Reply to reviewer comment RC1:

We thank the reviewer for his/her efforts to evaluate the quality and potential impact of our manuscript. We have read the comments carefully and reply to each comment individually below. The original reviewer comments are marked in blue.

1. English language must be significantly improved before the manuscript can be considered for acceptance. For example, one sentence in the abstract contains multiple grammatical mistakes: "This communication present a simple statistical seasonal forecast model able to predict the salinity intrusion up to 9 months ahead with high skill." The authors are requested to properly take care of the English writing throughout the whole manuscript.

Thanks for pointing this out. The language will be double-checked in the revised version.

2. Use of in-situ measurements of soil intrusion is considered in the forecast model, while it is rather time-consuming and cost-ineffective. Would the authors comment on the use of remotely-sensed salinity intrusion (e.g. https://doi.org/10.1186/s40645-019-0311-0) in the forecast model?

In-situ measurements were used, because surface water salinity is measured operationally by the hydro-meteorological service at various locations in the Mekong Delta. The hydro-meteorological service is also responsible for the official forecast of the salinity intrusion in the Mekong Delta. The data is thus readily available at the responsible agency, and therefore it is straight-forward to use this data set for our prediction model. However, it would be of course useful to get additional data based on remote sensing platforms, because remote sensing could provide a better overview on the spatial dimension of the salinity intrusion. If remote sensing can deliver reliable measurements of surface water salinity, I would certainly support the use of it. However, we cannot judge whether this is possible or not, as this is not our field of expertise. The cited paper covers the determination of soil salinity, which is not the target of our forecast, but rather the outcome of saline water used for irrigation.

3. The description about the salinity intrusion is rather comprehensive in the current version of the manuscript. It can be significantly shortened. In contrast, how the proposed forecast model is formulated and works are much less described and thus must be properly enhanced.

We think that the comprehensive description of the salinity intrusion in the Delta and their negative consequences is required to illustrate the necessity of a reliable seasonal forecast and to motivate the research presented in the manuscript. However, we agree that the method could be described in more detail, even though all applied methods are rather standard. In order to stay within the limits of a brief communication, we propose to provide more details in a supplement. We would ask the editor to give a statement about this suggestion. If a supplement is not favoured, we would shorten the motivation part and provide an additional paragraph about the methodological details.

4. Figure 1 shows the land use over the Mekong Delta, while it presents the 2010 status. How is the land use over the Mekong Delta changing with time? How does the evolving land use influence on the proposed forecast model?

The land use in the Mekong Delta is changing quite dynamically as a consequence of economic, political and environmental pressures. In the coastal regions the salinity intrusion is one of the main drivers of land use change. If sufficient amounts fresh irrigation water are not available, farmers and the provincial administration adapt to this situation by e.g. growing more saline tolerant crops, or by changing the farming systems. If the latter aspect this is supported by governmental incentives, as

e.g. in Soc Trang province, where the replacement of paddy rice crops by saline or brackish shrimp production was officially supported, significant changes in land use can occur in a short time. The map in figure 1 is thus mainly for illustrative purpose, showing the different land use in the coastal regions compared to more upstream areas, and to highlight which main land use types are mainly affected by salinity intrusion. In this context it is noteworthy that the differences in land use in the Mekong delta are mainly governed by salinity intrusion and different inundation dynamics.

However, changing land use in the coastal region does not influence the forecast model. The salinity intrusion is dominated by the interplay of tidal forces and river discharge during the low flow season (see e.g. Dang et al., 2019). Both factors are not influenced by land use in the coastal region. The dry season discharge can be altered by storage of flood water during the flood season in high-dike compartments in the upper parts of the Vietnamese Mekong Delta and its release during the early stages of the dry season, but only to a very limited extent (Thanh et al., 2020; Triet et al., 2017). Therefor even the hypothetical conversion of all flood compartments into areas protected by high dikes (i.e. a large scale land use change in the upper part of the Vietnamese part of the delta) would hardly impact on the salinity intrusion and thus the applicability of the proposed model.

5. How the human-made disturbance impacts on the water flow from upstream to downstream along the Mekong River should be addressed. The current manuscript only concerns with the impacts of natural disturbance, i.e. climate. Unfortunately, many reservoirs have been constructed over the upstream and have significantly modified the water flow. How such a human-made disturbance factor influences the performance of the proposed forecast model should be clarified before the model can be used for the operational purpose.

We agree to the statement that man-made disturbances, particularly the ongoing and planned development of hydropower dams, have a considerable impact on the hydrological regime of the Mekong, and thus also on the salinity intrusion. The dam development causes numerous problems ranging from shifts of the hydrological regime, reduced sediment delivery and thus problems for the morphological stability of the delta, disruption of the river ecological system and negative consequences for the Mekong fishery and livelihood of many people. With regard to salinity intrusion the dam induced shift of the hydrological regime towards lower flood season discharge and higher dry season discharge, it can be stated that the dams could partly alleviate the foreseen negative impacts of the rising sea levels on salinity intrusion. This would, from our point of view, be the only potential benefit of the dam development in the Mekong basin for the Mekong delta. This benefit is, however, compromised by the reduction of sediment delivery caused by dams. This causes a deepening of the river channels in the delta, which in turn causes a higher salinity intrusion (Hackney et al., 2020; Tu et al., 2019; Jordan et al., 2019). Moreover, as this potential benefit is subject to political and economic decisions taken in the upstream countries, it is not a reliable mitigation measure for salinity intrusion in the Delta.

Due to the complex nature of this subject, we would thus refrain from discussing the particular impacts of the dam development in the manuscript. Including such a discussion would surely go beyond a brief communication, and there are numerous papers out illustrating the negative effects of hydropower development in the Mekong basin. But we would include the dam issue as a general factor in the discussion, because if the hydrological regime will substantially change due to human interference, the presented forecast models needs to be re-fitted to the new regime, and potentially the operation or actual storage volume of the dams need to be considered as co-variate in the prediction models.

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Response to reviewer comment RC2 on "Brief communication: Seasonal prediction of salinity intrusion in the Mekong Delta" by Heiko Apel et al.

Reviewer comments in blue, authors response in black

Anonymous Referee #2

Received and published: 21 February 2020

The authors provided an interesting manuscript on a topic that has strong relevance for actual societal problems in Vietnam and likely beyond. A seemingly novel method for long-term forecasting of salt water intrusion in cultivated lowland areas is presented, which could provide useful early warning information for damage control in agricultural production. Statistical tests by the authors result in good confidence of model performance, leading to recommendations for wider application. However, a precise idea of the actual added value of the proposed model is not communicated clearly enough, due to several reasons. These are discussed in detail below, but can be summarised as a lack of description of similar existing models, the description of input data used, and the limited possibility for model adoption due to a limited description of the model itself and data requirements. In addition, certain aspects of style, grammar, accuracy of statements and embedding in literature should all be improved in order to achieve an appropriate quality for scientific publishing with this high-profile journal.

Nonetheless, the reviewer believes there is strong potential in the manuscript (especially due to the apparent societal demand for the model); and as such, a major revision is recommended with strong encouragement for follow-up by the authors. In order to allow improvements on the remarks made by the reviewer, a long but practical list of suggestions are provided in this document (general and specific comments), as well as in the marked manuscript document (single-word suggestions).

We sincerely thank the reviewer for the overall general feedback of our work, and the constructive comments for improvement of the manuscript. This is highly appreciated. We reply to the reviewer comments below.

General comments: The abstract is rather concise, and although this can be appropriate regarding the total length of the article, perhaps a few pieces of information could be inserted. For instance, the authors could improve the technical aspect of the abstract by briefly describing the type of data that predictions are nested in (i.e. drought or ENSO indices), or by providing some quantification to support the claim for "high skill".

We included some quantification of the data used and quantification of skill in the abstract, while keeping its length in the limits of an NHESS brief communication (100 words). This is the new abstract:

"The Mekong Delta is the most important food production area in Vietnam, but salinity intrusion during the dry season poses a serious threat to agricultural production and livelihoods. A seasonal forecast of salinity intrusion is required in order to mitigate the negative effects. This communication presents a statistical seasonal forecast model based on Logistic Regression using either the ENSO34 index or Streamflow as predictor. The model is able to predict the salinity intrusion up to 9 months ahead with high skill (ROC scores > 0.8). The model can thus be used operationally as a basis for timely adaptation and mitigation planning."

The introduction section (chapter 1) clearly emphasises the importance of forecast models with an extended lead time (i.e. months rather than weeks). However, it is unclear whether such models already exist, and thus what is the novelty of the existing work. The authors should dedicate a few lines nested in scientific references to clarify this point, and thus to justify the relevance of their own contribution. In general, the use of literature is quite marginal in the manuscript, and embedding the proposed research in the scientific context is an integral part of scientific writing.

Thanks for pointing at the issue of novelty. In fact, publications dealing with forecasts of salinity intrusion in the Mekong Delta do not exist. This holds true for both short-term or seasonal forecasts. That was the reason for the missing references. The presented study is thus a novel work in this regional context, but also beyond. Publications about forecast models of salinity intrusion are rather scarce in general. There are just a few papers dealing with this issue. All of them apply different methods to the method presented in this study. The approaches of other studies are a) hydrodynamic modelling of salinity intrusion and the coupling of these models with meteorological and tidal forecast models (Risley et al., 1993), b) the use of Artificial Neural Networks (Lu and Chen, 2010;Roehl Jr. et al., 2013), c) kernel-based support vector machine (Rohmer and Brisset, 2017), and d) power law models derived from hydrodynamic models (Etemad-Shahidi et al., 2008). Logistic regression has to our knowledge never been used for salinity intrusion forecasts. Moreover, a seasonal forecast of salinity intrusion, i.e. a forecast with several months lead time, has not been published before. The presented work is thus also novel in this aspect. The use of ENSO as direct predictor also seems to be a novel aspect of the work, because relevant publication were not found. In the revised version of the manuscript, we will clearly underline these novelty aspects of the work. However, we will also take care to keep the number of citations in the allowed maximum number for a brief communication.

But besides publications in scientific literature, salinity forecasts are performed in Vietnam on an operational basis by the National Centre for Hydro-Meteorological Forecasting (NCHMF), and the Southern Institute of Water Resources Research (SIWRR). Both forecasts are based on a chain of hydrological and hydraulic models, which are fed by precipitation and tidal forecasts. The forecasts of NCHMF are short termed, i.e. with a lead time of 10 days. The forecasts of SIWRR cover also longer lead times up to a maximum of two months. The core of the forecast model of SIWRR is described in Toan (2014), but not the operational application. Because of the longer lead times and the low data requirements, the presented method is a valuable addition to the operational salinity forecasts, and can be easily ingested into the operational forecast schemes. Note that two of the co-authors are the responsible persons for the salinity forecasts at NCHMF and SIWRR, therefor a clear statement can be made in this regard.

In the meantime, the proposed forecast model has been tested by forecasting the salinity intrusion in the dry season of 2019-2020. Using the ENSO34 index of April 2019 the model predicted a probability of exceedance of 0.98 for the 3 g/l threshold of the mean salinity in February-March 2020, and a probability of 0.8 for an exceedance of the 4 g/l threshold. The forecast after the flood season using SSI3 in November and December gave probability of exceedance of the 4 g/l threshold of 0.95. This means the model predicted a severe salinity intrusion with high confidence. The actual salinity intrusion in the Mekong Delta is currently (start of March 2020) indeed very high, reaching levels as high or even more extreme than during the record salinity intrusion of 2015-2016 (MARD, 2020;UN Vietnam, 2020). This means that the current salinity intrusion in the Mekong delta could have been forecasted about nine months in advance. We suggest to add a paragraph highlighting this model validation in the discussion section.

The description of methodology (chapter 2) deserves some critical attention to ensure an appropriate description of processes, used data, and analysis methods. The reviewer

refers to the marked manuscript as well as the specific comments provided below for all of these points.

This point was also raised by reviewer 1. We will elaborate the method and the required data in more detail in the revised manuscript. The description of the method in the main text of the manuscript will be extended as follows, accompanied with some analytical plots/data analysis in the foreseen supplement.

Method description:

The forecast model is based on a Logistic Regression (LR), i.e. a linear statistical model for relating categorized values to continuous, real-number type predictors (Menard, 2009). The categories to be predicted by the regression are the mean FebMar salinity values falling in the categories above or below the defined salinity thresholds. The continuous predictors are the monthly ENSO and Standardized Streamflow Indices (SSI) values. For this kind of regression LR is the appropriate tool. LR is very flexible in its application, because it is not limited to normally distributed predictors, as e.g. the Linear Discriminant Analysis (Pohar et al., 2004). Regression models were developed with a single predictor using either ENSO indexes or SSI, following the causal chain leading to salinity intrusion in the MKD described above. The ENSO indexes tested were monthly ENSO1, ENSO3, ENSO4, and ENSO34 indexes. All of these indexes aim at representing the state of the El Niño Southern Oscillation by considering sea surface temperatures at different regions of the Pacific Ocean. Among these indices ENSO34 is regarded as the most appropriate sea surface temperature index representing the general state of the ENSO (Bamston et al., 1997). The testing of different indexes aims at the identification of the most robust predictor for salinity intrusion in the MKD. All of the ENSO indexes used in the forecast models start in April of the year before the dry season, i.e. with a lead time of up to 9 months before the start of the forecasted FebMar time period. For the streamflow predictors, the monthly discharges recorded at station Tan Chau, which is located about 100 km upstream of the salinity monitoring station Son Doc (Figure 1), were transformed into SSI. This transformation is similar to transforming precipitation into Standardized Precipitation Indexes (SPI), as typically done in drought studies and drought definitions (Mishra and Singh, 2010). SSI has been already applied in seasonal forecast studies, e.g. for predicting streamflow in Southern Africa (Seibert et al., 2017). SSI normalizes the monthly discharges by fitting a Gamma distribution to the observed long-term record of discharges (here from 1980 – 2016) and transferring it in a normal distribution with a mean of 0. An SSI value of 0 indicates thus the normal hydrological state, while negative values indicate a water deficiency. SSI has the advantage that a drought condition can be directly recognized by the SSI value, and that the prediction models can be easier transferred and compared to other gauging station with different streamflow magnitudes. Another strength of SSI is that it can be calculated for a variety of time scales. This is important, because droughts usually manifest over extended time periods. SSI was thus derived for different time scales ranging from 1 month (SSI1) to 6 months (SSI6), each starting in June prior to the dry season, i.e. with a maximum of 7 months lead time. The calculation of SSI was performed with the R-package SPEI (Vicente-Serrano et al., 2012). Table S1 in the supplement provides a list of all predictors used in the detection of the best performing forecast models.

The Logistic Regression models were fitted by iteratively reweighted least squares using the Rfunction *glm* for a binomial model type, which represents the Logistic Regression. A fitted LR model provides estimates of the probability of exceedance of the defined salinity thresholds depending on the predictor value. One model was fitted for all predictors and lead times, and the best performing ENSO and SSI predictors for the different lead times were manually selected according to the following criteria:

- The Receiver Operator Characteristic (ROC) score (Mason, 2008).
- The Akaike Information Criteria (AIC) (Burnham and Anderson, 2004).

- The Cragg and Uhlers (also known as Nagelkerke) Pseudo-R² (Nagelkerke, 1991), which is defined for categorical variables analogously to the normal R² for continuous variables.
- The accuracy (rate of correct forecasts).

In order to test the robustness of the linear models a Leave-One-Out Cross validation (LOOCV) was also performed, as in Apel et al. (2018) for forecasting seasonal streamflow in Central Asia. A robust model is characterized by a model, for which the performance values of the LOOCV do not deteriorate compared to the performance of the model using the full data set. In addition to the performance criteria listed above for the full model, the ROC scores and accuracies of the LOOCV were also used for the selection of the best models. The LR models estimate

With regards to the results (chapter 3), the authors seem to present a robust set of statistical testing for findings optimal predictors. In the final lines of this chapter, an interesting point is made about the validity of ENSO-based predictions (optimal on long-term) and SSI-based predictions (optimal for short-term). Was any performance testing done where the two indices were combined, as an "optimised predictor"? If not, the authors may discuss the possibilities for this in future explorations. In addition, chapter 3 in its current form does not provide any discussion with regards to previous scientific works (e.g. regarding other long-term forecasting models), but is mostly restricted to "results".

Preliminary tests have been conducted using both indices at the same time in a Multinomial Logistic Regression as a forecast model. The results did not improve compared to the presented models. This has two reasons:

1. The forecast were already quite good with the single predictors for long-term and short-term forecasts. Therefor there was little room for improvement.

2. The less performing forecasts during the flood seasons did not improve substantially. This can be explained by the hydrological rational outlined in the manuscript. The ENSO index has a meaning for the monsoon strength and thus the discharge during the flood and following dry season only in the months before the monsoon/flood season. During the monsoon season the actual state of the ENSO looses importance for the ongoing monsoon. The discharge measured after the flood season is on the contrary a good indicator for the overall dry season flow and thus salinity intrusion. During the flood season both predictors have limited predictive power for the dry season discharge, therefore a combination does not improve the forecast.

Following this rational, a third predictor indicating the rainfall over the Mekong basin would likely have better predictive power then ESNO and SSI during the flood season. Therefor we argue that a reasonable mid-term forecast of salinity intrusion in the dry season is likely best achieved using rainfall sums over the Mekong basin over the monsoon season, i.e. June to September/October. However, in order to provide forecast in a timely manner, a near-real time rainfall monitoring product should be used for this. The telemetric ground-based rainfall monitoring network of the Mekong River Commission could be one option, or a near-real time satellite product. The TRMM-based Multi-satellite Precipitation Analysis (TMPA / 3B4x) with its latency of 1-2 month might be an option worth testing. We will include this point of extension of the forecast model in the discussion.

In the conclusions section, potential application of the proposed model is well described and its wider use is encouraged. However, the requirements with regards to data availability are not entire clear. The authors mention that data availability should be "sufficient", but do not specify or quantify what is the required coverage of flow data and the expected impact on prediction accuracy. This actually links back to the method- ology section of the manuscript, where a quantification of data coverage in the presented study is missing as well. More clarity is required on this topic, both in described methodology and in recommendations for future applications.

We will be more specific with regards to the data requirements and transferability of the model. In short, in order to transfer the model to different locations, a continuous time series of salinity and discharge measurement is required (the ENSO index is readily available from public sources). The length of the time series should be sufficiently long for robust model fitting. There is no general rule for a sufficient length, but based on personal experience a time series covering a minimum of 15 dry season should be used. If it is less, the chances for model overfitting and spurious results are quite high. This recommendation will be added to the conclusion section.

Specific comments:

- Page1,Line7: While acknowledging the Mekong Delta as the most important Vietnamese food production area, the value of this zone with regards to agriculture and food security could be more strongly emphasised by adding two pieces of information: (1) the fraction of rice production out of total (staple) food production in Vietnam; (2) the importance of "nationally produced" food vs. imported food with regards to food security (or possibly exported value). A second line including such information would create a more solid argument as to the context of salt water intrusion and its negative impacts.

The Mekong delta is, as mentioned, the key food production area of Vietnam. In 2018, rice production was about 23.5 million tons (56% of the total production in Vietnam), 0.673 million tons of shrimp (70% of Vietnam total), 1.41 million tons of catfish (95% of Vietnam total) and 4.3 million tons of fruits (60% of Vietnam total). The total agriculture export value of the Mekong delta amounts to 8.43 Billion US dollars. This is 20% of the overall total agricultural exports of Vietnam (Son, 2020). We will add these information to the revised manuscript.

- P1,L19: Is indeed the frequency of droughts, rather than the likely duration of the most severe drought (period), the major manifestation of climate-induced intrusion?

It is both. The severeness as expressed by longer durations and higher intensities (i.e. low discharges and higher salinity levels in this context), as well as the higher frequency of droughts/salinity intrusion. Both factors are a consequence of sea level rise and climate change. In order to emphasis this, the sentence is changed to:

"Sea level rise and climate change aggravate this problem causing more severe, longer lasting, and more frequent droughts, with the consequence of more severe (longer lasting and higher salinity levels) and more frequent salinity intrusions during the dry season..."

- P1,L20: "... agricultural production system and peoples livelihood developed over historical periods and thus adapted to normal intensity of salinity intrusion (...)". This sentence reads slightly unclear and could likely be simplified, e.g. as ". . .agricultural production systems and livelihoods over time adapted to a given intensity of salinity intrusion (...)"

Changed as suggested.

- P1,L23: please specify "unprecedented high salinity intrusion"; i.e. was the 2015/2016 event characterised by the time duration of salinity issues, or rather its concentration, or the groundwater depth in which salt water was found, or measured in terms of agricultural losses, etc. etc.

"Unprecedented high salinity intrusion" is defined by salinity levels, duration and extent of salinity intrusion. In order to clarify this, the sentence will be changed to:

"This unprecedented severe salinity intrusion, which manifested by the earliest onset of high salinity levels, the highest observed salinity measurements in most estuaries of the Mekong, and the longest duration and the deepest penetration of saline water in the river system ever observed, caused...."

- P1,L29: the current figure fails to show what are "coastal areas of the delta" or rather landlocked areas (also see multiple comments posted in the PDF version of Figure 1). Please modify the map accordingly.

Figure 1 was completely re-worked. See the new figure in the answer to the specific comments on Figure 1 below.

- P1,L29: please provide the percentage of this economic damage in respect to total value of national agricultural production for reference.

We set the damage in relation to the national GDP of the agriculture, fishery and forestry sectors, as provided by the General Statistics Office of Vietnam. The damage accounts for 0.74% of the GDP in these sectors in 2016.

- P2,L35: is terming saltwater intrusion as agricultural drought an original idea by the authors, or has this been defined as such before by the scientific community (if the latter, please provide appropriate referencing).

To our knowledge this is an original definition by us. There are a few standardized drought indices available, but all refer to physical water availability, not water quality. Other studies used additional factors for defining agricultural droughts, but we could not find a study using salinity of irrigation water for a drought definition. In order to make this clear we rephrased the text as follows:

"Therefor salinity intrusion in the Mekong Delta can be termed as agricultural drought. The general definition of agricultural drought is a situation, in which plant water demands cannot be satisfied by water availability (Mannocchi et al., 2004;Mishra and Singh, 2010). By terming salinity intrusion an agricultural drought we hereby extend the definition of water availability from a pure physical, quantitative view to a water quality perspective. This agricultural drought is a serious hazard for large parts of the population, for which agriculture is still the basis of its livelihood."

- P2.L40: please clarify what type of "flow" data is required for these hydrological models.

Flow means daily river discharges. The text is changed accordingly.

- P2.L44: please clarify what is meant by "rainfall anomalies deficiencies"

This is an error, thanks for spotting it. Negative rainfall anomalies (or rainfall deficiencies) is meant. The sentence is changed to:

"A drought such as in 2016 is expected to occur more often in future, as negative rainfall anomalies occurring with El Nino events are expected to occur more frequently..."

 P2.L45: please rephrase the following sentence while using correct usage of verbs and grammar: "Additionally sea levels around the Mekong Delta continue to rise (Smajgl et al., 2015), thus causing increasing backwater effects restricting the discharge during the dry

season and consequently promote salinity intrusion."

The sentence is changed to:

"Moreover, sea levels around the Mekong Delta are rising and are expected to rise further in future (Smajgl et al., 2015). Rising sea levels cause increasing backwater effects in the river channels, and thus promote salinity intrusion during the dry season."

- P2.L54: "whereas" suggests a contradiction between the previous and following sentence parts, but this is not the case. Please rephrase.

The sentence is changed to:

"The climate and hydrology of the Mekong Delta and Mekong basin are dominated by the monsoonal climate, separating the hydrological year into distinct rainy/high flow and dry/low flow seasons. The hydrological regime lags the climate regime depending on the location in the basin."

- P2.L54: in addition, this is an unnecessarily long sentence that could easily be split into two.

See answer above.

- P2.L61: this statement is hydrologically disputable: if the authors are describing the long-term processes that connect monsoon rainfall and river flow that follows weeks/months later, "runoff" seems the wrong terminology. Where the latter describes the fast process of overland flow, the former is generally related to processes of infiltration, groundwater processes and surface water buffering such as retention.

In order to avoid definition problems, the sentence is re-phrased to:

"In the delta of the Mekong this lag is most noticeable due to the time required for transforming rainfall in the about 800,000 km² large basin to river discharge and routing the discharge to the delta."

- P3.L77: "The salinity intrusion in the Delta is measured by the hydro-meteorological services. . . . ": Firstly: how is this being measured (what instrumentation)? Secondly: please clarify "services" that are measuring the process.

The salinity is measured by collecting water samples, which are then analyzed in the laboratory. The "services" we refer to is actually the Southern Regional Hydro-Meteorological Center (SRHMC), which is the official agency for collecting this data. We will change the sentence accordingly in order to avoid misunderstanding.

- P3.L78: "The measurements are, however, not continuous, but typically performed for several days in a row, with some days without measurements in between." Are there any conditions that determine whether measurements are taken (such as high expected intrusion)? This may create a bias in measurements, which should be discussed by the authors.

Salinity measurements are performed at 39 locations in the Mekong Delta during the dry season, starting in January until June (until 2013 the measurements started in February). The measurements are taken in mid-river at 0.2, 0.5 and 0.8 of the water depth. The reported salinity is the mean of these three measurements. If the water depth is below 3 m, only one sample is taken at 0.5 of the depth. Due to constraints in personal and monetary resources,

the monitoring is, however, not time continuous. The general scheme is to measure 2-3 days in a row at 2 hours intervals (i.e. 12 measurements per day). This measurement period is followed by a 2-4 days without measurements, after which the monitoring resumes. The exact monitoring scheme is defined for each monitoring location individually, depending on the hydrodynamics and the tidal regime. Because of the different sampling schemes per station (and possibly also per year) it is difficult to describe the monitoring and the resulting salinity time series in a general way. In the revised manuscript we would thus present the salinity time series of the gauging station Son Doc, which was used for the development of the forecast models.

The following figure shows the time coverage of salinity measurements at Son Doc:



salinity data coverage Son Doc

Every dot represents a day with measurements, i.e. 12 samples at 2-hour intervals. The figure shows that the measurements are almost similarly distributed during February and March (the gray shaded area) in the different years. The mean salinity in February and March, which is the predictand of the forecast model, is calculated from these 2-hourly measurements.

The mean number of samples in February and March from 1997 - 2016 is 310 samples with a standard deviation of 38. These sample statistics along with the similarity of the temporal sampling shown in the figure above means that the sampling schemes (in terms of numbers and schedule) of the individual years are well comparable, and a bias caused by the sampling scheme is unlikely. The exception is the year 1996, which has continuous measurements without breaks. In order to test a possible bias in the 1996 data in relation to the other years, the 1996 data was resampled 1000 times with the mean number of samples of the other years (i.e. 312 samples of 719 samples in February-March 1996). The resampled mean FebMar salinity in 1996 is 3.28 g/l, which is practically identical to the mean of all samples (3.27 g/l). Therefor we can reject the assumption of a bias in the data introduced by the sampling scheme.

We will explain the sampling in short in the main part of the revised manuscript, and add the figure and statistics outlined above in the supplement.

- P3.L81: "The salinity measurements covered the time span 1996 – 2016": please specify whether this was a 100% coverage or provide another grounded estimate.

Yes, the time series is continuous, i.e. it covers all dry seasons in the time span 1996 – 2016. An according statement was inserted in the paragraph. Details of the sampling are provided in the reply to the previous comment, and will be added in a supplement to the manuscript.

- P3.L85: what is the reference for this salinity threshold? Please clarify sources (same in L90).

This threshold is used by the authorities in Vietnam for warnings of a severe salinity intrusion. It is always stated in governmental reports of salinity intrusion. Therefor this threshold was primarily selected, in order to enable a comparison with official short term forecast and to raise the acceptability of the model within the governmental agencies of Vietnam.

Moreover, the 4 g/l threshold can be correlated to studies showing significant decreases in crop yield or even crop failures with higher salinity levels (Grattan et al., 2002;Kotera et al., 2014;Zeng and Shannon, 2000;Zeng et al., 2001). In order to clarify this, the sentence is changed as follows, including a reference to a study analyzing the effect of salinity on rice crop growth and yield:

"For paddy rice a salinity of the irrigation water exceeding 4 g/l is generally regarded as too high for the plants to survive during the vegetative stage by the authorities in Vietnam (compare Zeng and Shannon, 2000)."

- P4.L96: what do these ENSOxx indices represent, and how is the selection of these particular indices justified?

We added some lines explaining the different ENSO indexes. However, we will not provide an extended explanation and discussion of the indexes, because they are described in numerous papers and even in many internet resources, e.g. from the US National Oceanic and Atmospheric Administration (NOAA). The text section will be changed to:

"The ENSO indexes tested were monthly ENSO1, ENSO3, ENSO4, and ENSO34 indexes. All of these indexes aim at representing the state of the El Niño Southern Oscillation by considering sea surface temperatures at different regions of the Pacific Ocean, whereas ENSO34 is regarded as the most appropriate sea surface temperature index representing the general state of the ENSO (Bamston et al., 1997). The testing of different indexes aims at the identification of the most robust predictor for salinity intrusion in the MKD. All of the ENSO indexes used in the forecast model start in April of the year before the considered dry season, i.e. with a lead time of up to 9 months before the start of the forecasted FebMar time period."

- P4.L109: please provide adequate sources for reference with regards to statistical methods applied (throughout L106-109).

The methods and goodness-of-fit measures are very standard statistical methods and can be found in any good statistical handbook. However, we added references as examples, as already listed in the reply to the request for an extension of the method description above. The references to the performance criteria read now:

"One model was fitted for all predictors and lead times, and the best performing ENSO and SSI predictors for the different lead times were manually selected according to the following criteria:

- The Receiver Operator Characteristic (ROC) score (Mason, 2008).
- The Akaike Information Criteria (AIC) (Burnham and Anderson, 2004).
- The Cragg and Uhlers (also known as Nagelkerke) Pseudo-R² (Nagelkerke, 1991), which is defined for categorical variables analogously to the normal R² for continuous variables.
- The accuracy (rate of correct forecasts)."

- P6.L174: the meaning of the final part of the final sentence is not very evident. This vague statement contrasts the practical and specific recommendations made in the previous sentences. Please rephrase for clarity.

We will rephrase the final sentence to: "Mitigation actions should include negotiations with the riparian countries aiming at an adaptation of the operation schedule of reservoirs in the Mekong basin in order to maintain sufficient flow during the dry season."

We will, however, change the context of the sentence, because the statements before about the expected severe salinity intrusion are already outdated, as the dry season 2020 is already ongoing. We suggest, as stated in a previous reply above, to include the model forecast of the dry season 2020 and the ongoing salinity intrusion as model validation. The statement of early negotiations among the Mekong riparian countries based on the long-term forecast will follow this validation.

- Figure 1: major revision recommended with regards to style, intuitiveness and clarity, see marked manuscript document for all comments.

Many thanks for the thorough and critical review of the figure. The comments were all ingested, resulting in the new Figure 1 shown below:



Figure 1: Overview map of the study area Mekong Delta. Top left: Regional overview showing South-East Asia with the Mekong basin and delta, and the neighbouring countries. The background country, ocean and topography maps are made with Natural Earth (Free vector and raster map data @ naturalearthdata.com). Bottom: The Vietnamese part of the Mekong Delta with the location of the main official and permanent hydrometeorological monitoring stations and the salinity monitoring station Son Doc. The land use map of the Mekong Delta as in 2010 is shown as reference illustrating the different land use types in the different regions of the delta. The map was derived at 500m resolution from Moderate Resolution Imaging Spectrometer satellite (MODIS) images (Source: Catch-Mekong Knowledge Hub, https://catchmekong.eoc.dlr.de/Elvis/, provided by the German Aerospace Center DLR. The method of land use classification is described in Leinenkugel et al. (2013)).

Technical corrections: See marked manuscript attached for any technical corrections related to wording or style.

All the comments will be considered in the revised manuscript.

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Brief communication: Seasonal prediction of salinity intrusion in the Mekong Delta

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- 10 Abstract. The Mekong Delta is the most important food production area in Vietnam. Salinity, but salinity intrusion during the dry season poses a serious threat to agricultural production and local livelihoods. A seasonal forecast of salinity intrusion is required in order to mitigate the negative effects. This communication presentpresents a simple statistical seasonal forecast model based on Logistic Regression using either the ENSO34 index or Streamflow as predictor. The model is able to predict the salinity intrusion up to 9 months ahead with high skill-(ROC scores > 0.8). The model can thus be used operationally as a
- 15 basis for timely adaptation and mitigation planning, which is urgently needed for the imminent severe salinity intrusion expected in spring 2020.

1 Problem setting

- The Mekong Delta (MKD) is the most important food production area in Vietnam, responsible for about 560% of the rice production of Vietnam aloneand 20% of the agricultural exports of Vietnam as a whole (source: General Statistics Office of Vietnam (GSO), http://www.gso.gov.vn). As a low lying coastal area in a monsoonal climate with distinct wet and dry season it is naturally prone to salt water intrusion into the river and channel network during the dry low flow season. Sea level rise and climate change aggravate this problem causing increasingmore severe, longer lasting, and more frequent droughts, with the consequence of more severe (longer lasting and consequenthigher salinity intrusionlevels) and more frequent salinity intrusions during the dry season (Smajgl et al., 2015). While the The current agricultural production systemsystems and peoples
 livelihood developedlivelihoods over historical periods and thustime adapted to normala given intensity of salinity intrusion, but these changes pose a serious threat to the agricultural production and livelihood of the population. A drastic example of the immense negative effects of a strong salinity intrusion is the dry season of 2015/2016. This unprecedented high salinity intrusion, which manifested by the earliest onset of high salinity levels, the highest observed salinity measurements in many places, the longest duration and the deepest penetration of saline water in the river system ever observed, caused widespread
- 30 crop losses throughout the delta. 9 of Of the 13 provinces in the Mekong Delta, 9 were affected by severasevere salinity

intrusion, all provinces were affected by water shortageshortage (Nguyen, 2017). Approximately 400,000 ha of cropland were subject to saline irrigation water, of which 238,276 ha were paddy rice fields. The salinity intrusion also affected 6,575 ha of vegetables, 29,277 ha of fruit trees and 79,000 ha of aquaculture, mainly of brackish water shrimp. Figure 1 provides an overview of the land use in the Mekong Delta, as observed and classified in 2010 by satellite remote sensing. It illustrates

- 35 roughly the main affected cropping types in the coastal areas of the delta. The overall economic damage amounted to 5,500 billion VND, equivalent to about 236 million US\$-\$ and 0.74% of the National Gross Domestic Product of the agriculture, fishery and forestry sectors in 2016 (source: GSO). Furthermore the Vietnamese National Steering Center for Natural Disaster Prevention and Control reported that 194,000 households lacked freshwater for domestic use in the Mekong Delta (VDMA, 2016).
- 40 The main damaging effect is the lack of fresh water required for irrigation of rice paddies, but also of fruit orchards and vegetable farming. Because of this lack the <u>The</u> crops <u>are damaged or even</u> die either by lack of water, or by the adverse effects of high salt concentration in the irrigation water. <u>Therefor Because of this</u> salinity intrusion in the Mekong Delta can also be termed as agricultural drought and is a serious hazard for large parts of the population, for which agriculture is still the basis of its livelihood. because the general definition of agricultural drought is a situation, in which plant water demands cannot be
- 45 satisfied by water availability (Mannocchi et al., 2004;Mishra and Singh, 2010). By terming salinity intrusion an agricultural drought we hereby extend the definition of water availability from a pure physical, quantitative view to a water quality perspective. This agricultural drought is a serious hazard for large parts of the population, for which irrigation-based agriculture is still the basis of its livelihood. An important factor for the large damages were the lack of appropriate mitigation plans, and a timely early warning of the serious salinity intrusion in order to prepare and adapt the agricultural practices for damage
- 50 reduction.

However, studies and publications dealing with direct forecasts or early warning of salinity intrusion in the Mekong Delta do not exist. This holds true for both short-term or seasonal forecasts. The presented study is thus a novel work in this regional context, but also beyond. Publications about forecast models of salinity intrusion are rather scarce in general. There are just a few papers dealing with this issue. All of them apply different methods to the method presented in this study. The approaches

- 55 of other studies are a) hydrodynamic modelling of salinity intrusion and the coupling of these models with meteorological and tidal forecast models (Risley et al., 1993), b) the use of Artificial Neural Networks (Lu and Chen, 2010;Roehl Jr. et al., 2013), c) kernel-based support vector machine (Rohmer and Brisset, 2017), and d) power law models derived from hydrodynamic models (Etemad-Shahidi et al., 2008). The approaches applied in these studies are quite complex and require an extensive set of data and models.
- 60 <u>However</u>, operational <u>f</u>Forecasts of salinity intrusion in the Mekong Delta is provided by the Southern Regional Hydro-Meteorological Center SRHMC. Those are made by the National Centre for Hydro-Meteorological Forecasting (NCHMF), and the Southern Institute of Water Resources Research (SIWRR) under the authority of the Ministry of Agriculture and Rural Development (MARD). The forecasts are provided to MARD and distributed among governmental agencies and provincial governments in the MKD. Both forecasts are based on a complex chain of hydrological and hydraulic models, which are fed

- 65 by precipitation and tidal monitoring data and forecasts. The forecasts of NCHMF are short termed, i.e. with a lead time of 10 days and are issued on a regular basis every 5-10 days. The forecasts of SIWRR cover also longer lead times up to a maximum of two months. The core of the forecast model of SIWRR is described in Toan (2014). -forecasts are based on a complex chain of hydrological models, thus requiring a large amount of input data and computational demand. Those forecast require flow and rainfall data until the end of October, thus enabling lead times of 4.6 weeks to the planting of the winter crops only. This
- 70 lead time is, however, too short to plan and adapt the cropping system well ahead of the drought event. Forecasts with lead times of several months are required to change the cropping system and to prepare for the crop during the dry (December to April) season.

A drought such as occurred in 2016 is expected to occur more often in the future, as negative rainfall anomalies deficiencies occurring with El Niñno events are expected to occur more frequently (Azad and Rajeevan, 2016). Additionally Moreover, sea

75 levels around the Mekong Delta continueare rising and are expected to rise further in future (Smajgl et al., 2015), thus causing. <u>Rising sea levels cause</u> increasing backwater effects and reverse flow restrictingin the discharge during the dry seasonriver channels, and consequentlythus promote salinity intrusion during the dry season. The 2016 event was a wake-up call for the society and officials in Vietnam, as it proved that large structural problems in drought management and mitigation exist. In order to support disaster management this study aims at the development of a reliable and simple salinity intrusion forecast

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system enabling lead times of several months, and thus a better <u>early warning</u>, adaptation to and mitigation of the adverse <u>impacts of to</u> salinity intrusion and agricultural droughts in the Mekong Delta.

2 Hydrology, data and method

The climate and hydrology of the Mekong Delta and Mekong basin are dominated by thea monsoonal climate, separating the hydrological year into distinct rainy/high flow and dry/low flow seasons, whereas the. The hydrological regime lags the climate 85 regime depending on the location in the basin. In the Mekong Delta this lag is most noticeable due to the time required for transforming rainfall in the about 800,000 km² large basin into runoff formation and discharge concentration in the basin and routing to the delta. The lag time in the delta between onset and end of rainy and flood season can be up to 2 months. This lag time opens the possibility of a hydrological forecast, i.e. flow magnitude, by anteceding discharge in general. In fact, anteceding discharge is still the main predictor for the flow forecast published by the Mekong River Commission MRC 90 (Shahzad and Plate, 2014). Moreover, the dry season discharge in the Mekong Delta crucially depends on the runoffto river discharge and routing the discharge to the delta. The lag time in the delta between onset and end of the rainy and flood season can be up to 2 months. Moreover, the dry season discharge in the Mekong Delta crucially depends on the discharge generated in the Mekong basin, which is in turn depending on the amount of rainfall in the basin during the monsoon period, i.e. depending on the monsoon intensity (Delgado et al., 2012). discharge in the Mekong basin and delta is highly correlated to the 95 monsoon intensity (Delgado et al., 2012; Räsänen and Kummu, 2013). The SE-Asian monsoon intensity is itself determined by the periodically changing sea surface temperatures in the western central Pacific Ocean (West Pacific Warm Pool),

associated with the El NinoNiño Southern Oscillation (ENSO-). Of particular importance for the monsoon strength is the situation of ENSO in winter and spring prior to the monsoon season, when the general circulation and moisture fluxes for the monsoon season are initiated (Ju and Slingo, 1995). Strong events of the South-East Asia monsoon are associated with La

- 100 Niña events, while weak monsoons and thus higher chances of salinity intrusion intrusion in the dry season are associated with El Niño events (Ju and Slingo, 1995). Therefore, the followinga general causal chain for dry season discharge and thus salinity intrusion in the Mekong Delta can be formulated as follows: ENSO determines the intensity of the SE-Asian monsoon, the monsoon intensity determines the rainfall amount over the Mekong basin, the rainfall amount determines the flood season discharge, the flood season discharge is itself indicative for the following dry season discharge, and the dry season discharge 105 determines controls the salinity intrusion into the Mekong delta.
- This general causal chain forms the basis for the simple salinity intrusion forecast model presented in this study. FirstFirstly, an early forecast will be attempted utilizing ENSO indexes as predictor. Secondly, an additional forecast will be tested using flood season and early dry season discharge as predictor. Monthly ENSO indexes were collected from the Asia PacifiePhysical Sciences Division (PSD) of the Earth System Research Centre in HawaiiLaboratory (ESRL) of the National Oceanic and 110 Atmospheric Administration (NOAA) (http://apdre.soest.hawaii.edu/projects/monsoon/dailydata.html/montar).https://www.esrl.noaa.gov/psd/data/climateindices/list/). Furthermore, monthly discharge data were collected from the Southern Regional Hydrometeorological Center (SRHMC) for the gauging station Tan Chau-in the Vietnamese part of the Mekong Delta, situated_located at the Mekong (Tien in Vietnam) branch of the Mekong in the Delta (Figure 1). The salinity intrusionof surface water in the DeltaMKD is also_measured by the hydro-meteorological 115 servicesSRHMC, but during the dry season only. Salinity is monitored at 39 locations in the MKD, and is determined by
- collecting water samples in mid-river at 0.2, 0.5 and 0.8 of the water depth. The samples are analysed in the laboratory, and the reported salinity is the mean of these three measurements. If the water depth is below 3 m, only one sample is taken at 0.5 of the depth. Due to constraints in personal and monetary resources, the monitoring is, however, not time continuous. The general scheme is to measure 2-3 days in a row at 2 hours intervals (i.e. 12 measurements per day). This measurement period
- 120 is followed by a 2-4 days without measurements, after which the monitoring resumes, at several non-permanent gauging location in the Mekong Delta usually at 2 hour intervals. The measurements are, however, not continuous, but typically performed for several days in a row, with some days without measurements in between. The longest-salinity time series used in the model development was recorded at of these measurements was available for-gauge Son Doc in Ben Tre province in the estuary of the Mekong (Tien) river branch (Figure 1). Son Doc is located about 175 km downstream of the gauge Tan Chau,
- 125 and about 24 km upstream of the river mouth (Figure 1). -The salinity measurements covered all dry seasons in the time span 1996 2016. The temporal coverage of the salinity measurements at Son Doc is shown in Supplement S1. In order to derive a meaningful predictand of salinity intrusion, the mean salinity of February and March (FebMar) was calculated from the available salinity measurements. This aggregation time period was chosen, because it coincides with the vegetative stage of irrigated paddy grown during the dry season, which is the most sensitive phase of paddy rice to high salinity levels (Kotera et al., 2014).(Zeng et al., 2001).

The envisaged seasonal forecast of salinity intrusion does not aim at forecasting the exact mean salinity intrusion of this period, but rather at forecasting the probability of <u>exceedance of</u> critical levels of salinity intrusion-are likely to be exceeded. For paddy rice a salinity of the irrigation water exceeding 4 g/l is seen as too high for the plants to survive during the vegetative stage-by the authorities in Vietnam as too high for the plants to survive during the vegetative stage (compare Zeng and Shannon,

- 135 2000). Thereforce a mean salinity of 4 g/l during February and March (FebMar) is adopted as critical salinity level for the forecast model. The mean salinity threshold during this period means that this threshold will be exceeded at 436% of the time, considering the negative exponential distribution of the data (cf. Supplement S2), and assuming that the discontinuous measurements are representative for the whole time period. In addition to the critical salinity level a threshold of 3 g/l mean FebMar salinity is used as predictand. This threshold is exceeded at 536% of the time in February and March (cf. Supplement)
- 140 S2) and serves as a warning threshold, indicating a strong salinity intrusion with chances of salinity also exceeding 4 g/l at times. Rice irrigated with this salinity threshold might survive depending on the duration of the irrigation with saline water, but losses in crop yield have to be expected (Grattan et al., 2002;Zeng and Shannon, 2000). The forecast model is based on a Logistic Regression (LR), i.e. a linear statistical model for relating categorized values to

continuous, real-number type predictors (Menard, 2009). LR has to our knowledge never been used in forecasting salinity intrusion. Moreover, a seasonal forecast of salinity intrusion, i.e. a forecast with several months lead time, has not been

published before. The presented work is thus also novel in this aspect. Compared to the published approaches of salinity intrusion listed in the introduction and the model chains used for the operational forecasts, forecasting with LR is a very simple and data-sparse approach.

The categories to be predicted by the LR are the mean FebMar salinity values categorized in bins above or below the defined

- 150 salinity thresholds (4 g/l and 3 g/l). The continuous predictors are monthly ENSO indexes and Standardized Streamflow Indices (SSI) values. For this kind of regression LR is the appropriate tool. LR is very flexible in its application, because it is not limited to normally distributed predictors, as e.g. the possible alternative method, the Linear Discriminant Analysis (Pohar et al., 2004). Regression models were developed with a single predictor using either ENSO indexes or SSI, following the causal chain leading to salinity intrusion in the MKD described above. The ENSO indexes tested were monthly ENSO1, ENSO3,
- 155 ENSO4, and ENSO34 indexes. All of these indexes aim at representing the state of the El Niño Southern Oscillation by considering sea surface temperatures at different regions of the Pacific Ocean. Among these indices ENSO34 is regarded as the most appropriate sea surface temperature index representing the general state of the ENSO (Bamston et al., 1997). The testing of different indexes aims at the identification of the most robust predictor for salinity intrusion in the MKD. All of the ENSO indexes used in the forecast models start in April of the year before the dry season, i.e. with a lead time of up to 9
- 160 months before the start of the forecasted FebMar time period. For the streamflow predictors, the monthly discharges recorded at station Tan Chau were transformed into SSI. This transformation is similar to transforming precipitation into Standardized Precipitation Indexes (SPI), as typically done in drought studies and drought definitions (Mishra and Singh, 2010). SSI has been applied as predictand in seasonal forecast studies, e.g. for predicting streamflow in Southern Africa (Seibert et al., 2017). SSI normalizes the monthly discharges by fitting a Gamma distribution to the observed long-term record of discharges (here

- 165 from 1980 2016) and transferring it in a normal distribution with a mean of 0. An SSI value of 0 indicates thus the normal hydrological state, while negative values indicate a water deficiency. SSI has the advantage that a drought condition can be directly recognized by the SSI value, and that the prediction models can be easier transferred and compared to other gauging station with different streamflow magnitudes. Another strength of SSI is that it can be calculated for a variety of time scales. This is important, because droughts usually manifest over extended time periods. SSI was thus derived for different time scales.
- 170 ranging from 1 month (SSI1) to 6 months (SSI6), each starting in June prior to the dry season, i.e. with a maximum of 7 months lead time. The calculation of SSI was performed with the R-package SPEI (Vicente-Serrano et al., 2012). Supplement S3 provides a list of all predictors used in the detection of the best performing forecast models. The Logistic Regression models were fitted by iteratively reweighted least squares using the R-function glm for a binomial model type, which represents the Logistic Regression. A fitted LR model provides estimates of the probability of exceedance
- 175 of the defined salinity thresholds depending on the predictor value. One model was fitted for all predictors and lead times, and the best performing ENSO and SSI predictors for the different lead times were manually selected according to the following criteria:
 - The Receiver Operator Characteristic (ROC) score (Mason, 2008).
 - The Akaike Information Criteria (AIC) (Burnham and Anderson, 2004).
- The Cragg and Uhlers (also known as Nagelkerke) Pseudo-R² (Nagelkerke, 1991), which is defined for categorical variables analogously to the normal R² for continuous variables.
 - The accuracy (rate of correct forecasts).

In order to test the robustness of the linear models a Leave-One-Out Cross validation (LOOCV) was also performed, as applied in Apel et al. (2018) for forecasting seasonal streamflow in Central Asia. A robust model is characterized by a model, for

185 which the performance values of the LOOCV do not deteriorate compared to the performance of the model using the full data set. Therefore, the ROC scores and accuracies of the LOOCV were used in addition to the performance criteria listed above for the selection of the best performing forecast models.

The forecast model is then based on a logistic regression (LR), i.e. a linear statistical model. The logistic regression is selected because categories (exceedance of the salinity thresholds or not) are forecasted by continuous variables. For this kind of regression the logistic regression is the appropriate tool. LR is very flexible, as it is not limited to normally distributed

- predictors, as e.g. the Linear Discriminant Analysis. Regression models are tested using either ENSO indexes or antecedent streamflow indexes as predictors. The ENSO indexes tested were monthly ENSO1, ENSO3, ENSO4, and ENSO34 indexes starting in April before the dry season, i.e. with a lead time of up to 9 months before the start of the forecasted FebMar time period. For the streamflow predictors the monthly discharges at Tan Chau were transformed into Standardized Streamflow
- 195 Indexes (SSI). This is similar to transforming precipitation into Standardized Precipitation Indexes (SPI), as typically done in drought studies and drought definitions. SSI has been applied e.g. for predicting streamflow in Southern Africa (Seibert et al., 2017), and has the advantage that a drought condition can be directly recognized by the SSI value, and that the prediction models can be easier transferred and compared to other gauging station with different streamflow magnitudes. SSI was derived

for different aggregating time spans ranging from 1 month (SSII) to 6 months (SSI6), each starting in June prior to the dry season, i.e. with a maximum of 7 months lead time.

The forecast models were tested with all predictors, and the best performing ENSO and SSI predictors were manually selected according to the Receiver Operator Characteristic (ROC) score, the Akaike Information Criteria (AIC), the Cragg and Uhlers Pseudo R^2 , which is defined for categorical variables analogously to the normal R^2 for continuous variables, and the accuracy (rate of correct forecasts). In order to test the robustness of the linear models a Leave one-Out Cross validation (LOOCV) was also performed, as in Apel et al. (2018) for forecasting seasonal streamflow in Central Asia.

3 Results and discussion

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The performance testing of the ENSO predictors identified the ENSO34 index as best performing ENSO index. The best forecast could be obtained with the April index, i.e. with a lead time of 9 months. Figure 2 (top) illustrates the performance of the forecast model. Using only the ENSO34 index of April a ROC score of 0.98 and 0.8 and an accuracy of 95% and 71% could be achieved for the 3 g/l and 4 g/l thresholds, respectively. Also the performance of 3 g/l threshold) and 0.4 (4 g/l threshold) confirm this excellent performance with 0.89 and 0.4 are very high, considering the usually-typically lower values of pseudo-R² compared to normal R² values. This performance is extraordinary exceptionally high for a seasonal forecast with such a long lead time. The LOOCV resulted in similar high performances, thus indicating the robustness of the statistical model. The logistic regression curves in the top-right insets show that the 3 g/l threshold can be very well discriminated by the

- 215 ENSO34 index. The steep slopes of the probabilities changing from drought classification to non-drought classification illustrate this. For the 4 g/l threshold the slopes are more gentle, indicating a less pronounced discrimination, which is expressed by the lower performance values. The bottom insets in the figure panels show the observed drought events with reported high salinity intrusion and the forecasts of the model, including the LOOCV forecasts. It can be seen that only 1 out of 21 dry seasons would have been misclassified as drought for the 3 g/l threshold. For the 4 g/l threshold 6 out of 21 events would have
- 220 been wrongly predicted. In this context it has to be noted that the probability threshold for classifying a forecast as droughts was set to 0.5. Using different probability thresholds for drought classification has been tested and resulted in different classification errors, but the number of wrong classifications and thus the performance values remained the same. The forecast performance with ENSO is decreasing with decreasing lead times, as shown in Figure 3 by decreasing ROC
- scores and increasing AIC values. This finding is in line with the causal chain explained above, where ENSO is preceding the monsoon development. During the monsoon period ENSO changes already to a different state, but having less impact on the monsoon intensity (Ju and Slingo, 1995), thus the value of ENSO as predictor for the salinity intrusion is decreasing. An opposite behaviour is observed for the SSI predictors (Figure 3). These show in general an increasing performance with decreasing lead time. This behaviour also reflects the hydrological system of the Mekong, where the streamflow at the late flood (October-November) and early dry (December) season (December) are an aggregated measure of the total monsoonal
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rainfall amount over the Mekong basin, which is more reliable compared to streamflow during the early and high flood season.

The SSI3 predictor, i.e. an aggregated index of three months of discharge, performs best, but only slightly better than SSI4 and SSI6 (not shown). The best forecasts were obtained for November and December, i.e. with 1 - 2 month(s) lead time. Interestingly the SSI forecasts were in general better for the 4 g/l threshold than for the 3 g/l threshold (Figure 3), which is also opposite to the forecasts with ENSO. The 4 g/l threshold exceedance can be forecasted with a ROC score of 0.85 and an

235 accuracy of 85% with SSI3 in December and November (Figure 2, bottom panel). Only 3 out of 21 events were wrongly classified for this salinity threshold. This means that the early salinity intrusion forecast by ENSO for the critical salinity threshold of 4 g/l can be further improved with SSI forecasts a few months prior to the dry season, which is important for the actual implementation of disaster mitigation plans.

However, in order to obtain a continuous, well performing forecast model, the forecasts during the flood season (July-October)

240 need to be improved. Suitable predictors during this period would be rainfall estimates over the Mekong basin, following the causal chain of salinity intrusion in the MKD outlined in the method section. These rainfall predictors could be derived from the real-time monitoring rainfall network in the Mekong basin, or near-real time satellite-based rainfall products, as e.g. the TRMM-based Multi-satellite Precipitation Analysis (TMPA/3B4x) with its latency of 1-2 month. This needs to be tested during further developments of the model.

245 **<u>4</u>**Conclusions and outlook

The proposed simple linear seasonal forecasting model of salinity intrusion in the Mekong Delta based on ENSO and SSI predictors proved to be a useful tool for an early warning of salinity intrusion during the dry, low flow season in the Mekong delta. The exceedance and non-exceedance of critical and high levels of salinity at the Son Doc gauging station could be forecasted with high probabilities. Combining the ENSO and SSI forecast models results in a forecasting system that could

- 250 deliver an early warning as early as 9 months prior to the period of the dry season most critical for paddy rice, but also for other crops and fruit orchards. The early forecasts with ENSO in April before the actual flood and the following dry season could serve as an early warning of a likely high salinity intrusion. The later forecasts based on SSI would then provide more reliable forecasts of a severe salinity intrusion that would cause high damages and negative impacts of the livelihood of the population in the coastal provinces of the Mekong Delta, if no mitigation actions are initiated in time. Based on the long lead
- 255 times of the forecasts appropriate mitigation measures can be planned already during the flood season, i.e. well ahead of the dry season, and then activated if the early forecasts are confirmed by the late forecasts based on SSI, i.e. actual observed discharges. Therefore the proposed forecasting model could thus be used as a data-based support for disaster mitigation planning. However, it could be further improved to obtain robust forecasts during the flood season, i.e. lead times of 5-7 months, by testing rainfall estimates over the Mekong basin as predictor.
- 260 Due to its simplicity the model can easily be transferred to other gauging stations in the Mekong Delta thus providing a larger wider picture on a larger data base. This requires mainly sufficiently long, if sufficient time series of salinity datameasurements, because long term discharge records for the calculation of SSI are readily available for the main gauges in the VMD, and the

time series of ENSO indexes are available from public sources. As a rule of thumb, salinity time series of about 15 years and longer should be sufficient for fitting the model (cf. Apel et al., 2018) is available. While the studied gauge Son Doc can be

- 265 seen-regarded as representative for the general salinity intrusion in the Mekong Delta, but-forecasts of a larger number of stations would increase the data-based evidence of an imminent severe salinity intrusion affecting the whole delta. Moreover, due to the simple model structure and data requirements, the model could be applied beyond the Mekong delta inshould also be easily transferable to other coastal areas draining larger basins in a monsoonal climate, where similar hazards of, which face similar hazards by dry season salinity intrusion exist.
- 270 After the model development, the model was also validated by forecasting the salinity intrusion in the dry season 2020. It predicted the observed high salinity intrusion with high confidence using both the ENSO34 predictor of April 2019 and the SSI3 predictors of November and December 2019. This mean that the observed severe salinity intrusion in the dry season of 2020 could have been predicted with a lead time of 9 months. This lead time is certainly sufficient for tFimely mitigation and adaptation planning is particularly advisable for the coming dry season 2019/2020, because of the very strong El Nino event
- 275 recorded in spring 2019. The ENSO34 index value in April 2019 is 28.45, which is just slightly lower than in April 2015 (28.52) prior to the record breaking salinity intrusion in the following dry season 2015/2016. Based on ENSO34 April value the proposed forecast model predicts the exceedance of the 3 g/l and 4 g/l thresholds to 100% and 88.8% respectively for the dry season 2019/2020. The proposed model could have provideds a data-based support for the rumours in the media⁴ and among authorities in Vietnam, fearing a severe salinity intrusion in the presence of El Nino and the already observed
- 280 exceptional low flows in the upper part of the Lower Mekong basin. The model forecasts could thus support a decisions of the Vietnamese government to plan in time for disaster mitigation, in order to avoid severe damages and negative impacts as occurred in 2015/2016, when no preventive and mitigating actions were taken. This couldMitigation actions should include not only local measures in the VMD, but also negotiations with the Mekong riparian countries to adaptwith the aim of adapting the operation schedule of reservoirs in the Mekong basin in order to maintain sufficient flow during the dry season-for
- 285 mitigation of the impacts of the expected very low dry season flow in 2020, as well as sharing the operation information to downstream countries for mitigation planning. Particularly this aspect needs long term preparation, both in terms of reservoir operation planning and for the required political discussions among the riparian countries.

Data availability. Data are available upon request from the corresponding author (heiko.apel@gfz-potsdam.de).

290 Author contributions. HA developed the method and wrote the original draft of the paper. All authors contributed to the preparation of this paper.

Competing interests. The authors declare that they have no conflict of interest.

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⁺ <u>https://www.nationalgeographic.com/environment/2019/07/mekong-river-lowest-levels-100-years-food-shortages/</u> <u>https://vietnamnet.vn/en/sci-tech-environmennt/mekong-delta-forecast-to-have-small-floods-this-year-555838.html</u>

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295 Vietnamese Mekong Delta: A case study in Ben Tre province-". Funding was provided by the German Ministry of Education and Research (BMBF, FKZ: 02WM1338C) and by the Vietnamese Ministry of Science and Technology (MOST, grant number: KHCN-TNB-DT/14-19/C20).

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Figure 1: Land use map of the Mekong Delta in 2010 derived at 500m resolution from MODIS images (Source: Catch-Mekong Knowledge Hub, https://catchmekong.eoc.dlr.de/Elvis/, provided by the German Aerospace Center DLR, (Leinenkugel et al., 2013)

: Overview map of the study area Mekong Delta. Top left: Regional overview showing South-East Asia with the Mekong basin and delta, and the neighbouring countries. The background country, ocean and topography maps are made with Natural Earth (Free vector and raster map data @ naturalearthdata.com). Bottom: The Vietnamese part of the Mekong Delta with the location of the main official and permanent hydro-meteorological monitoring stations and the salinity monitoring station Son Doc. The land use

map of the Mekong Delta as in 2010 is shown as reference illustrating the different land use types in the different regions of the delta. The map was derived at 500m resolution from Moderate Resolution Imaging Spectrometer satellite (MODIS) images (Source: Catch-Mekong Knowledge Hub, https://catchmekong.eoc.dlr.de/Elvis/, provided by the German Aerospace Center DLR. The

375 method of land use classification is described in Leinenkugel et al. (2013)).





Figure 2: Best prediction models using ENSO34 index (top row) and SSI3 (bottom row) as predictors for forecasting exceedance of the 3 g/l (left) and 4 g/l (right) salinity threshold ("salthresh"). The top-left insets show the ROC curves with the following performance criteria: R2 = Cragg & Uhlers pseudo-R², ROC = ROC score, ROC_cv = ROC score of the LOOCV, Acc = accuracy (fraction correct predictions), Acc_cv = accuracy of the LOOCV. Top-right insets show the logistic regression results with the probabilities of exceedance and non-exceedance of the salinity thresholds in dependence of the predictor. The bottom insets show

the observed mean February-March salinity levels at Son <u>doeDoc</u> and the predictions in terms of exceedance of the salinity thresholds.





Figure 3: Performance of logistic model with ENSO34 and SSI3 predictors at different lead time in terms of ROC and AIC. The months of the x-axis denote a forecast at the end of the indicated month prior to the dry season. For the mean February-March predictand a forecast in December means 1 month lead time for the predictand season, in April a lead time of 9 months.