 572-574: "This over-estimation of flood levels for a given return period from Method 3 can potentially lead to over-conservative estimation of flood risk and costly flood prevention infrastructure." Or does using method 2 under-estimate flood levels and lead to under design?

Response:

There is no evidence that Method 2 underestimates flood levels. It is well known that Method 3 over-estimates flood levels, due to the assumption of static ocean levels and associated assumptions discussed in section 2.4. and section 6.

Additional discussion on this is added at the end of section 5.4:

"This over-estimation of flood levels for a given return period from Method 3 due to the use of a static tail water level and the associated assumption that the peaks of the two flood drivers with always concede can potentially lead to over-conservative estimation of flood risk and costly flood prevention infrastructure. "

Specific comment 32

Table 2: "Generally more difficult to account for a large number of flood drivers." Please expand on this. There are methods which allow the extension to more variables without restrictive assumptions regarding the nature of the dependence.

Response:

This is discussed in section 5.4. For example the current DVM can only account for two flood drivers.

Specific comment 33

Table 2: "Can be used to assess future conditions with dependence structure reflecting future changes". Very general and also could be true for approach 2 if the continuous simulation was run for future projected climatic conditions?

Response:

The key advantage of method 3 compared to method 2 is that time consuming hydrodynamic model runs can be avoided. This point has been added to improve clarity.

Specific comment 34

Line 583: Perhaps "established" is more suitable than "well-developed"?

Response:

This has been changed as suggested.

Specific comment 35

Line 607: "maintain key dependence between the boundary conditions". The dependence may change with time. I would highlight the fact that the method has the potential to account for climate change (unlike approach 1) as a benefit of the approach. The fact that the data is readily available is more of an (important) aside rather than a strength or limitation of the model.

Response:

This section has been changed to:

"…that reflect key dependence between the boundary conditions (e.g. of rainfall and the wind/pressure data that drive storm surge). Although, these high-resolution and temporally consistent data are at present not widely available under future climate scenarios, they can potentially be developed in the future allowing Approach 2 to be used to assess compound flood probability under future changes."

Specific comment 36

Line 611-613: "By separating the dependence estimation from the flood probability estimating process, future flood probability can be estimated by updating the dependence structure between flood drivers under these conditions without the requirement of additional flood simulation runs." Again, under the assumption that the dependence structure remains stationary.

Response:

This section points out that no additional hydrodynamic runs are required, while the dependence structure can be 'updated' to reflect future changes. Comments on the stationary assumption have been added in section 2.4.

Specific comment 37

L616-622: Some mention of this should go at the end of the results section.

Response:

Discussion on advantages/limitations of different methods are included section 6 not the results section. This is consistent for all three methods used. Therefore, this discussion over Method 3 is not included in the results section.

Estimating the Probability of Compound Floods in Estuarine Regions

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Abstract

The quantification of flood risk in estuarine regions relies on accurate estimation of flood probability, which is often challenging due to the rareness of hazardous flood events and their multi-causal (or 'compound') nature. Failure to consider the compounding nature of estuarine floods can lead to significant underestimation of flood risk in these regions. This study provides a comparative review of alternative approaches for estuarine flood estimation; namely, traditional univariate flood frequency analysis applied to both observed historical data and simulated data, and multivariate frequency analysis applied to 'flood events'. Three specific implementations of the above approaches are evaluated on a case study ~~-~~— the estuarine portion of Swan River in Western Australia~~,~~ — highlighting the advantages and disadvantages of each approach. The theoretical understanding of the three approaches, combined with findings from the case study, enable generation of guidance on method selection for estuarine flood probability estimation, recognising issues such as data availability, complexity of the application/analysis process, location of interest within the estuarine region, computational demands and whether or not future conditions need to be assessed.

Keywords: Compound flood; Estuarine flood; Flood probability estimation

1 Introduction

Estimates of the probability of future floods represent a critical information source for applications such as land use zoning and planning, reservoir operation, flood protection infrastructure design and dam safety assessments (e.g. Ball et al. (2019)). Such probability estimates form the basis for calculations of the 'design flood' (a hypothetical flood with a defined probability of exceedance, such as the 1% annual exceedance probability flood or 1 in 100 years flood), as well as for risk-based approaches that consider the integration of both probability and consequence. Indeed, the estimation of flood probability represents one of the core objectives of the field of engineering hydrology (Maidment, 1993), with methodological developments dating back to early flood frequency estimation approaches ~~(Condie and Lee, 1982;~~ (Condie and Lee, 1982; Riggs, 1966; Singh, 1980; Woo, 1971) and the development of rainfall intensity-frequency-duration (IFD) curves ~~Riggs, 1966; Singh, 1980; Woo, 1971)~~(Koutsoyiannis et al., 1998; Niemczynowicz, 1982; Yu and Chen, 1996)~~ and the development of rainfall intensity-frequency-duration (IFD) curves (Koutsoyiannis et al., 1998; Niemczynowicz, 1982; Yu and Chen, 1996)~~.

Although many aspects of the flood probability calculation are strongly supported by theory and embedded in engineering practice (e.g. Ball et al. (2019) and Robson and Reed (1999)), there are several challenges specific to applications in estuarine regions that make this a unique category of ~~problems~~problem. Primary amongst these is that estuarine floods have the potential to be caused by several separate but physically connected processes, including high water levels from the ocean resulting from storm surge and/or high astronomical tide, and riverine floods due to intense 'flood-producing' rainfall in the contributing catchments (Couasnon et al., 2020; IPCC, 2012; Leonard et al., 2014; Zscheischler et al., 2018). In addition, many estuaries around the world and their contributing catchments have exhibited substantial changes in land use (e.g. urbanisation, agricultural expansion), channel modification (dredging~~,~~ straightening and damming), coastal engineering works and various other modifications (Climate Change Risks to Coastal Buildings and Infrastructure, 2011; Habete and Ferreira, 2017; Hallegatte et al., 2013), with the implication that historical flood records may provide a poor guide to future hazard and risk (Milly et al., 2008; Razavi et al., 2020). Climate change adds a further layer of complexity, resulting in increasing ocean levels~~ as well as~~, changes to storm dynamics that in turn will lead to changes in both storm surges and rainfall patterns (Lowe and Gregory, 2005; Wasko and Sharma, 2015; Westra et al., 2014) ~~and potentially their dependence (Wu and Leonard, 2019).~~as well as their dependence (Ganguli and Merz, 2019; Wahl et al., 2015; Wu and Leonard, 2019). The combination of these factors means that conventional approaches for flood risk estimation as commonly applied to inland catchments are rarely~~, if ever,~~ suitable for estuarine situations (Couasnon et al., 2020; Zscheischler et al., 2018).

To illustrate these challenges, consider Typhoon Rammasun, in which intense rainfall combined with storm surge produced a compound flood. As one of only two Category 5 super typhoons recorded in the South China Sea, Rammasun made landfall at its peak intensity over the island province of Hainan in China on 18th July 2014. It brought both heavy rainfall and strong surge with return periods of more than 100 years to the City of Haiko, the capital of Hainan province located on the estuary of Nandu River (Xu et al., 2018). Heavy rain caused widespread flooding in Haiko City and nearby urban areas. Storm surge over three meters was observed on the northern coast of the island, which prevented water from the Nandu River from draining into the sea, further exacerbating the impacts of floods in and nearby Haiko City (Wang et al., 2017). Yet flood estimation in this region proved problematic (Wang et al., 2017; Xu et al., 2018): historical flood records are short, the region has experienced rapid and extensive urbanisation including significant hydraulic changes in Nandu River leading to non-stationarity, and climate change is already modifying key flood-generating processes such as mean sea level and heavy rainfall (IPCC, 2012). This is not an isolated example; with large human populations situated at low elevations in close proximity to where rivers meet the ocean, there are many cases where interacting processes lead to complex flood dynamics and substantial impacts (e.g. Hanson et al. (2011) and Couasnon et al. (2020)). On top of this, recent studies show that the joint probability of flood drivers in estuarine areas is affected by long-term climate phenomena, such as the El Niño Southern Oscillation (Wu and Leonard, 2019) and may also be experiencing long-term changes (Arns et al., 2020; Bevacqua et al., 2019), making it a more challenging task to estimate future flood risk in these areas.

A generalised schematic for how the flood~~-~~producing processes interact in an estuarine region is provided in Figure 1. Conceptually, elevated estuarine water levels are often represented as the combined effect of two separate mechanisms. The first mechanism arises from extensive rainfall occurring in the upstream catchments, leading to elevated riverine flows and high water levels in the lower catchment reaches. The magnitude, timing and duration of the ensuing flood wave driven by this mechanism depends on a combination of meteorological factors (e.g. intensity, duration and spatial extent of the 'flood-producing' rainfall event) and catchment attributes (e.g. size, topography, the wetness of the catchment prior to the 'flood-producing' rainfall event, and other factors influencing the rainfall-runoff relationship). The second mechanism arises through the combination of astronomic tides and a set of meteorological processes (e.g. tropical or extra-tropical cyclones) that produce on-shore winds and an inverse barometric effect, which in turn leads to storm surges~~.~~ and strong waves. The magnitude, timing and duration of elevated ~~estuarine~~oceanic water levels due to this mechanism depends on the dynamics (e.g. timing and duration) of the storm surge, its superposition on the astronomic tide (with the greatest effects during 'spring tides' (Cowell and Thom, 1995)), and various bathymetric effects that influence propagation of the flood wave up the estuary (Resio and Westerink, 2008; Wu et al., 2017).

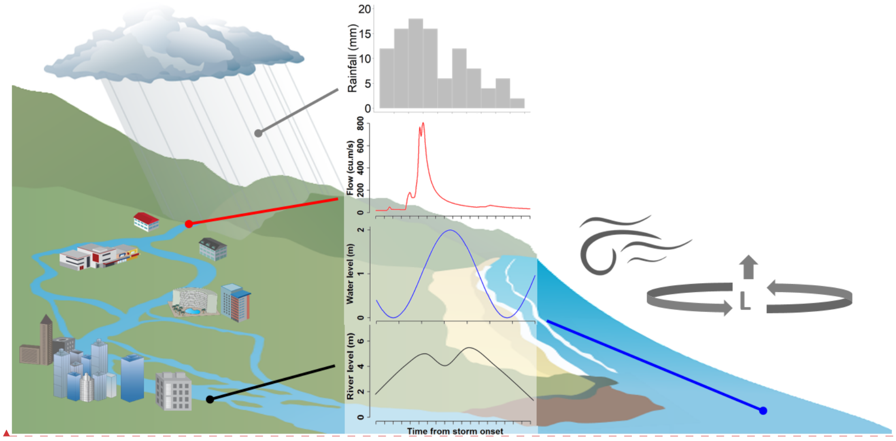

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Figure 1 Processes that commonly lead to flooding in estuarine regions with common meteorological drivers such as wind and the inverse barometric effect. Extreme rainfall can cause significant streamflow events in upstream or local urban regions, which may combine with elevated ocean levels at the lower estuarine boundary. The specific flood magnitude depends on the timing and magnitude of constituent processes.

Although these two physical processes are often treated separately, the flood level within an estuary is not a simple addition of a fluvial hydrograph and an elevated coastal water level~~.~~ (Bilskie and Hagen, 2018; Ikeuchi et al., 2017; Santiago-Collazo et al., 2019). In particular, complex estuarine hydrodynamics need to be considered, and the potential for co-incident or offset timing of each component (in terms of the coincidence between the arrival of the hydrograph peak, the storm surge peak and the interaction with tidal cycles) can add considerable complexity to probability calculations. Furthermore, the meteorological drivers are sometimes (but not always) common between heavy rainfall events and storm surges, such that the catchment and oceanic processes that drive estuarine floods can exhibit a non-negligible probability of occurring simultaneously (Bevacqua et al., 2017; Leonard et al., 2014; Wahl et al., 2015; Wu et al., 2018; Zheng et al., ~~2015~~2015a; Zscheischler et al., 2018). Methods have only started to be developed relatively recently that explicitly address this 'compounding' behaviour (Zscheischler et al., 2020).

To address this complexity and provide credible estimates of flood probability in estuarine regions, it is necessary to make methodological decisions based on factors including:

- the dominant processes that have the greatest potential to produce estuarine flooding;
- the extent to which key coastal, estuarine and/or catchment properties (e.g. land use change and hydraulic structures) have changed or are anticipated to change in the future;
- the extent to which key meteorological and climatic drivers have changed or are anticipated to change in the future;
- the availability of data on either historical flooding in the estuary and/or data on the dominant flood drivers; and
- a range of other factors (e.g. availability of numerical models, methodological expectations articulated in engineering guidance documents, available budget) that ultimately will have a significant bearing on method selection.

The purpose of this paper is to provide a detailed conceptual overview of the broad approaches for estimating the probability of compound floods in estuarine regions, and review a set of specific methods available from each approach, given availability of data, calibrated models and computational power. Advantages and disadvantages of a subset of these methods are then illustrated using a real-world case study of an estuarine river system in Australia.

The rest of the paper is organised as follows. A ~~topology~~typology of three approaches for estimating the probability of flood in estuarine regions is provided in section 2. A description of the case study area and data used in this study is provided in section 3. ~~Then details~~Details of a set of specific methods selected from the three approaches and how they are applied to the case study are provided in section 4. The flood estimates produced by applying the selected methods to the case study are summarised in section 5. The discussion of main findings is included in section 6~~. Finally~~, followed by conclusions ~~are provided~~ in section 7.

2 A Typology of Approaches for Estimating the Probability of Estuarine Floods

2.1 Background

A typology of different approaches for estimating estuarine flood probability is given in Figure 2. Given the requirement for probability estimation, common to all approaches is the use of a probability distribution (often, but not always, an extreme value distribution) to convert historical and/or simulated flood records or their drivers into an exceedance probability. In defining the typology, three general approaches for the probability calculation have been identified and considered here:

- Approach 1: univariate flood frequency analysis applied directly to observed compound flood data;
- Approach 2: univariate flood frequency analysis applied to simulated compound flood data; and
- Approach 3: multivariate frequency analysis applied to key compound flood generating processes.

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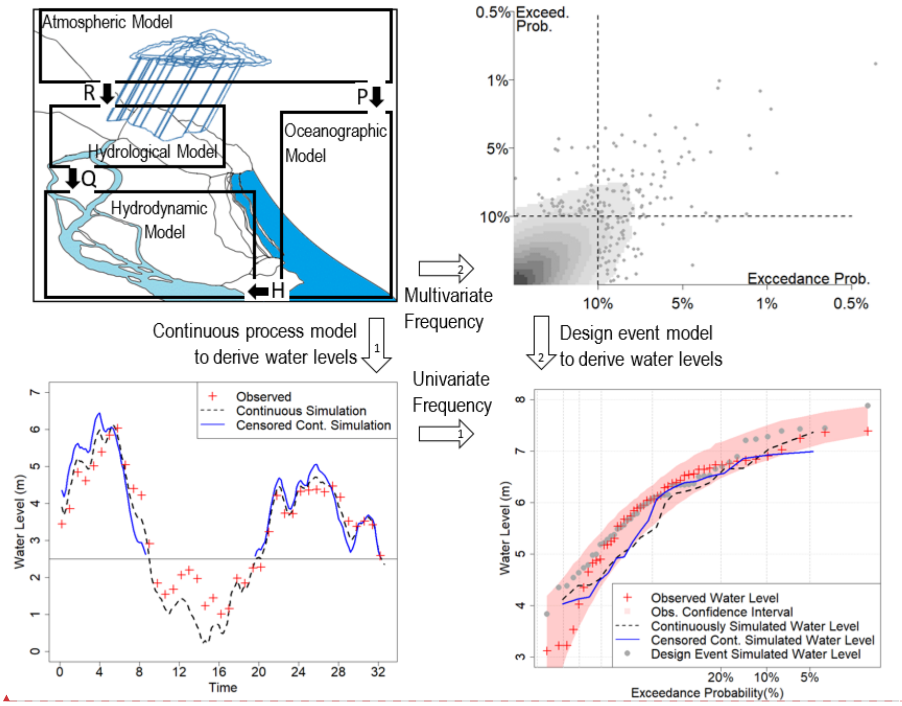

Figure 2 Pathways for relating process modelling and statistical modelling to determine extremal water levels in estuarine river reaches, where the top left panel shows typical system boundaries for identifying relevant modelling domains (atmospheric, hydrological, oceanographic and riverine hydrodynamic) as well as key variables crossing between model domains (R – rainfall, P – pressure, W – wind, Q – streamflow, H – ocean height). Pathway 1: First transform variables to water level via continuous time-stepping process models and then apply univariate frequency analysis. Pathway 2: First abstract the system to multivariate events represented via multivariate frequency analysis, then apply design event process model to derive the compound flood water levels and their corresponding probability of exceedance.

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These approaches are defined by two key methodological decisions. The first decision is the extent to which key processes need to be explicitly resolved through numerical models, or are embedded as stationary 'boundary conditions'. In the first approach (i.e. univariate flood frequency analysis applied to observed flood data), all the physical processes that have led to the historical flood record are embedded in the observed flood data, and thus no physical modelling is required. In contrast, the remaining approaches all involve some level of numerical or statistical modelling of the key physical processes that lead to flooding, albeit with significant differences in the specific models used to implement the approaches, and the manner in which they are combined. Each of the modelling approaches therefore requires identification of a modelling domain and a set of 'boundary conditions' that delineate this domain (top left panel of Figure 2). These boundary conditions may trace back to the meteorological drivers (e.g. barometric pressure and wind data that would inform ocean models such as ROMS (Shchepetkin and McWilliams, 2005); or rainfall data that would inform hydrological models to convert rainfall to flow), or to some intermediate variable(s) such as the historical ocean levels and/or historical fluvial flows that represent inflows to the estuary.

The second decision is the point at which a probability model is applied (i.e. directly to the variable of interest, such as flood height at a critical location, or to the drivers of flooding some distance up a modelling chain). Approaches 1 and 2 both apply a univariate probability model directly to the flood data (e.g. flood level) at the location of interest, the difference between them being whether the probability model is applied to observed historical data (Approach 1) or numerically simulated flood data (Approach 2). The univariate probability calculation is illustrated in Figure 2 by moving from the bottom left panel to the bottom right panel. Approach 2 requires the additional step of using continuous or censored continuous simulation models to move from the top left panel of Figure 2 (describing the physical processes to be simulated) to the bottom left panel (providing the continuous or censored continuous sequences of flood levels or similar flood metrics), before conducting the univariate probability calculation. In contrast, Approach 3 applies multivariate probability approaches further up the modelling chain to define multivariate ‘design events’ (shifting from top left to top right panel in Figure 2), which are then converted to flood levels by dynamically modelling the individual multivariate ‘design events’ (top right to bottom right in Figure 2).

The three primary approaches are described further in the sections below. Within each approach there is significant variety in terms of specific methods and modelling assumptions used, and a detailed review is provided for alternative implementations for each approach.

2.2 Approach 1: Univariate flood frequency analysis applied to observed flood data

Arguably the simplest approach is the application of a univariate probability model to observed historical flood data at the location of interest. This method is well developed (Robson and Reed, 1999) and requires sufficient historical data (~~nominally~~to ensure sufficient accuracy in flood estimates, with a typical rule-of-thumb being the requirement of at least 30 years to estimate flood levels corresponding to probabilities ~~such as~~up to the 1% annual exceedance probability~~ event~~ (Ball et al., 2019)). Once this data is obtained, a univariate probability model is applied, usually to annual maxima or block maxima time series of water levels (Bezak et al., 2014; Machado et al., 2015; Wright et al., 2020). As such there is no explicit physical modelling of any constituent processes; rather, all the physical processes are considered to be embedded in the observed historical flood data.

A key assumption is that the physical ‘generating processes’ that gave rise to this historical record of flooding will continue into future floods (in a statistical sense), so that the probability distribution fitted to the historical data can be assumed to be stationary. Although there are many benefits to this approach—including its simplicity and transparency—there are a number of limitations:

- Historical gauges are rarely available precisely at the location(s) of interest within an estuary, with the complexity of flood wave attenuation throughout estuarine systems making it problematic to simply extrapolate information from one location to the next without consideration of the hydrodynamic processes~~;~~. The lack of gauges within estuaries are likely to be at least in part due to the fact that there has historically been greater interest in measuring either the sea level or the river discharge and therefore there is less interest to place stations at the interface between the two (Paprotny et al., 2018).

- Frequency approaches are more commonly applied to flood volume (i.e. flow) data rather than flood water level data, which can be problematic in estuarine regions where flows can be bidirectional~~;~~ and water levels are influenced by both upstream and downstream processes.
- Complex bathymetry and other physical features of estuarine flooding make it difficult to extrapolate the frequency curve when using observed historical records to estimate rare design events that are greater than the largest observed flood~~;~~.
- Historical and/or future changes to either the estuary itself (e.g. changes to bathymetry due to dredging, coastal engineering works, natural littoral drift and fluvial sediment transport processes) and/or the upstream catchment (e.g. urbanization, agricultural expansion, reservoir construction, channel modification) can mean that historical flood record may be a poor guide to future flood probabilities~~; and~~.
- Historical and/or future changes to the atmospheric and oceanic drivers of flooding due to climate change, including sea level rise, storm surge and changes to rainfall patterns, can also result in the historical record being a poor guide to future flooding.

As a result of these limitations, traditional univariate flood frequency analyses applied to observed historical flood data are rarely directly appropriate for estimates of future probabilities of estuarine flooding (Yu et al., 2019), and thus one of the alternative approaches outlined below will be required for most real-world applications. Note that in situations where historical records of estuarine flooding levels are available, these data are still likely to be highly valuable to help calibrate numerical models and/or otherwise benchmark probability calculations.

2.3 Approach 2: Univariate flood frequency analysis applied to simulated flood data

The second approach (tracing from top left to bottom left and then to bottom right panels in Figure 2) is often referred to as 'continuous simulation', and involves simulating the dynamical flood response to continuous time series of the modelling boundary conditions using process-based models~~.~~ (Boughton and Droop, 2003; Sopelana et al., 2018). For example, if extended continuous historical data of catchment inflows (upper boundary condition) and ocean levels (lower boundary condition) are available, then it becomes possible to run a hydrodynamic model forced by those conditions to achieve continuous water level time series at all relevant locations within the estuary. This in turn can form the basis of a univariate flood frequency analysis applied to the simulated flood level data at the location(s) of interest. An advantage of this approach is that flood levels can be calculated at all desired locations throughout the estuary, and that changes within the estuary (e.g. changes in bathymetry, engineering works) can be explicitly captured in the model. However, the approach assumes that the physical 'generating processes' that lead to the boundary conditions are and will continue to be stationary, which is increasingly unlikely to be valid for a range of applications.

A possible solution for addressing boundary condition non-stationarity is to widen the modelling chain, thereby explicitly representing a broader range of physical processes in the model~~.~~ (Heavens, 2013). For example, land-use change or the construction of a reservoir in the upstream catchment can lead to significant non-stationarity in streamflow time series (the upper boundary condition in the preceding example), and this could be addressed by extending the boundary condition further up to time series of historical rainfall~~.~~ (Hasan et al., 2019). From there it becomes possible to explicitly model the key flow-generation processes (including the effects of land-use change and/or reservoirs) before coupling this to a hydrodynamic model of the estuary. This would enable continuous flood height data in the estuary to be generated based on current or future catchment conditions (which would need to be parameterized into the hydrological and hydraulic models), forced in this case by historical rainfall time series. Although this approach explicitly addresses some sources of non-stationarity, evidence of climate change shifting both rainfall patterns and storm surge patterns (Lowe and Gregory, 2005; Wasko and Sharma, 2015; Westra et al., 2014) means that the assumption of stationary meteorological forcing is also increasingly questionable. Addressing this issue would lead to further widening of the boundary conditions. This is represented as ever larger boxes in the top left panel of Figure 2, defining the components of the system to be modelled and the boundary conditions to those models.

~~Although widening~~ Widening the modelling chain to explicitly represent an ever-increasing set of time-varying processes ~~may be conceptually attractive as a means of explicitly addressing non-stationarity of key flood generating processes, a corollary is that this will~~is certainly an attractive means to explicitly address non-stationarity of key flood generating processes. This is especially the case considering that some datasets from climate models already exist as boundary conditions for hydrodynamical modelling runs (e.g. Kanamitsu et al. (2002) and Naughton (2016)), which are helpful to assess climate change impact on compound flooding with Approach 2. However, it is important to recognise that widening the modelling chain can also lead to evermore complex models, with greater possibility of inducing biases and other forms of modelling errors into the results~~.~~ (Zaehle et al., 2011). This is particularly the case for climate model outputs, with the lack of hydrological validity of precipitation fields from climate models often leading to the requirement for significant bias correction or other forms of post-processing (e.g. Nahar et al. (2017)).

Furthermore, ~~as indicated above~~in the context of estuarine applications, the implications of anthropogenic climate change ~~means~~mean that it may be necessary to explicitly resolve the multivariate meteorological ~~forcings, yet~~forcing variables that drive estuarine floods. Yet very little research has been conducted on the generation of continuous multivariate meteorological ~~forcings~~forcing variables for estuarine catchments while preserving the interactions between these ~~forcings~~variables (e.g. the joint probability of extreme rainfall and the meteorological drivers of storm surge~~).~~ such as pressure and wind) and eliminating their respective biases. Although approximate approaches may be available in certain instances (e.g. manually scaling the rainfall or storm surge boundary conditions), the complexity of possible future changes (e.g. heavy rainfall events being more likely to coincide with storm surge events in the future, see Seneviratne et al. (2012) and Bevacqua et al. (2019)) could render simple scaling approaches invalid. Therefore, many aspects of how to correctly apply continuous simulation approaches to estuarine floods remains an open research question.

2.4 Approach 3: Multivariate frequency analysis applied to key flood generating processes

The third approach involves the application of multivariate probability distributions, and is often referred to as 'event-based' because of the emphasis on ~~translating the boundary conditions into~~deriving a series of multivariate 'design events' ~~that are then simulated in discrete form~~for further simulation through a modelling chain. These approaches are the multivariate analogy of applying IFD curves for delineating design rainfall 'events' with pre-defined probabilities, which are then converted into streamflow events ~~of an~~that are assumed to have equivalent probability to the driving rainfall event.

These methods factorise the flood estimation problem into two separate ~~steps~~components:

1) the ~~conversion of continuous boundary conditions into~~ estimation of a multivariate (commonly bivariate) probability distribution function based on the continuous boundary conditions; and
2) the estimation of the flood magnitude (i.e. water levels) for each combination of boundary conditions, ~~to produce~~using what is often referred to as a 'structure variable' or 'boundary function'.

A range of multivariate approaches have been applied to compound flood estimation problems, including Vine copula (Bevacqua et al., 2017), standard copulas (Muñoz et al., 2020), unit Fréchet transformations (Zheng et al., 2014), regression type models (Serafin et al., 2019) and conditional exceedance models (Jane et al., 2020). The use of copulas or equivalent formulations (e.g. unit Fréchet transformations) enables the factorisation of multivariate distributions into a set of marginal distributions ~~that capture~~and a dependence structure (i.e. a joint probability distribution). This joint probability distribution captures the defining features of the variables of interest~~, together with a joint probability distribution that describes~~ and their interaction. For example, in Australia, a bivariate logistic extreme value distribution has been fitted to tide (observed and simulated) and rainfall data throughout the Australian coastline, and the dependence parameter of this distribution has been made available to flood practitioners across the entire coastline to describe the dependence between storm tide levels and extreme rainfall (Wu et al., 2018; Zheng et al., 2014). To capture the full joint distribution (including both marginal distributions), the dependence parameter can be coupled with publicly available IFD curves that capture the rainfall exceedance probabilities of equivalent durations, and with a frequency analysis of storm tide to reflect the lower boundary condition~~.~~ (Ball et al., 2019). Similar approaches exist elsewhere (e.g. Bevacqua et al. (2017), Zellou and Rahali (2019) and Moftakhari et al. (2019)), and methods are available to estimate all the key parameters of a suitable distribution when the relevant parameters are unavailable.

There are several advantages of taking an event-based approach. First, because of the emphasis on simulating a smaller number of significant 'design events', the computational loads are much lower than multi-year continuous simulations of hydrodynamic models. Second, because the drivers of estuarine flooding are factorised through the multivariate distribution, it becomes easier to incorporate the effects of ~~climate change while preserving key dependencies between variables. Indeed, by factorising the flood estimation problem into the two steps indicated above, it could be possible under certain conditions to estimate the impact of climate change on estuarine flooding without additional hydrodynamic simulations, simply by re-calculating the probabilities of the drivers under a changed climate~~future changes. This is particularly the case if one is able to assume that the dependencies between variables are either not greatly affected by climate change or that changes in dependencies produce second-order effects on flood probability compared to changes in the marginal distributions. Under these conditions, the method can capitalise on published information on uplift factors to changes in the key marginal distributions (e.g. scaling factors for IDF curves, or for peak ocean levels), which are becoming increasingly commonly available as part of engineering flood guidance in many parts of the world (Wasko et al., in press). A further advantage is that under the assumption that the relative timing of different flood drivers is not considered (see discussion in the paragraph below), the flood surface produced using hydrodynamic models will not change under climate change; rather it is how the flood surface is converted into flood probability based on the dependence model that will change. Indeed, by separating the flood estimation problem into the two components indicated above, it could be possible under certain conditions to estimate the impact of future changes such as climate change on estuarine flooding without additional hydrodynamic simulations, simply by re-calculating the probabilities of the flood drivers and their dependence structure under changed future conditions.

Despite these advantages, there are several simplifications involved in this approach when converting continuous meteorological data into a set of multivariate 'design events', which could lead to significant misspecification of flood probability if not taken into account. This is illustrated through an analogy of the application of IFD curves to estimate design flood hydrographs, whereby the process of calculating IFD curves involves collapsing complex rainfall events into average rainfall intensities for different durations, resulting in the loss of the spatial and temporal dynamics of individual storm events. To convert IFDs into design floods, this additional temporal and spatial information of the rainfall event is then typically re-introduced through 'temporal patterns' and 'areal reduction factors', respectively. Translating this analogy to multivariate design events for estuarine conditions, intensity-frequency relationships for storm tides are often derived from time series of daily maximum storm tide~~, and in doing so~~. During this process information on the temporal dynamics of storm surges and astronomical tides is discarded. Although it may be possible to introduce this information on oceanographic temporal patterns through the use of 'basis functions' such as applied by Wu et al. (2017) or a similar approach by the UK Environment Agency (2019), a significant difficulty arises when trying to align the timing of the storm surge and astronomical tide events with the timing of the flood-producing rainfall in the upstream catchments~~. Indeed, this problem has not been resolved, with most current methods~~ (Santiago-Collazo et al., 2019). Indeed, this problem has not been resolved, with most current methods using a stochastic method to account for the temporal shape of surge peaks (MacPherson et al., 2019) or taking a simplified approach such as assuming 'static' lower boundary conditions rather than explicitly resolving the tidal dynamics ~~(Zheng et al., 2015). The extent to which this~~(Zheng et al., 2015a). The extent to which this simplification leads to mis-specified flood risk (and whether this misspecification leads to an under- or over-estimation of probabilities) is not known.

3 Case Study and Data

3.1 Case study area and hydrodynamic model

The case study is the Swan River system in the lower part of the Swan-Avon Basin in Western Australia, as shown in Figure 3. The total catchment area of the Swan-Avon River system is approximately 124,000 km^2, which makes it one of the largest river basins in Australia. The river system runs from the town of Coolgardie 500 km east of Perth to its outlet to the Indian Ocean at Fremantle. The catchment covers a large proportion of the south-western region of Western Australia and consists of a wide range of hydrological regimes and land uses, including the relatively wet and forested areas of the Darling Scarp in the west, the Wheat belt in the middle and the semi-arid Goldfield region in the east. Due to its large size and hydrological complexity, there is currently no hydrological model available for the catchment. However, there are a few stream flow gauges~~, including~~ near the outlet of the catchment but outside of the zone of tidal influence. These gauges include the Walyunga stream gauge and the Great Northern Highway stream gauge~~, near the outlet of the catchment but outside of the tidal influence~~ and are shown in Figure 3.

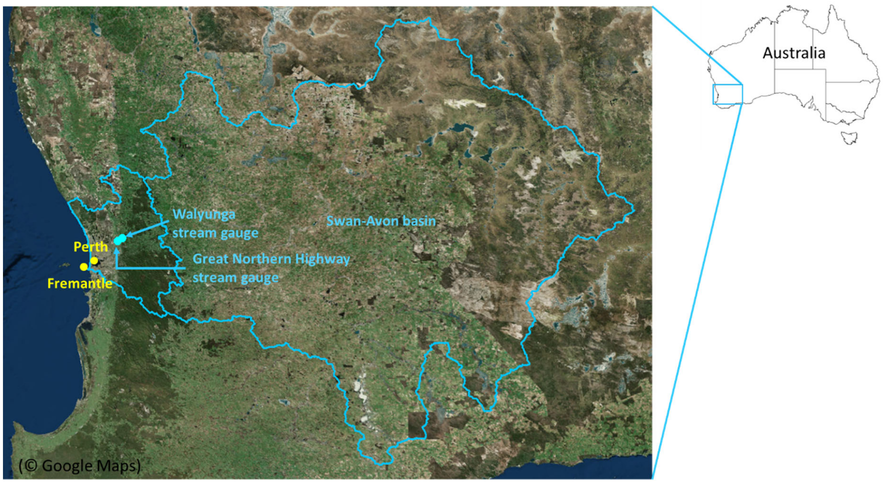

Figure 3 Locations of Perth, Fremantle, Great Northern Highway and Walyunga stream gauges and Avon basin. The yellow dots represent the locations of major urban areas and the blue dots represent the locations of the stream gauges. (Note: This figure is created using © Google Maps.)

The case study area is shown in Figure 4, which covers Swan River from the Great Northern Highway Bridge to its outlet at Fremantle. A two-dimensional flexible mesh hydrodynamic model is available for the study area. The model was developed using the DHI Modelling Suite MIKE21 by URS on behalf of the Department of Water and Environmental Regulation in Western Australia to simulate water levels within the Swan and Canning Rivers' estuarine region (URS, 2013). The model domain extends from Fremantle to the Great Northern Highway Bridge 40 km north east of Perth on the Swan River, and the Pioneer Park gauge station 20 km south east of Perth on the Canning River. The main area of interest is the Swan River between Fremantle and Meadow Street Bridge, where model results are most representative of historical calibration events (URS, 2013). Therefore, 19 locations are marked within this region and labelled from Sw1 at Fremantle to Sw19 at Meadow Street Bridge (represented by red dots in Figure 4), where flood level results are extracted from the model. The downstream boundary of the MIKE21 model is an offshore arch-shaped water level boundary located 4 km from Fremantle. The upstream boundaries are located at the Great Norther Highway Bridge on the Swan River and Pioneer Park on the Canning River. The region downstream of Sw10 is mainly storm tide dominated; the region upstream Sw16 (near the Perth Airport) is mainly flow dominated; and the region between Sw10 and Sw16 has significant joint impact from both tail water levels at Fremantle and upstream flow, and therefore is referred to as the 'joint probability zone'~~.~~ or 'transition zone'.

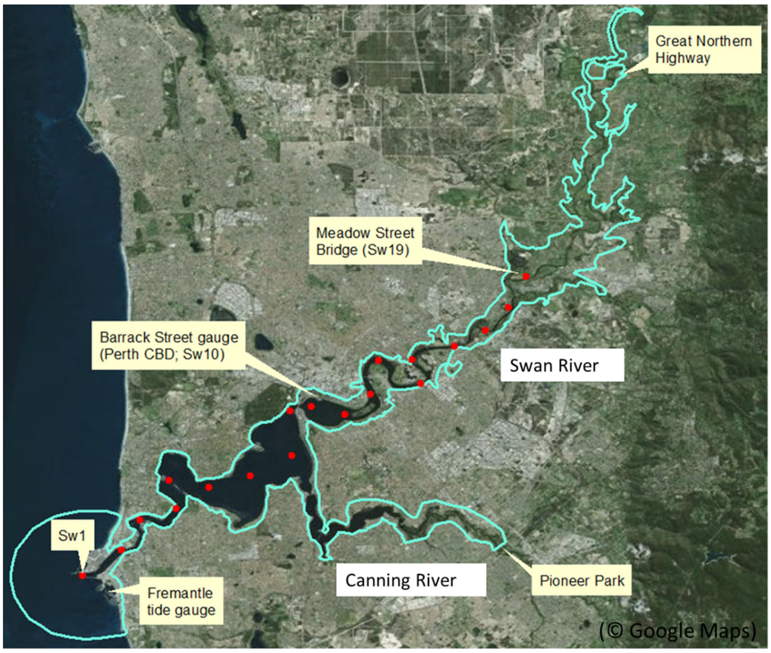

Figure 4 Model extent and key locations for the case study system. The blue line represents hydrodynamic model extent. The red dots represent the 19 locations where flood level results are extracted, from Sw1 at Fremantle to Sw19 at Meadow Street Bridge. (Note: This figure is created using © Google Maps.)

3.2 Observed data available

Water level data (i.e. not flow volume) within the estuarine regions of the Swan River is available at one gauge located at the end of Barrack Street in the City of Perth (near location Sw10 in Figure 4). The data is available from Department of Transport, Western Australia, between July 1990 and June 2015 at 15 minutes intervals with approximately 10% missing or erroneous values. This leads to about 22 years of ~~good quality~~ data, with no missing or erroneous values, and with water levels ranging from 0.06 m to 1.92 m.

Sea level data at Fremantle are available at hourly intervals for 118 years between 1897 and 2015 from the Bureau of Meteorology, with about 10% missing or erroneous data. The sea level data represent the combined influence of astronomical tides, storm surge and other factors that have an impact on ocean water levels, and therefore are also referred to as storm tide. The recorded sea levels range between 0.1 m and 1.95 m.

Hourly stream flow data from both the Walyunga and the Great North Highway Bridge gauge stations are obtained from the Department of Water and Environmental Regulation, Western Australia. Data from the Great North Highway Bridge gauge are available for 14 years between 1996 and 2010, which is considered to be too short for analysis of extreme events. Consequently, stream flow data from the Walyunga gauge, available between 1970 and 2016, are used. The Walyunga gauge is about 4km upstream of the Great Northern Highway Bridge, and this distance is considered to have minimal impact on model results considering the size of the catchment. After removing missing and erroneous data, there are in total 31 years' data available. No stream flow data are available for the Canning River. This is not considered a problem, as the inflows upstream of Canning River have little impact on water levels within the study area along the Swan River (URS, 2013). Consequently, a constant small flow of 1 m^3/s is used as the boundary condition at Pioneer Park (URS, 2013).

4 Methodology

As described in section 2, each of the general approaches to the estimation of estuarine flood probabilities can be implemented in many different ways, and one specific method is applied on the real-world case study to demonstrate the advantages and disadvantages of each approach. The details of these specific methods and how they are implemented over the case study are presented in this section.

4.1 Method 1: Peak-over-threshold model based flood frequency analysis applied to observed flood data

Univariate flood frequency analysis is the simplest approach for estimating flood probabilities when flood data are available~~,~~ and this method has been used extensively in previous studies (Guru and Jha, 2016; Seckin et al., 2014; Xu and Huang, 2011; Zhang et al., 2017). It generally involves fitting a specified distribution (e.g. Gumbel distribution, Log-Pearson Type III distribution or generalized extreme value distribution) to flood data so that the magnitude of floods can be associated with their occurrence probability (Tao and Hamed, 2000). For this study the peak-over-threshold representation of extremes is used.

The peak-over-threshold representation for extreme value analysis is based on the Pickands–Balkema–de Haan Theorem, which leads to the generalized Pareto distribution (GPD) family (Coles, 2001). Let $\{X_1, X_2 \dots, X_n\}$ be a sequence of independent and identically-distributed random variables that follow a generalized extreme value (GEV) distribution:

$$G(x) = \exp\left\{-\left[1 + \xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-1/\xi}\right\} \qquad \text{Eq. 1}$$

where, $\mu, \sigma > 0$ and ξ are the location, scale and shape parameters, respectively. Then, for a high threshold u_x, the distribution of values $Y = (X - u_x)$ conditional on $X > u_x$ converges to the GPD:

$$G(y) = 1 - \left[1 + \frac{\xi(y)}{\tilde{\sigma}}\right]^{-1/\xi} \qquad \text{Eq. 2}$$

where $y = x - u_x$ and $\tilde{\sigma} = \sigma + \xi(u - \mu)$, with σ and ξ being the scale and shape parameters of the associated GEV. Then the maximum likelihood method can be used to fit a GPD (Coles, 2001).

One challenge associated with a GPD-based frequency analysis is the choice of the threshold value u. If the threshold value is too low, it will violate the basic asymptotic assumption of the peak-over-threshold model and lead to high bias in estimation. On the other hand, if the threshold value is too high, there will be insufficient data for fitting the distribution, which can lead to high variance. The basic principal for threshold selection is to choose as low a threshold value as possible that does not ~~invalid~~invalidate the asymptotic assumption of the model. In this study, the commonly used mean residual life (MRL) plot method (Coles, 2001) is used for threshold value selection. At the suitable threshold value, the MRL plot should be approximately linear as a function of threshold value u (Coles, 2001).

4.2 Method 2: Peak-over-threshold model based flood frequency analysis applied to simulated flood data

For Approach 2, univariate flood frequency analysis is applied to flood level data simulated using a 2D hydrodynamic model. To be consistent with the method selected for Approach 1, the GPD is also used. One advantage of using the peak-over-threshold model for Approach 2 is that censoring can be used to improve the efficiency of full continuous simulation using a 2D hydrodynamic model, as only values above certain high thresholds are fully accounted for. This assumption is also based on the fact that floods are relatively rare events, and therefore~~,~~ data from the majority of the record will not be used to estimate the probability of floods. Therefore, it is more efficient to only simulate water levels above an appropriately high threshold value, which will reduce simulation time significantly.

Censored continuous simulation for generating compound flood levels resulting from high tail water level T and large river discharge Q is illustrated in Figure 5. By selecting all of the time periods when at least one of the boundary conditions is above the pre-determined threshold, this approach aims to simulate all water levels H above a specified high threshold value. One challenge to implementing this approach is that it is not possible to know *a priori* (i.e. without simulating the full time series of joint boundary conditions) the exact value of the boundary condition thresholds that will guarantee all water levels H above the GPD threshold are simulated. For example, extreme water levels H may also be driven by non-extreme conditions of either of the flood drivers. However, the relative rareness of the extreme conditions of each flood driver and the selection of relatively low threshold values for the boundary conditions can provide reasonable assurance that flood levels above a very high threshold value required for fitting a GDP are simulated (i.e. the 'flood periods' depicted in Figure 5 always cover the periods when flood levels H are above the suitable GPD threshold value). When implementing the censored continuous simulation method, a time buffer is also defined to separate different flood periods identified. The use of a time buffer accounts for the travelling time of water in the hydrodynamic model, and further ensures that the periods when flood level H are above the suitable GPD threshold value (e.g. generated by combination of moderate flood driver levels) will be fully simulated. The combination of the flood periods and the time buffer periods is referred to as the high water level periods, when flood level time series is fully simulated using the 2D hydrodynamic model. The time periods outside these high water level periods are referred to as the 'low water level periods' and are accounted for using a resampling approach described below.

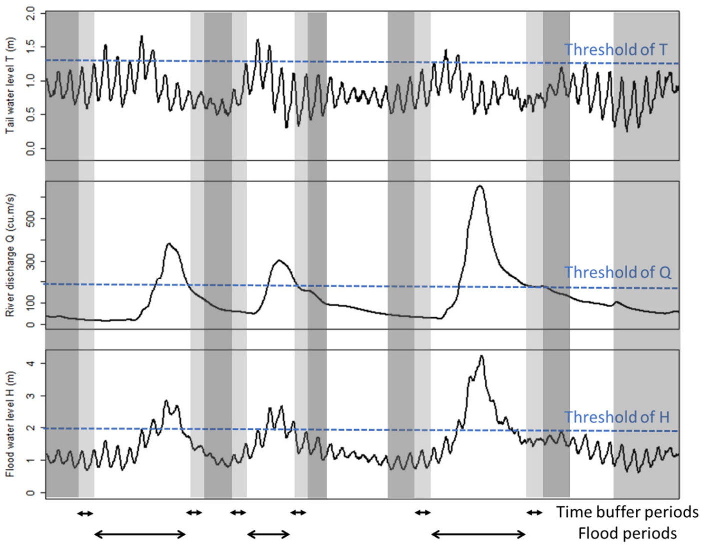

Figure 5 Conceptual illustration of censored continuous simulation for simulating compound flood level H in estuarine regions caused by high tail water level in the ocean T and large river discharge Q. The time periods highlighted in dark grey are low water level periods; while the remaining time periods are high water level periods, which include flood periods and the time buffer.

Since water level information below the selected threshold for fitting a GPD is censored in the frequency analysis, a resampling approach is used to fill in water level information during the low water level periods. During the resampling process, a random sample of the simulation period (e.g. 1,000 hours) is selected from the original flood driver time series, subject to values of both flood drivers being below their pre-determined thresholds described above~~, i.e. selected in~~. In other words, only a fraction of the low water level periods is simulated and resampling with replacement is used to fill in flood data across the entire low water level periods. Then the corresponding flood levels are simulated using the hydrodynamic model. Thereafter, all river water level information that is not included in the high water level periods is sampled with replacement from the simulated low water level sample based on the nearest-neighbour rule applied to both the storm tide T and river flow Q values. Thus, water level information for the entire analysis period is obtained by combining the simulated water level information during the high water level periods and resampled water level information during the low water level periods.

As part of the method selected for Approach 2, the 31 years' concurrent historical sea level and river flow data are used as the basis for driving the 2D hydrodynamic model of the Swan River system. A 99th percentile threshold value is selected for both flood drivers to select flood periods for censored continuous simulation. This is equivalent to a sea water level of 1.32 m at Fremantle and a river flow of 150 m^3/s at the Walyunga station. A time buffer of 12 hours is selected, as the average travel time of water from the upper boundary to the lower boundary of the model is under 10 hours. In addition, a low water level period sample of 1,000 hours is randomly

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selected. Thus, this process leads to a total of 29,792 hours simulation time, which is approximately 10% of the entire 31 year period under consideration. The censored simulation runs are carried out using a Windows server (with 2 × Xeon E5-2698 V3 @2.6Ghx 256 GB RAM and 2 X K80 Telsa GPU).

Once the simulated water levels are obtained, the same GPD-based frequency analysis described under Method 1 is used to estimate flood probabilities at selected locations based on these simulated water level data.

4.3 Method 3: Event-based design variable method considering multivariate frequency analysis over key flood generating processes

~~For Approach 3, the design variable method (DVM) (Zheng et al., 2015) is selected. The DVM was initially developed as a simpler and efficient alternative to the full continuous simulation method and it includes four major steps described as follows.~~

~~First,~~For Approach 3, the design variable method (DVM) (Zheng et al., 2015a) is selected. The DVM was initially developed as a simpler and efficient alternative to the full continuous simulation method and it includes four distinct steps: (1) event selection; (2) dependence model development; (3) flood surface simulation; and (4) final probability estimation. The details of these four steps are described as follows.

In the first step, compound flood events caused by different flood drivers, such as storm tide and river discharge (i.e. combinations of boundary conditions with different return periods) need to be selected for simulation. Flood levels generated from these flood events will be interpolated to form flood surfaces or response surfaces with different flood magnitudes. The DVM only requires the simulation of a limited number of 'flood events' (often on a regular grid, e.g. 10 by 10 flood events generated from combinations of flood drivers with different return levels) to produce a reasonable cover of the bivariate probability surface formed by two flood drivers (Zheng et al., ~~2015~~2015a; Zheng et al., 2014). In this study, both historical and synthetic flood events on an irregular grid are used to ensure flood events from drivers with significantly longer return period than the estimated flood required are included. This is recommended in order to have reasonable confidence in the estimates (Zheng et al., 2014). In total, 28 flood events with flood drivers (i.e. storm tide and river discharge) with return periods of up to 1 in 250 years are selected based on historical record to produce a flood response surface with flood levels up to a return period of 1 in 100 years for the case study area. A summary of these flood events is provided in Table S1 in the supporting material.

~~Second~~In the second step, the dependence model reflecting the dependence structure between the two flood drivers and their marginal distributions needs to be ~~identified.~~developed using either observed or simulated data (associated with component 1 of Approach 3, see section 2.4). This study follows the approach developed by Zheng et al. (~~2015~~2015a; 2014; 2013), where the bivariate logistic threshold excess model (Coles, 2001) is used to quantify the dependence between the two flood drivers. The model can be described using the following equation:

$$\Pr[X \leq x \cap Y \leq y] = G_{XY}(x, y) = \exp\left[-\left(\tilde{x}^{-1/\alpha} + \tilde{y}^{-1/\alpha}\right)^{\alpha}\right] \quad \text{Eq. 3}$$

for $x > u_x$, $y > u_y$ and $0 < \alpha \leq 1$. Here, X and Y are the two stochastic variables, i.e. storm tide T and river discharge Q; x and y are realizations of X and Y; G is the bivariant distribution function of X and Y; $\tilde{x}$ and $\tilde{y}$ are the Fréchet-transformed values of x and y; u_x and u_y are the threshold values of x and y, above which function G is valid; and α is the dependence parameter, with α = 0 representing complete dependence and α = 1 representing complete independence. The maximum censored likelihood method can be used to estimate parameter α (Tawn, 1988). For the case study, the dependence between flood drivers are estimated using observed data of storm tide and river discharge.

~~Third~~In the third step, the hydraulic response (i.e. simulated flood levels) of the selected flood events is simulated~~.~~ (associated with component 2 of Approach 3, see section 2.4). This is often done with a 2D hydrodynamic model, which can simulate the interaction between the two flood drivers. For this study, the ~~MIKE FLOOD~~MIKE21 model for the Swan ~~river~~River is used.

~~Finally, flood levels at the locations of interest (Step 3) are superimposed onto the bivariate dependence model (Step 2) to estimate associated return periods. For this step, the bivariate integration method introduced by Zheng (2015) is used.~~

~~5 Results~~

~~The advantages and disadvantages of each approach are illustrated using the Swan River system case study. The results obtained from the specific implementation of each of the three approaches are summarised in this section.~~

~~5.1 Method 1~~

In the fourth and final step, the probability of different compound flood levels simulated in Step 3 can be derived based on the bivariate dependence model developed in Step 2 using the bivariate integration method introduced by Zheng (2015a). More details of this integration method can be found in Zheng et al. (2015b).

5 Results

The advantages and disadvantages of each approach are illustrated using the Swan River system case study. The results obtained from the specific implementation of each of the three approaches are summarised in this section.

5.1 Method 1

The first method based on the univariate flood frequency analysis approach is only implemented at the Barrack Street tide gauge in the City of Perth near location Sw10 in Figure 4, as this is the only location where relatively long records of observed water level data are available. The mean residual life (MRL) plot (Figure S1 in supporting material) for water levels observed at Barrack Street gauge is used for threshold selection. The mean excess stabilized around 1.37 m, which is selected to be the threshold value for fitting a GDP. The estimated return levels and their 95% confidence interval (estimated using a bootstrap method) are shown in Figure 6. The estimated flood levels range from 1.64 m for a return period of one year to 1.97 m for a return period of 200 years. The confidence intervals become increasingly wide with increasing return period, and it is important to note that return periods have been calculated based on only 22 years of historical water level data.

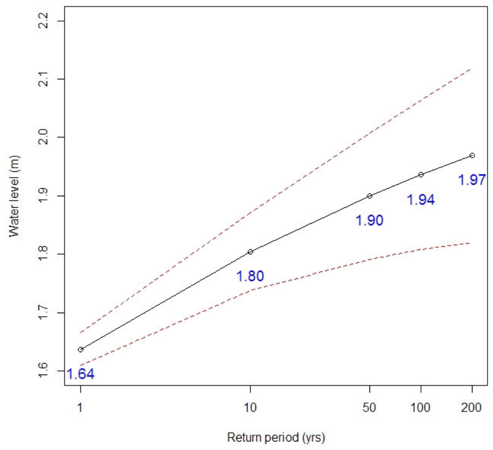

Figure 6 Results of Method 1 applied to observed flood level data at Barrack Street gauge near location Sw10. The black line represents estimated flood levels. The red dashed lines indicate the 95% confidence interval.

5.2 Method 2

For the second method adopted in this case study, hourly flood inundation data are generated using the MIKE21 model for the entire model domain for both high water level periods and the sampled low water level periods. Water level estimates from the 19 marked locations (see Figure 4) are extracted from the MIKE21 model for analysis. Since the hourly water levels are highly correlated, the de-clustering method described in Coles (2001) is used before fitting the GPD model. In addition, the MRL plot is used to select a suitable threshold value for frequency analysis using the GPD. The MRL plots for de-clustered river level data at all 19 marked locations are provided in Figure S2 in supporting material.

In this section, results from four representative locations are selected for detailed analysis. These locations include: location Sw1 from the tide dominated zone, locations Sw10 and Sw12 from the joint probability zone and location Sw19 from the flow dominated zone (see Figure 4). Location Sw10 is specifically selected as it is located near the Barrack Street gauge, where the only observed water level data within the river system are available~~.~~ (i.e. this is where the results of Method 1 and Method 2 can be directly compared). Based on the MRL plots, a threshold value of 1.3 m is selected for locations Sw1, Sw10 and Sw12; and a threshold value of 1.4 m is selected for location Sw19.

The estimated flood levels up to a return period of 200 years and their 95% confidence intervals at these four locations are plotted in Figure 7. The results for the remaining 15 locations are provided in Figure S3 in the supporting material. The estimated return levels at Sw1, Sw10 and Sw12 are similar, with the 1 in 100 years return levels being 1.91 m, 1.89 m and 1.87 m at the three locations, respectively. The estimated 1 in 100 years flood level at location Sw19 is much higher at 3.67 m. In addition, the 95% confidence interval for location Sw19 is much wider (higher variance) compared to the other three locations. This is mainly because location Sw19 is flow dominated and high flood levels are dominated by relatively few flood events in the historical record, ~~and therefore there are~~leading to a more highly skewed distribution with fewer data points above the threshold for flood estimation at location Sw19 compared to the other locations.

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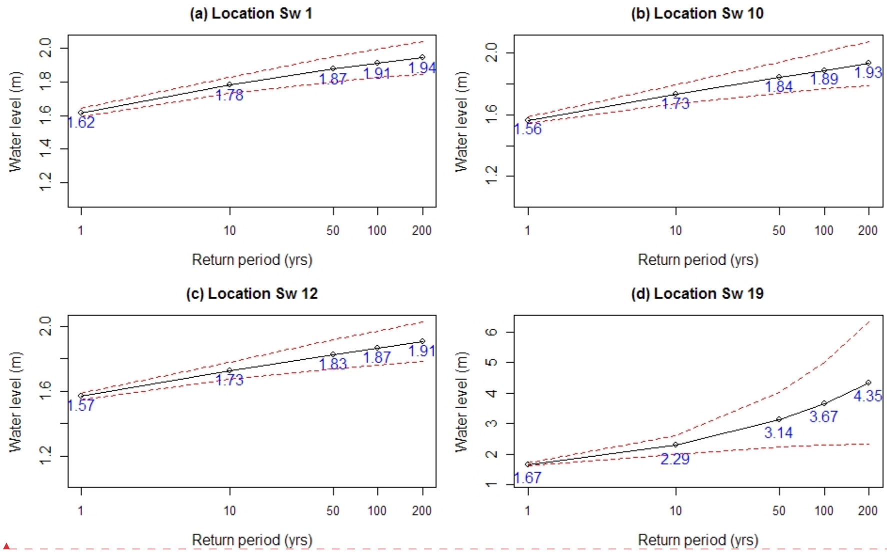

Figure 7 Results of Method 2 applied to simulated flood level data at locations Sw1, Sw10, Sw12 and Sw19. The black lines represent estimated flood levels. The red dashed lines indicate the 95% confidence interval.

5.3 Method 3

For the design variable method (DVM), the dependence between storm tide T and fluvial flood Q is first estimated using the bivariate logistic threshold excess model. The results are summarized in Figure S4 in the supporting document for a range of time lags between T and Q. The results show that the maximum dependence between storm tide T and fluvial flood Q occurs at a lag of three days with an α value of 0.88, indicating that the peak of flow often comes three days after the peak of storm tide. ~~Therefore, the α value of 0.88 is used for flood estimation using the DVM.~~This lag is not surprising given that the large catchment size generates significant lags between rainfall events (which are more likely to co-occur with the storm surge peak) and the runoff towards the catchment outlet. Therefore, an α value of 0.88 is used for flood estimation using the DVM. This is because in this method the information on the temporal dynamics of storm surges and astronomical tides is discarded and only the only the peaks of flood drivers and their joint dependence are considered, as discussed in section 2.4.

Flood response surfaces (i.e. flood contours) obtained for the four selected locations are presented in Figure 8. At location Sw1 where storm tide dominates the flood responses, it can be seen that as the storm tide T becomes more extreme, the flood contours become horizontal and river flow Q has little impact on flood levels. Similar phenomena can be observed for location Sw19, which is flow dominated - as river flow Q becomes more extreme (especially with a return period of 20 years or longer), flood contours become vertical and storm tide T has little impact on resulting flood levels. In contrast, within the joint probability zone (i.e. locations Sw10 and Sw12), the flood levels are influenced by both flood drivers for the majority of the bivariate probability surface.

It can also be observed in Figure 8 that there are some variations in estimates of flood levels with very short return periods (e.g. return periods of 1 in 1 year or below), with the increase in one flood driver leading to decreased compound flood levels. Careful inspection of the results shows that this feature does not apply to any of the simulated data points, in the sense that simulation points with larger values of the boundary conditions always yield larger flood levels. Rather, the 'inflection' only occurs in a sparsely sampled region of the plot, and is thus suggestive of the limitations of using a log-linear interpolation scheme in this region. This therefore highlights the importance of carefully considering the sampling scheme as part of the analysis.

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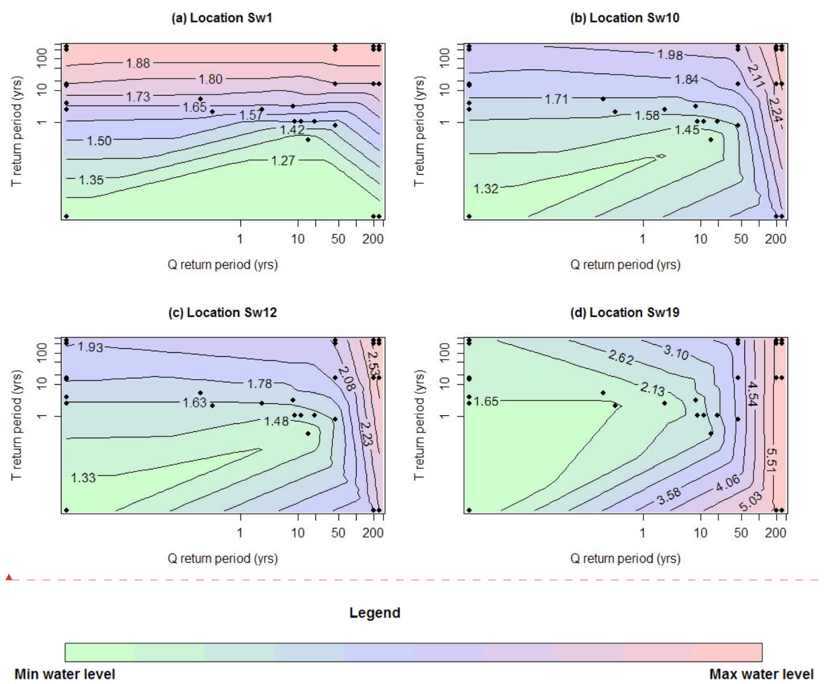

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Figure 8 Flood response surfaces (i.e. flood contours) obtained at locations Sw1, Sw10, Sw12 and Sw19. The values on the contour lines represent water levels in meters. The black dots represent the locations of the 28 flood events on the flood response surface.

The flood exceedance probabilities estimated using this method are plotted in Figure 9, including flood levels estimated assuming the two flood drivers are completely dependent (the red dotted lines in Figure 9), completely independent (blue dotted lines in Figure 9) and with the dependence parameter α of 0.88 (the black lines in Figure 9). ~~As pointed out in the original study on the DVM (Zheng et al., 2015)~~As pointed out in the original study on the DVM (Zheng et al., 2015a), the maximum return period of each flood driver needs to be significantly longer than that of the response variable (i.e. flood level); therefore flood levels up to a return period of only 100 years (rather than the 200 years return period for the first two methods) are estimated here.

As shown in Figure 9, the level of dependence between the two flood drivers has little impact on the resulting flood levels at location Sw1, where water levels are dominated by storm tide. In contrast, there is a large difference in flood levels between the complete dependence and the complete independence cases in the joint probability zone (i.e. locations Sw10 and Sw12), where flood levels are determined by both tide and stream flow. Interestingly, at location Sw19 there is a large difference in flood levels resulting from the complete dependence and complete independence cases, with the largest difference of over one meter observed at a return period of 50 years. This indicates that although historically being labelled a flow-dominated zone due to high water levels being dominated by a few large riverine flood events, tidal levels also have some impact on flood levels in this area. This can also be confirmed by the results in Figure 8 that flood levels resulted from flood drivers with shorter return periods (e.g. 20 years or shorter) can be influenced by both flood drivers, although large floods at location Sw19 ~~are predominately resulted~~result predominantly from riverine flooding. These results highlight the importance of considering the dependence between all relevant flood drivers as part of the flood estimation methodology~~.~~, as has been pointed out in previous studies (Moftakhari et al., 2019; Serafin et al., 2019).

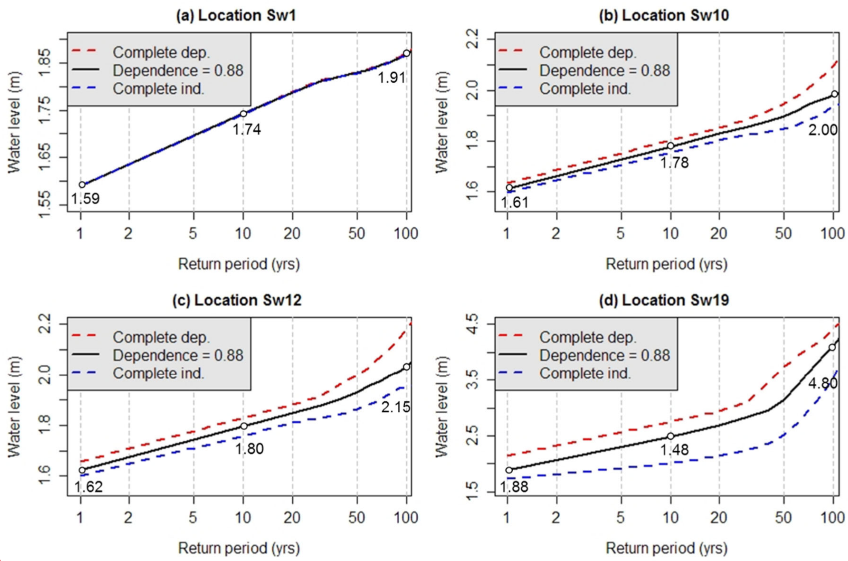

Figure 9 Results of Method 3 applied to locations Sw1, Sw10, Sw12 and Sw19. The complete dependent and independent cases are estimated using an alpha value of 0 and 1, respectively (see section 4.3).

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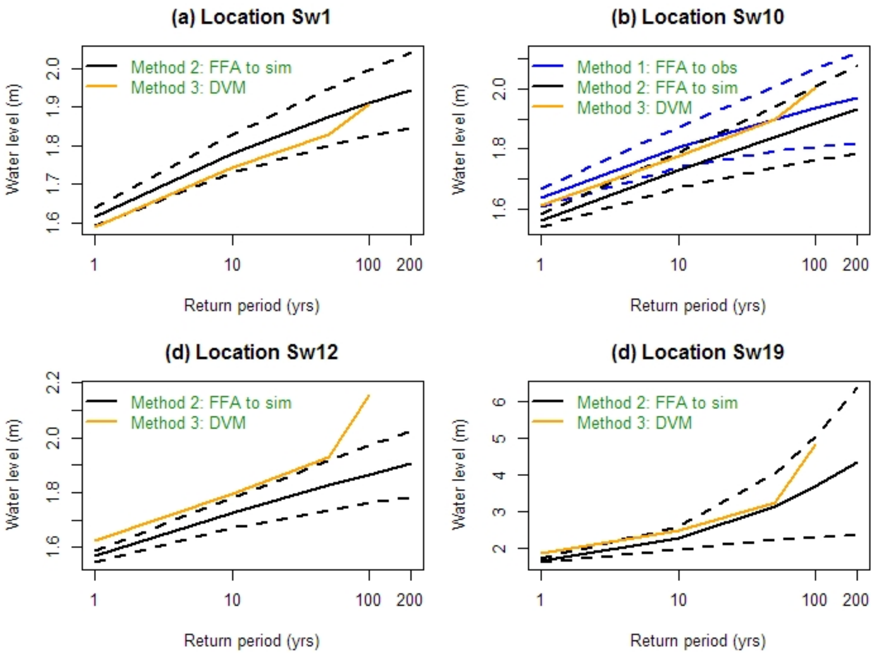
5.4 Results comparison

A comparison between flood exceedance probabilities estimated using the three different methods is summarized in Table 1 and plotted in Figure 10. Results from Method 1 are only available at the Barrack Street gauge (near location Sw10), where observed flood data are available. Method 1 produces relatively higher flood ~~estimation~~estimates at this location compared to the other methods, especially for return periods of 10 years or shorter. This is very likely due to the systematic difference between the observed flood level data (with a maximum value of 1.92 m within the 22 years' data) and flood levels simulated using the MIKE21 model (with a maximum level of 1.86 m within the 31 years' analysis period) at this location. In addition, the (short) distance between the tide gauge and the modelling location Sw10 could also be a contributing factor to this difference.

Table 1 Flood estimation results comparison

Loc.	Return period (yrs)	Method 1: POT[a] based FFA[b] to Observed historical data (from Approach 1)			Method 2: POT based FFA to simulated data (from Approach 2)			Method 3: DVM considering MFA to key flood drivers (from Approach 3)		
		Lower Bound (95% CI[c])	Est.	Upper Bound (95% CI)	Lower Bound (95% CI)	Est.	Upper Bound (95% CI)	Com. Dep.	Est.	Com. Ind.
Sw1	1	-[d]	-	-	1.59	1.62	1.64	1.59	1.59	1.59
	10	-	-	-	1.73	1.78	1.83	1.74	1.74	1.74
	100	-	-	-	1.82	1.91	1.99	1.87	1.91	1.92
	200	-	-	-	1.85	1.94	2.04	na[e]	na	na
Sw10	1	1.61	1.64	1.67	1.54	1.56	1.59	1.64	1.61	1.6
	10	1.74	1.8	1.87	1.67	1.73	1.79	1.8	1.78	1.75
	100	1.81	1.94	2.06	1.77	1.89	2.01	2.1	2	1.94
	200	1.82	1.97	2.12	1.79	1.93	2.07	na	na	na
Sw12	1	-	-	-	1.55	1.57	1.59	1.66	1.62	1.6
	10	-	-	-	1.67	1.73	1.78	1.83	1.8	1.76
	100	-	-	-	1.76	1.87	1.97	2.18	2.15	1.98
	200	-	-	-	1.78	1.91	2.03	na	na	na
Sw19	1	-	-	-	1.62	1.67	1.72	2.15	1.88	1.74
	10	-	-	-	1.99	2.29	2.6	2.75	2.48	2.01
	100	-	-	-	2.32	3.67	5.02	4.42	4.80	4.9
	200	-	-	-	2.35	4.35	6.35	na	na	na

a: POT= point-over threshold. B: FFA= flood frequency analysis c: CI = confidence interval. d: "-" indicates no data available. e: "na" indicates not applicable for extrapolation.


(a) Location Sw1
(b) Location Sw10
(d) Location Sw12
(d) Location Sw19
Method 1: FFA to obs
Method 2: FFA to sim
Method 3: DVM
Water level (m)
Return period (yrs)

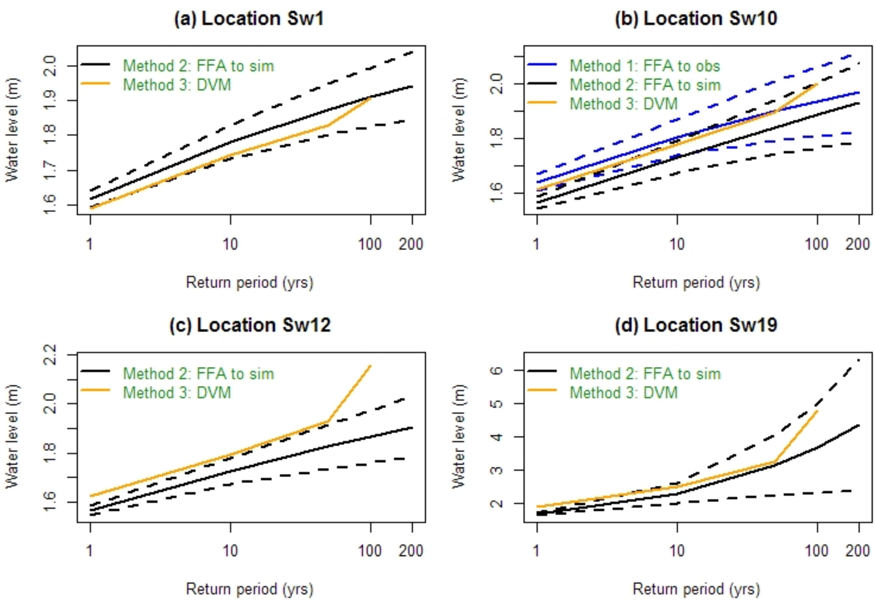

(a) Location Sw1
(b) Location Sw10
(c) Location Sw12
(d) Location Sw19
Method 1: FFA to obs
Method 2: FFA to sim
Method 3: DVM
Water level (m)
Return period (yrs)

Figure 10 Comparison between the three different methods for flood estimation. The solid lines represent estimates using each method. The ~~docted~~dotted lines represent the 95% confidence interval where applicable.

In regions where only one of the flood drivers dominates flood response (i.e. locations Sw1 and Sw19), Method 3 based on multivariate frequency analysis applied to flood events results in similar estimated flood levels to Method 2 based on univariate flood frequency analysis applied to simulated flood data. Estimates obtained from Method 3 are within the 95% confidence interval generated using Method 2 for most of the return periods considered. However, in the joint probability zone (e.g. locations Sw10 and Sw12) where both flood drivers have a significant impact on resulting flood levels, the event-based Method 3 results in significantly higher flood levels for a given return period compared to Method 2. This is especially the case for location Sw12, where flood levels estimated using Method 3 are above the upper bound of the 95% confidence interval generated using Method 2 based on censored continuous simulation data. This over-estimation of flood levels for a given return period from Method 3 due to the use of a static tail water level and the associated assumption that the peaks of the two flood drivers with always concede can potentially lead to over-conservative estimation of flood risk and costly flood prevention infrastructure.

6 Discussion

Each of the three approaches for flood probability estimation has their advantages and disadvantages, and these are reviewed in Table 3 and elaborated upon in the sections below.

Table 2 Comparative summary of flood estimation approaches for estuarine floods

Approach	Advantages	Disadvantages
1. Univariate frequency analysis applied to observed historical flood data	• Results are based directly on observed water level data (i.e. no flood modelling required). • The dependence of and interactions between different flood drivers are implicitly represented within the historical water level data. • Frequency analysis relies on univariate statistical theory and therefore comparatively easy to implement. • Compared to multivariate methods it is easier to extrapolate to provide estimate with longer return periods.	• Long-term high-quality observed water level data is often not available. • Assumes stationarity of key processes (e.g. related to hydrodynamics in the estuary or hydrology/hydraulics of the upstream catchment), which is likely to be rare in practice. • Location specific, so transferability to other locations is difficult without modelling. • No obvious method to incorporate the effects of climate change to estimate future flood probabilities.
2. Univariate frequency analysis applied to simulated flood data	• Can be applied to entire estuarine regions. • Dependence between flood drivers are taken into account implicitly based on the boundary condition data. • Dynamic interactions between (i.e. the relative timing	• Requires long term good quality simultaneous flood driver (i.e. boundary condition) data. • Relatively computational expensive, although this can be partially addressed using censored approaches.

	between and shapes of) flood drivers, are taken into account implicitly. • Compared to multivariate methods it is easier to extrapolate to provide estimate with longer return periods. • Can easily account for a large number of flood drivers (e.g. concurrent flows) in the modelling process.	• Difficult to assess future conditions, for example due to climate change, given the need to capture marginal and joint changes of the boundary conditions.
3. Multivariate frequency analysis applied to selected 'flood events'	• Can be applied to entire estuarine regions. • Can be used to assess future conditions with dependence ~~structure~~model reflecting future changes without additional hydrodynamic model runs. • Computationally more efficient than Approach 2, with limited flood events to be simulated.	• Dependence ~~structure~~model between flood drivers needs to be quantified explicitly and is location-specific. • Dynamic interactions between flood drivers are ignored when using static implementations such as the DVM, leading to conservative estimation of flood risk. • More difficult to extrapolate for longer return periods. • Generally more difficult to account for a large number of flood drivers.

The first approach is most straight forward to apply as it does not require any additional modelling and can take into account all flood drivers and their dependence, which are implicitly represented in the observed water level data. It is also ~~a well-developed~~an established approach that has been used extensively by flood researchers and practitioners. However, Approach 1 can often involve significant extrapolation, as there are often very limited observed historical flood level data available compared to the maximum return period that needs to be estimated. In this case, 22 years observed data are used to estimate flood probability up to a return period of 200 years. This leads to large uncertainty of the estimates—although for the case study presented here, the confidence intervals are similar to the results from Approach 2 (where 31 years of boundary condition data are used). In addition, the ~~observed data are often~~method is restricted to the locations where the observations are recorded. Furthermore, this approach is based on the assumption of stationarity in the estuarine characteristics and associated forcing variables, which is unlikely to be true for most locations. For example, the Swan River has experienced significant changes historically, with the majority of the low-lying areas being reclaimed land (Piesse, 2017). Moreover, the estimates obtained from historical data cannot reflect future changes in the estuarine regions.

The second approach also uses a univariate distribution, but applied to simulated water level data in the estuary. A significant advantage of this approach is that, by applying univariate frequency analysis to simulated flood level data using a 'continuous simulation' approach, flood return levels at any location within the model domain can be estimated. This approach also enables the dependence between flood drivers to be implicitly taken into account by using concurrent historical boundary condition data that include the relevant dependencies between flood drivers. A further advantage is that there are often more long-term flood driver data (e.g. tide data and rainfall/streamflow data) than water level data in estuarine rivers, and that elements of non-stationarity (such as change to land use, hydraulic structures, bathymetry etc) can be explicitly incorporated into the modelling framework. However, depending on the nature of the models (and particularly for high-resolution hydrodynamic models), runtime can be a significant issue, which is only partially being addressed using censored methods such as implemented in the Swan River case study. A further challenge with this method is the inclusion of climate change. In particular, given the 'continuous simulation' nature of the method, incorporation of climate change would require estimation of continuous (usually sub-daily) boundary condition time series (e.g. rainfall and storm tide) that ~~maintain~~reflect key dependence between the boundary conditions (e.g. of rainfall and the wind/pressure data that drive storm surge). ~~These~~Although, these high-resolution and temporally consistent data are at present not widely available under future climate scenarios~~.~~, they can potentially be developed in the future allowing Approach 2 to be used to assess compound flood probability under future changes.

The third approach based on multivariate frequency analysis applied to key flood generating processes is an efficient alternative to the traditional full continuous simulation. By separating the dependence estimation (including marginal distribution estimation of individual flood drivers, and a dependence structure) from the flood probability estimating process, future flood probability can be estimated by updating the dependence ~~structure~~model between flood drivers under these conditions without the requirement of additional flood simulation runs. However, by translating continuous flood time series data into a set of 'flood events', the information on coincident timing between different flood drivers is often lost, and various simplifying assumptions often need to be made. For example, when implementing the design variable method (DVM), the tail water level is assumed to be static (i.e. no tidal dynamics) with a value that corresponds to the specified exceedance probability. This simplifies the probability estimation process by assuming that the peak of tail water will always intercept with the peak of fluvial flood at any given location within the model domain, but it ignores the dynamic interactions of the two flood drivers, including the possibility that the peak fluvial flood wave will not occur at precisely the same time as the peak tidal cycle. ~~Consequently, this method will always lead to over-estimation of flood levels (Zheng et al., 2015)~~Consequently, this method will always lead to over-estimation of flood levels (Zheng et al., 2015a), as have been observed from results for the case study system. Finally, other challenges with the DVM include: 1) incorporating more than two dimensions (e.g. at confluence of two rivers within an estuary) will significantly increase the complexity of the method and therefore further simplifying assumptions may be required; and 2) the dependence between the two flood drivers is location specific (Zheng et al., ~~2015~~2015a).

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7 Conclusions

In this study, we provide a comparative review of different approaches for probability estimation of compound floods in estuarine regions. Three commonly used approaches are considered, including two approaches based on univariate frequency analysis (one applied to observed historical flood data and the other applied to simulated flood data) and one approach based on multivariate frequency analysis applied to flood drivers of selected 'flood events'. Three specific implementation methods, one from each approach, are selected and applied to a real-world estuarine system in Australia to investigate their advantages and disadvantages in the context of estimating estuarine flood probabilities. The theoretical underpinnings of the approaches, combined with findings from the case study, enable the provision of indicative guidance for selecting a suitable method for estuarine flood probability estimation, taking into account factors such as data availability, complexity of the application/analysis process, location of interest within the estuarine region, computational demands and whether or not future conditions need to be assessed.

It should be emphasised that there is no such thing as a one-size-fits-all approach. Each approach has its own advantages and disadvantages. Flood frequency analysis using observed water level data is likely to be the simplest to apply, but will only be accurate under a range of assumptions (availability of record, stationarity of key processes, etc). If these assumptions are not valid, alternative approaches including univariate frequency analysis applied to simulated (censored) continuous flood data (Approach 2), or multivariate frequency analysis applied to the boundary conditions of simulated discrete 'flood events' (Approach 3) are required. Approach 2 based on (censored) continuous simulation can fully account for the dynamic interactions between storm tide and river flow; however, it requires long term good quality data for both processes and it is relatively computational demanding. It is also difficult to be applied to assess future conditions, as new simulation models may need to be developed and simulation runs to be repeated. Approach 3 based on simulated 'flood events' is computational efficient, as only limited 'flood events' need to be simulated. It can be applied relatively easily under future conditions, as only the dependence between the flood drivers needs to be re-calculated and no additional simulation runs are required. However the inability of Approach 3 to account for the full dynamic interactions between storm tide and river flow (e.g. timing, duration, shape and their variability) in event-based simulation and the resulting simplification by using a static storm tide value will lead to conservative estimates of flood probability.

Although this study provides a comprehensive comparative reviews of the three general approaches used for flood probability estimation through the implementation of one specific method from each approach, there are a large number of alternative implementations of each approach available. Acknowledging this, further comparison including different specific methods is required to provide a holistic picture of methods for compound flood probability estimation in estuarine regions. In addition, some of the limitations of the methods considered (e.g. the issue related to the relative timing of flood drivers and the resulting simplification for the event-based method) requires further investigation and can potentially be improved. Finally, the development of a method that can account for a large number of flood drivers and can be easily applied under future conditions remains a research challenge.

Data Availability

The data and hydrological models used for this study are provided by the Bureau of Meteorology in Australia, and the Department of Transport and the Department of Water and Environmental Regulation in Western Australia, and are restricted for research purposes only. The data may be made available upon request subject to approval from corresponding departments.

Author Contributions

All authors collaboratively designed the experiments. WW carried out the analysis. WW wrote the initial draft of the paper. All authors contributed to the subsequent editing and revision of the paper.

Competing Interests

The authors declare that they have no conflict of interest.

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