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Performance evaluation of Auto-Regressive Integrated Moving Average Models for forecasting saltwater intrusion into the Mekong river estuaries of Vietnam

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ABSTRACT

The Mekong Delta is the most severely affected area by saltwater intrusion in Vietnam. Recent studies have focused on predicting this disaster with weekly and decade lead times rather than seasonal forecasts, which are important for planning crop selection, crop structure, and sowing time. This study aims to forecast the spatial distribution of saltwater intrusion into the Mekong river estuaries of Vietnam during the dry season of 2021 by integrating Auto-Regressive Integrated Moving Average (ARIMA) with Geographic Information System (GIS). ARIMA models were trained with a single input of water salinity measurements from 2012 to 2020. Compared to the weekly salinity observations in 2021, these models predicted very well in the My Tho and Ham Luong rivers but unsatisfactorily in the Co Chien river. The GIS-based maps of salinity concentration reveal that the deepest saltwater intrusion was predicted to occur between March 19 and April 16 of 2021, when the 4‰ saline front could penetrate the farthest distance of 41, 41, and 44 kilometers inland from the sea through the My Tho, Ham Luong, and Co Chien rivers, respectively. The entire river system will be exposed to a moderate risk of saltwater intrusion. Freshwater zones will decrease significantly to 0.73% of the whole area of Ben Tre province. These findings provide a valuable scientific foundation for the appropriate management of coastal aquifers to control or reduce saltwater intrusion.

Keywords: Auto-Regressive Integrated Moving Average, Empirical Bayesian Kriging, Mekong river estuary, saltwater intrusion, water salinity forecast.

1. Introduction

Saltwater intrusion (SWI), which is the induced flow of saline or brackish water into freshwater aquifers, occurs increasingly in many coastal areas (Maliva, 2020) due to the intense economic activity in these regions and the consequences of exploiting their groundwater resources (Baena-Ruiz et al.,

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2018). With a coastline of 3,658 kilometers, excluding islands, shared by 28 coastal provinces (Dung and Khanh, 2016), Vietnam is susceptible to SWI. The two most severe events of drought and SWI in recorded history in 2016 and 2020 caused widespread shortages of freshwater supply for domestic and agricultural demands and 18,201 billion VND in national damage (Vietnamese Disaster Management Authority, 2019, 2020). An important factor leading to these large losses was the lack of timely forecasting and warning of SWI to prepare and respond proactively (Apel et al., 2020).

Mathematical and statistical approaches have been used to simulate and forecast SWI in estuaries. Possessing the ability to provide a mechanistic understanding of physical processes at both small and regional scales (Tran et al., 2021), mathematical models are widely applied to predict the extent of SWI into inland and coastal aquifers (Abdullah et al., 2016; Mastrocicco et al., 2019; Hai et al., 2019; Lam, 2019; Vinh et al., 2019; Nhung et al., 2019). However, these models are not always feasible since they are complex, data-intensive, and time-consuming (Melesse et al., 2020). To overcome the above drawbacks, statistical models are a powerful alternative because they require less input data and computational time while providing comparable results (Tran et al., 2021).

Auto-Regressive Integrated Moving Average (ARIMA) is a flexible model for linear and stationary time series as they can include different types of time series (Qie et al., 2015), e.g., auto-regression (AR), moving average (MA), and combined AR and MA (ARMA) series. It was tested for water quality forecasting in the United States (Sun and Koch, 2001), China (Qie et al., 2015; An and Zhao, 2017), Iran (Ranjbar and Khaledian, 2014; Ahmadianfar et al., 2020), Palestine (Abuamra et al., 2021), Malaysia (Lola et al., 2018), Vietnam (Tran et al., 2020).

In Vietnam, the Mekong Delta (MKD) is the most severely affected area by SWI (the Socialist Republic of Vietnam, 2004). Salinization in this region occurs mainly in the dry season lasting from November to April next year (Tran et al., 2019). A great deal of work has been done to understand this issue by using different approaches. Hydrologic and hydraulic models have been coupled to forecast SWI in MKD with the longest lead time of ten days (National Centre for Hydro-Meteorological Forecasting, 2021) or five months (Southern Institute of Water Resources Research, 2021). A simulation system based on the MIKE-11 model for 7-day forecasting of water salinity, streamflow, and water level in MKD has been developed on the WebGIS platform (Lam, 2019). MIKE-11 was also applied to understand the spatial distribution of freshwater (Vinh et al., 2019) or to forecast SWI under the combined effects of upstream flow variations and climate change (Hai et al., 2019) in the coastal area of MKD. State-of-the-art machine learning algorithms were evaluated for predicting groundwater salinity and identifying its influencing factors in the coastal multi-layer aquifers of Soc Trang province (Tran et al., 2021). A multi-linear regression model was built to detect SWI in MKD through the relationship between surface reflectances from Landsat-8 satellite images and in situ measurements of salinity (Nguyen et al., 2018). The patterns of annual salinity variations in agricultural land and their relationship to drought in Ben Tre province were examined using multi-temporal Landsat images and spatial regression (Tran et al., 2019). A logistic regression model using either the ENSO34 index or streamflow as a predictor could reliably forecast SWI up to nine months ahead in MKD (Apel et al., 2020). An ARIMA model was built to forecast the Ham Luong river (Tran et al., 2020). Overall, existing studies provided SWI prediction with weekly, seasonal, and decade lead times. Little effort has been made to consider seasonal water salinity, which is important for planning crop selection, crop structure, and sowing time.

This study aims to forecast the spatial distribution of SWI into the Mekong river estuaries of Vietnam during the dry season of 2021. This was done by applying the ARIMA model with input data of saltwater observed at salinity monitoring stations from 2012 to 2020. Then, these predicted values were inputted into Geographic Information System (GIS) to produce saltwater maps for the study area. Finally, observed saltwater of the 2021 dry season at the stations was used to evaluate the goodness-of-fit of the predictive model.

2. Data and Methods

2.1. Study area

MKD is located in the most downstream region of the Mekong river basin, with approximately 40,500 square kilometers. The Mekong river flowing through MKD divides the delta into two distributaries of the Mekong (or Tien) and the Bassac (or Hau) rivers before draining into the East Sea via nine river mouths. Accretion processes on four branches of the Mekong river, including My Tho, Ba Lai, Ham Luong, and Co Chien, have formed the Ben Tre province of Vietnam (Fig. 1). Thanks to its location, Ben Tre province has a diverse ecosystem of salty, brackish, and freshwater, which is favorable for agricultural diversification based on two key sectors of garden and ocean economies. In 2019, the agricultural sector contributed about 35% of Gross Regional Domestic Product, with 75% of land area used for agriculture and 70% of employment in agriculture (Ben Tre Statistical Office, 2020).

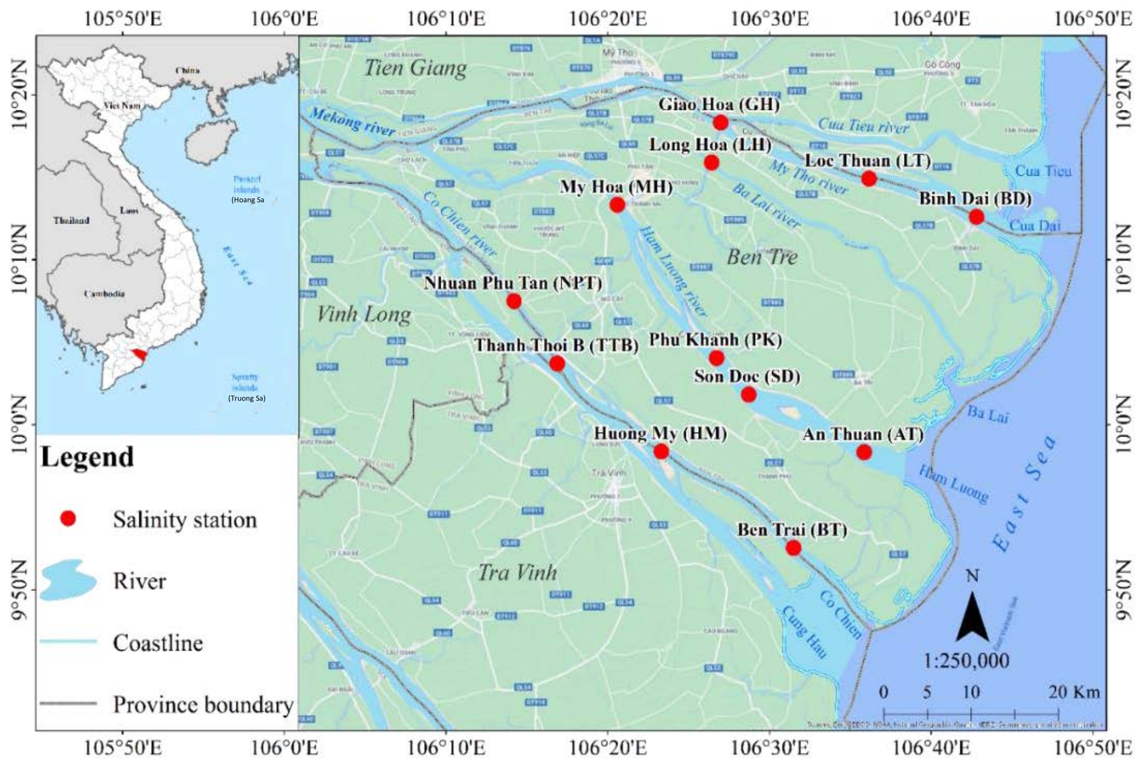

Figure 1. Locations of the study area and salinity monitoring stations

The climate in Ben Tre province is typified by the equatorial monsoon with an average temperature of 26-27°C. There are two distinct seasons in the year, including the dry season from November to April next year and the wet season from May to October. The rainfall amount is about 1,250-1,500 mm/year, with only 2-6% of this falling in the dry season. Two prevailing winds are the Northeast monsoon and the Southwest monsoon. A significant obstacle to agriculture in the region occurs during the dry season when the reduction of upstream flows combined with strong Northeast winds cause saltwater to penetrate further inland, negatively impacting crop yields in coastal areas. SWI in the province is critical, especially during the 2015/2016 El Niño year (Nguyen et al., 2019).

Salinization has caused serious damage to agricultural production and farmer livelihoods in Ben Tre province. Salinity concentrations greater than 4‰ cause damage to coconuts (Japan International Cooperation Agency, 2016) and are not suitable for striped catfish farming (De Silva et al., 2011). The intense encroachment of saltwater inland with a salinity concentration of 30‰ in the dry season has seriously affected most poor households’ livelihoods that are mainly dependent on hired employments in aquaculture and crop cultivation (Renaud et al., 2015). However, farmers’ motivations and abilities to apply alternative models vary substantially among different groups, driven by their perceptions of triggers and opportunities (Nguyen et al., 2019).

2.2. Data sources

Due to data availability, this study focused on the My Tho, Ham Luong, and Co Chien rivers. We collected water salinity data at 12 monitoring stations (Fig. 1, Table 1): Binh Dai, Loc Thuan, Giao Hoa, Long Hoa, An Thuan, Son Doc, Phu Khanh, My Hoa, Ben Trai, Huong My, Thanh Thoi B, Nhuan Phu Tan along the rivers. At each station, water salinity was measured weekly from January to June from 2012 to 2021 for a total of 23 weeks (Table 2). Ben Tre Hydro-Meteorological Centre provided the data.

Table 1. Locations of salinity monitoring stations

Station	River	Coordinates		Address
		Latitude (N)	Longitude (E)	
Binh Dai	My Tho	10°12'36.7"	106°42'48.5"	Binh Thang commune, Binh Dai districts
Loc Thuan		10°14'55.2"	106°36'09.8"	Loc Thuan commune, Binh Dai district
Giao Hoa		10°18'19.4"	106°26'59.0"	Giao Hoa commune, Chau Thanh district
Long Hoa		10°15'54.0"	106°26'25.7"	Long Hoa commune, Binh Dai district
An Thuan	Ham Luong	9°58'20.4"	106°35'51.8"	Tiem Tom town, Ba Tri district
Son Doc		10°01'50.4"	106°28'43.3"	Hung Le commune, Giong Trom district
Phu Khanh		10°04'03.4"	106°26'44.3"	Phu Khanh commune, Thanh Phu district
My Hoa		10°13'20.2"	106°20'36.3"	Ben Tre city
Ben Trai	Co Chien	9°52'32.5"	106°31'30.0"	An Thuan commune, Thanh Phu district
Huong My		9°58'23.4"	106°23'19.5"	Huong My commune, Mo Cay Nam district
Thanh Thoi B		10°03'43.2"	106°16'53.5"	Thanh Thoi B commune Mo Cay Nam district
Nhuan Phu Tan		10°07'30.4"	106°14'13.2"	Nhuan Phu Tan commune, Mo Cay Bac district

Table 2. Weekly schedule for monitoring water salinity

Week	Period	Week	Period	Week	Period
1	Jan 1 - Jan 8	9	Feb 26 - Mar 5	17	Apr 23 - Apr 30
2	Jan 8 - Jan 15	10	Mar 5 - Mar 12	18	Apr 30 - May 7
3	Jan 15 - Jan 22	11	Mar 12 - Mar 19	19	May 7 - May 14
4	Jan 22 - Jan 29	12	Mar 19 - Mar 26	20	May 14 - May 21
5	Jan 29 - Feb 5	13	Mar 26 - Apr 2	21	May 21 - May 28
6	Feb 5 - Feb 12	14	Apr 2 - Apr 9	22	May 28 - Jun 4
7	Feb 12 - Feb 19	15	Apr 9 - Apr 16	23	Jun 4 - Jun 11
8	Feb 19 - Feb 26	16	Apr 16 - Apr 23		

2.3. Fitting ARIMA models

ARIMA is a predictive time series modeling approach based on the idea that time series can be decomposed into the present, past values, and random errors. It is a combination of auto-regression AR(p) (an additive linear function of p past observations), moving average MA(q) (q random errors), and d, which is an integer making a series to be stationary (Phan and Nguyen, 2020). To determine the parameters of an ARIMA model, we used the Box-Jenkins method, which is a common approach that includes three steps: model identification and selection, parameter estimation, and diagnostic checking (Box et al., 2008).

In this study, the input data were divided into two parts for training and testing ARIMA models. The training datasets from 2012 to 2020 accounted for 90% of the data, and the remaining observed samples (10%) in 2021 were used to assess the forecasting models. Then, we applied Statgraphics Centurion 18 software to fit ARIMA models. The best fit ARIMA model must satisfy two selection criteria (Goh and Case, 2016; StatPoint Technologies, 2017): (i) minimizing Akaike Information Criterion (AIC); and (ii) p-value for five tests (RUNS-Test for excessive runs up and down, RUNM-Test for excessive runs above and below the median, AUTO-Ljung-Box test for excessive autocorrelation, MEAN-Test for the difference in mean 1st half to 2nd half, VAR-Test for the difference in variance 1st half to 2nd half) greater than or equal to 0.05.

2.4. Forecasting water salinity

The best fit ARIMA model was employed to detect SWI during the 2021 dry season from January 1 to June 11 at locations where in situ water salinity measurements were available. To evaluate the goodness-of-fit of the model in predicting water salinity, we used three statistical metrics: (1) the coefficient of determination (R^2), an indicator of the percentage of observed variation explained by predicted salinity; (2) Nash-Sutcliffe modeling efficiency (NSE) (Nash and Sutcliffe, 1970), which indicates how well the plot of observed versus predicted data fits the 1:1 linear regression line; (3) mean absolute error (MAE) (Willmott and Matsuura, 2005), a measure of the mean of the absolute values of individual salinity prediction errors. The formulas of R^2, NSE, and MAE are expressed below.

$$R^2 = \left[\frac{\sum_{i=1}^{n}(O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2}\sqrt{\sum_{i=1}^{n}(P_i - \bar{P})^2}}\right]^2 \quad (1)$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \quad (2)$$

$$MAE = \frac{\sum_{i=1}^{n}|O_i - P_i|}{n} \quad (3)$$

where P_i and O_i are predicted and measured salinity concentration in observation i, respectively; $\bar{P}$ and $\bar{O}$ are the mean values of predicted and measured salinity concentration, respectively; n is the number of observations.

2.5. Mapping saltwater intrusion

To geo-visualise the forecasted water salinity across the study area, spatial interpolation was used. Specifically, we used Kriging, which is the most commonly used interpolator for estimating water quality (Bouteraa et al., 2019). This technique provides the best linear unbiased estimator for the unknown spatial and temporal variables (Chung et al., 2019). The general formula for Kriging is expressed as:

$$Z_K^* = \sum_{i=1}^{N} \lambda_i Z_i \quad (4)$$

where $Z_K{}^*$ is the estimated value at prediction location, Z_i is the measured value at the *i*th location, λ_i is the weight for Z_i, and N is the number of measured values.

The present study used the Empirical Bayesian Kriging (EBK), one kind of Kring, to map salinity concentration. Unlike other Kriging methods, EBK automatically calculates the parameters of a valid Kriging model to get accurate results through the process of subsetting and simulating measured data. The main advantage of EBK is it uses a large number of variogram models instead of just a single model, offering a great benefit compared to other Kriging models (Magesh and Elango, 2019). Thus, this interpolator is more accurate than other Kriging methods for small datasets.

3. Results and Discussion

3.1. Analysis of saltwater intrusion in last nine years (2012-2020)

The annual average fluctuations of water salinity in the Mekong river estuaries of Vietnam from 2012 to 2020 are shown in Fig. 2a. Based on salinity peaks, we split the temporal salinity patterns into different periods: 2012-2014, 2014-2018, and 2018-2020. During 2012-2014, salinization peaked in 2013 with a salinity concentration of 4‰ moving inland 39, 26, and 31 kilometers, from the East Sea in the My Tho, Ham Luong, and Co Chien rivers, respectively. The highest average values of salinity concentration measured in these rivers were 22.3, 22.8, and 20.8‰ at Binh Dai, An Thuan, and Ben Trai stations in that order. SWI in 2014-2018 was more severe than in the previous period because the highest average salinity concentrations at the coastal stations of Binh Dai, An Thuan, and Ben Trai reached 22, 24.6, and 21.8‰, respectively, in 2016. Saltwater correspondingly moved inland 39, 46, and 46 kilometers through the My Tho, Ham Luong, and Co Chien rivers. SWI in 2020 was the most extreme event in the 9-year time series from 2012 to 2020 when the 4‰ salt waterfront penetrated inland with a distance of 46 kilometers at all rivers. The highest average salinity concentrations of 25.4, 26.1, and 19.9‰ were observed at Binh Dai, An Thuan, and Ben Trai stations in the order given. Four main anthropogenic drivers could explain the exacerbation of SWI in the study area: upstream dams, riverbed mining, sea-level rise, and land subsidence (Loc et al., 2021). Besides, the occurrences of El Niño phenomena in 2016 and 2020 worsened the situation. In terms of intensity, there was significant spatial differentiation of SWI severity over past years. In the My Tho River, a low SWI risk with 1‰ salinity moving inland from 25 to 50 kilometers (The Prime Minister, 2021) occurred in 2012, 2014, 2017-2019 equivalent to a frequency of 55.56%; a moderate SWI risk with 4‰ salinity moving inland from 25 to 50 kilometers (The Prime Minister, 2021) occurred in the other years equivalent to a frequency of 44.44%. Meanwhile, moderate SWI risk was predominant in the Ham Luong and Co Chien rivers. In the Ham Luong river, moderate SWI risk took place in most years, except in 2014 when SWI risk was low with a frequency of 88.89%. In the Co Chien river, moderate risk SWI occurred in 2013, 2015-2020, equivalent to a frequency of 77.78%.

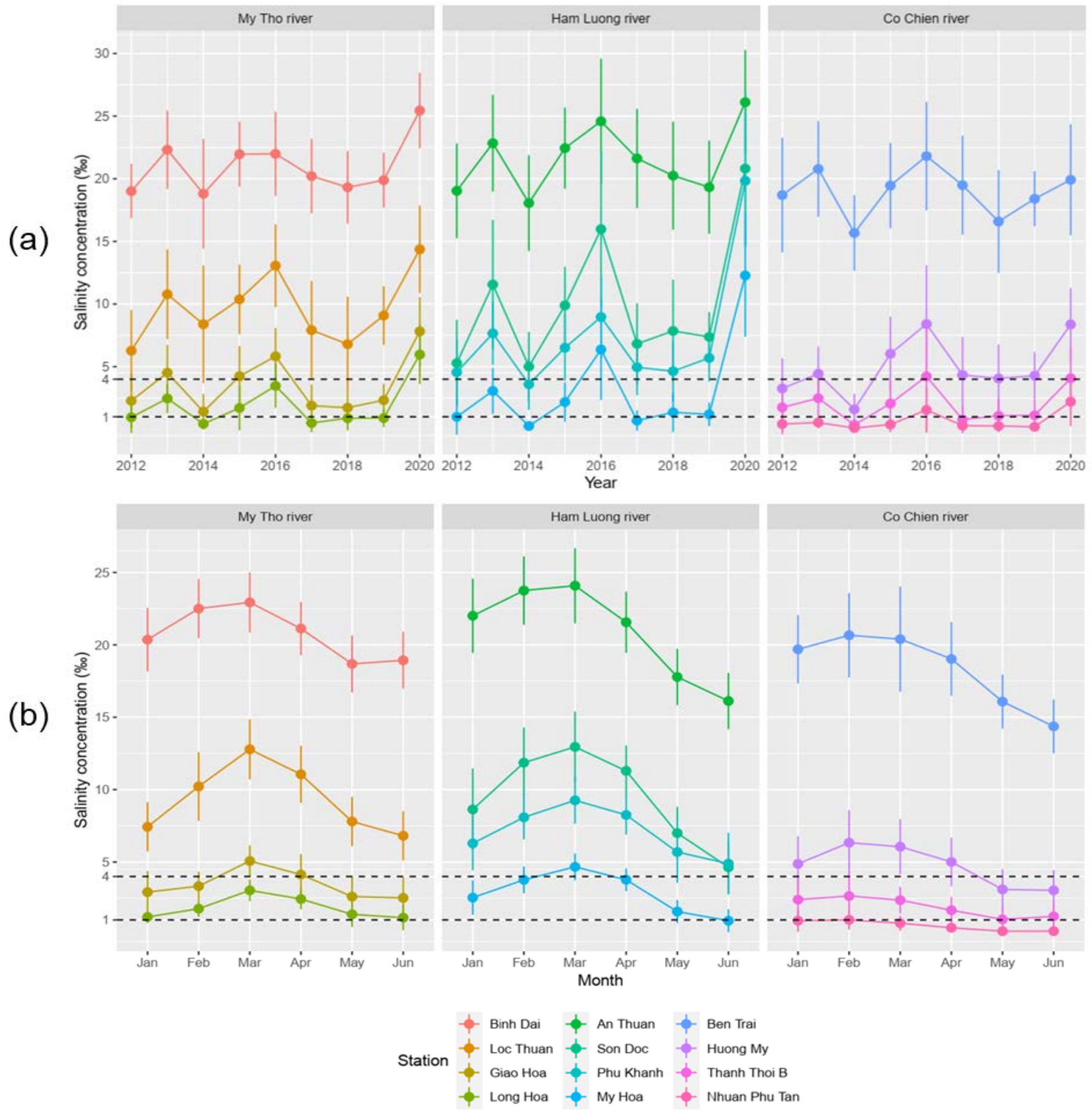

Figure 2. The annual (a) and monthly (b) average changes of salinity in My Tho, Ham Luong and Co Chien rivers from 2012 to 2020. The break values of 1‰, 4‰ are assigned according to the saltwater intrusion severity levels of Vietnam (The Prime Minister, 2021)

The variation of annual salinity tended to increase gradually from the estuary to the mainland. Whereby, the coefficient of variation (CV, standard deviation divided by mean) of salinity at three most coastal stations of Binh Dai, An Thuan, Ben Trai varied between 11 and 25%, compared with CV at three most inland stations of Long Hoa, My Hoa, Nhuan Phu Tan which ranged from 39 to 192%. However, there was no significant difference in the variation of annual salinity between rivers when CV of salinity at stations located along the My Tho, Ham Luong, and Co Chien rivers varied 11-144%, 14-144%, and 12-192%, respectively.

The monthly average variations of water salinity in the Mekong river estuaries of Vietnam from January to June are shown in Fig. 2b. Salinity concentration in the My Tho and Ham Luong rivers reached its highest point in March with the 4‰ salt waterfront moving inland 39 and 46 kilometers, respectively, from the sea. The highest average values of salinity concentration measured in these rivers were 22.9 and 24.1‰ at Binh Dai and An Thuan stations in that order. In the Co Chien river, a salinity peak of 20.7‰ was recorded at Ben Trai station in February when a salinity concentration of 4‰ penetrated inland with a distance of 31 kilometers. The intensity of SWI was highest in the Ham Luong river, followed by the Co Chien and My Tho rivers. In the Ham Luong River, a moderate SWI risk occurred continuously from January to June. Meanwhile, a moderate SWI risk existed in the first four months in the Co Chien river and in March and April in the My Tho River. During other months on these two rivers, low SWI risk was observed. Similar to the variation of annual salinity, monthly salinity trended upward from the estuary to the mainland. CV of salinity at three most coastal stations of Binh Dai, An Thuan, Ben Trai ranged from 9 to 18%, compared with CV at the three most inland stations of Long Hoa, My Hoa, Nhuan Phu Tan, which varied between 20 and 81%.

3.2. Best fit ARIMA models

The best fit ARIMA model with the lowest AIC value for each salinity monitoring station is shown in Table 3. Five tests for the randomness of the residuals of these models were performed to determine whether each model was appropriate for its training data. For these tests, if the p-value is less than 0.05, we reject the null hypothesis that residuals are indeed random. On the contrary, if the p-value is greater than or equal to 0.05, we fail to reject the null hypothesis. The results showed that most of the perfect ARIMA models were appropriate, except for Phu Khanh, Ben Trai, Huong My, and Thanh Thoi B stations.

Table 3. Best fit ARIMA models and the results of their residuals randomness test

Station	ARIMA model	AIC	RUNS	RUNM	AUTO	MEAN	VAR
Binh Dai	(2,1,2)×(2,0,2)23	1.91	N.S	N.S	N.S	N.S	N.S
Loc Thuan	(1,0,0)×(2,1,2)23	1.85	N.S	N.S	N.S	N.S	N.S
Giao Hoa	(1,0,2)×(2,1,2)23	0.98	N.S	N.S	N.S	N.S	N.S
Long Hoa	(2,0,0)×(2,1,2)23	-0.05	N.S	N.S	N.S	N.S	N.S
An Thuan	(2,1,1)×(2,0,2)23	2.29	N.S	N.S	N.S	N.S	N.S
Son Doc	(2,0,1)×(2,1,2)23	2.22	N.S	N.S	N.S	N.S	N.S
Phu Khanh	(2,0,1)×(2,1,2)23	1.64	N.S	N.S	*	N.S	N.S
My Hoa	(1,0,1)×(2,0,2)23	0.50	N.S	N.S	N.S	N.S	N.S
Ben Trai	(1,0,0)×(2,1,2)23	2.26	N.S	N.S	**	N.S	N.S
Huong My	(1,0,0)×(2,1,2)23	1.69	N.S	N.S	***	N.S	N.S
Thanh Thoi B	(1,0,1)×(2,0,2)23	1.09	N.S	N.S	N.S	N.S	***
Nhuan Phu Tan	(2,0,2)×(2,0,2)23	-0.29	N.S	N.S	N.S	N.S	N.S

ARIMA (p, d, q)x(P, D, Q)S models with non-seasonal parameters p, d, q, seasonal parameters P, D, Q, and seasonality s that consists of several terms: A non-seasonal autoregressive term of order p, a nonseasonal differencing of order d, a nonseasonal moving average term of order q, a seasonal autoregressive term of order P, a seasonal differencing of order D, a seasonal moving average term of order Q.

N.S = not significant ($p > 0.05$), * = marginally significant ($0.01 < p \leq 0.05$), ** = significant ($0.001 < p \leq 0.01$), *** = highly significant ($p \leq 0.001$).

3.3. Forecast of saltwater intrusion in the dry season of 2021

The forecasts of salinity concentration based on best fit ARIMA models at salinity monitoring stations during the 2021 dry season from January 1 to June 11 are shown in Table 4. The performance of these models in predicting water salinity was evaluated (Table 5). Whereby, ARIMA models of Giao Hoa, Son Doc, and An Thuan stations are the best predictive models with $R^2 > 0.6$, NSE > 0.5, and MAE < 2.6‰. With $R^2 > 0.6$, NSE < 0.5, and MAE < 2.2‰, ARIMA models of Binh Dai and Phu Khanh stations ranked second-best models. The worst ARIMA models were observed at all stations located along the Co Chien river with R^2 close to 0, negative NSE, and MAE ranging from 0.91-6.95‰.

Table 4. Prediction and 95% confidence interval of water salinity (‰) at salinity monitoring stations from week 1 (Jan 1 - Jan 8) to week 23 (Jun 4 - Jun 11) of 2021

Week	Binh Dai	Loc Thuan	Giao Hoa	Long Hoa	An Thuan	Son Doc	Phu Khanh	My Hoa	Ben Trai	Huong My	Thanh Thoi B	Nhuan Phu Tan
1	20 (15/25)	5.6 (0.3/10.8)	1.9 (0/5.2)	0 (0/1.1)	13.7 (7.6/19.8)	6.5 (0.2/12.7)	9 (4.5/13.6)	0.4 (0/3)	17.2 (10.9/23.5)	4.9 (0.2/9.6)	0.7 (0/4.2)	0.4 (0/2.1)
2	21.7 (16.1/27.2)	5.9 (0/12.3)	1.9 (0/5.8)	0 (0/2.4)	19.2 (12/26.4)	6.6 (0/14.2)	8.9 (2.8/15.1)	0.8 (0/4.3)	16.7 (10.1/23.3)	4 (0/9.4)	1.2 (0/5)	2.8 (0/4.6)
3	22.1 (16/28.3)	6.4 (0/13.4)	1.5 (0/5.6)	0.2 (0/2.9)	22.9 (15/30.8)	6.9 (0/15.8)	7.2 (0/14.6)	0.5 (0/4.8)	21.4 (14.8/28)	3.7 (0/9.2)	0.3 (0/4.4)	1.5 (0/3.4)
4	21 (14.7/27.3)	7.2 (0/14.5)	4.3 (0/8.6)	0.8 (0/3.7)	23.1 (14.8/31.3)	10.2 (0.5/19.8)	12 (3.7/20.2)	0.3 (0/5.2)	22.8 (16.1/29.4)	4 (0/9.6)	0 (0/4.2)	0.8 (0/2.7)
5	21.9 (15.4/28.3)	8 (0.6/15.4)	4.7 (0.3/9.1)	0.8 (0/3.9)	25 (16.5/33.5)	13.2 (2.9/23.5)	11 (1.9/20)	0.2 (0/5.6)	21.2 (14.6/27.8)	7.3 (1.7/12.9)	0.2 (0/4.6)	1.7 (0/3.6)
6	23.3 (16.7/29.8)	10.5 (3/17.9)	3.9 (0/8.5)	0.9 (0/4.1)	25.7 (17/34.4)	13.1 (2.4/23.9)	12.5 (2.8/22.1)	1.2 (0/7)	25.6 (19/32.3)	7.1 (1.5/12.6)	1.9 (0/6.6)	3 (0/4.9)
7	25 (18.4/31.5)	9.5 (2/16.9)	2.8 (0/7.4)	0.5 (0/3.9)	25.1 (16.3/33.9)	13.6 (2.5/24.7)	10.4 (0.2/20.6)	0.3 (0/6.4)	21.6 (15/28.2)	5.9 (0.3/11.5)	0.2 (0/5)	2 (0/4)
8	24.4 (17.9/31)	10.8 (3.3/18.3)	4.9 (0.2/9.6)	1.3 (0/4.7)	24.6 (15.7/33.5)	12.9 (1.5/24.3)	14.4 (3.7/25)	1.5 (0/7.9)	23.5 (16.9/30.2)	10.3 (4.7/15.9)	1.8 (0/6.7)	1.8 (0/3.8)
9	25 (18.4/31.6)	10.6 (3.1/18.1)	3.9 (0/8.6)	1.9 (0/5.4)	25.7 (16.6/34.7)	11.1 (0/22.7)	12.5 (1.4/23.5)	1.1 (0/7.7)	19.6 (12.9/26.2)	5.6 (0/11.2)	1 (0/6)	1.5 (0/3.5)
10	27.3 (20.6/33.9)	12.9 (5.4/20.4)	5 (0.2/9.7)	1.9 (0/5.5)	25.2 (16.1/34.3)	12.5 (0.7/24.3)	13.4 (2/24.7)	1.1 (0/7.9)	21.2 (14.5/27.8)	5.9 (0.3/11.5)	1.2 (0/6.3)	2.2 (0/4.2)
11	26.9 (20.3/33.6)	13.6 (6.1/21.1)	6 (1.2/10.8)	2.9 (0/6.6)	26 (16.8/35.2)	12.8 (0.9/24.7)	13.8 (2.1/25.5)	1.1 (0/8.2)	20.7 (14.1/27.3)	3.4 (0/9)	1 (0/6.1)	1.9 (0/3.9)
12	24.4 (17.8/31.1)	13 (5.5/20.5)	5.8 (0.9/10.6)	2.4 (0/6.1)	24.8 (15.6/34)	14 (1.9/26)	13.8 (1.9/25.7)	0.6 (0/7.9)	23.2 (16.6/29.9)	4.3 (0/9.9)	0.6 (0/5.8)	1.4 (0/3.4)
13	23.6 (17/30.2)	15.3 (7.7/22.8)	7.4 (2.6/12.3)	3.3 (0/7)	24.3 (15/33.5)	15.1 (2.9/27.2)	15.2 (3.1/27.4)	0.3 (0/7.8)	19.4 (12.8/26)	7.8 (2.2/13.3)	0.6 (0/5.9)	1.3 (0/3.4)
14	26.6 (20/33.3)	14 (6.5/21.6)	6.6 (1.8/11.5)	3.5 (0/7.2)	24.2 (14.9/33.5)	12.5 (0.3/24.7)	13.3 (0.9/25.6)	0.3 (0/7.9)	21.9 (15.3/28.5)	8.3 (2.8/13.9)	1 (0/6.3)	0.8 (0/2.8)
15	27.1 (20.4/33.7)	13.2 (5.7/20.7)	4 (0/8.9)	2.6 (0/6.4)	26 (16.6/35.3)	12.2 (0/24.5)	12.2 (0/24.8)	0.5 (0/8.2)	21.4 (14.7/28)	5.4 (0/11)	0.3 (0/5.6)	0.6 (0/2.7)
16	25.5 (18.9/32.2)	9.3 (1.8/16.9)	3 (0/7.9)	1 (0/4.8)	22.6 (13.2/32)	9.8 (0/22.1)	9.9 (0/22.6)	0.3 (0/8.2)	19.5 (12.9/26.1)	4.7 (0/10.3)	0.7 (0/6.2)	0.8 (0/2.9)
17	24.7 (18/31.3)	8.7 (1.1/16.2)	3.8 (0/8.7)	1.3 (0/5.1)	20.4 (10.9/29.9)	10.1 (0/22.5)	11.5 (0/24.4)	0.4 (0/8.3)	18.3 (11.7/25)	4.3 (0/9.8)	0.7 (0/6.2)	1.2 (0/3.2)
18	23.7 (17.1/30.4)	11.1 (3.6/18.6)	3.8 (0/8.8)	1 (0/4.7)	22 (12.5/31.6)	10.7 (0/23.1)	10.4 (0/23.4)	0.8 (0/8.9)	19.6 (12.9/26.2)	4.7 (0/10.3)	1.1 (0/6.6)	1.4 (0/3.4)
19	21.4 (14.7/28)	9.1 (1.6/16.6)	3 (0/7.9)	1 (0/4.8)	19.3 (9.8/28.9)	9.8 (0/22.2)	9.4 (0/22.5)	0.9 (0/9)	21.1 (14.4/27.7)	5.4 (0/11)	0.6 (0/6.1)	0.5 (0/2.6)
20	21.4 (14.7/28)	6.8 (0/14.3)	2.1 (0/7)	0.5 (0/4.3)	17.5 (7.9/27.1)	7.1 (0/19.5)	7.7 (0/20.9)	0.7 (0/8.9)	17.5 (10.8/24.1)	3.5 (0/9.1)	0.7 (0/6.2)	0.5 (0/2.6)
21	20 (13.3/26.7)	6.9 (0/14.5)	0.7 (0/5.6)	0 (0/3.7)	16.4 (6.7/26)	5.7 (0/18.1)	5.6 (0/18.8)	0.3 (0/8.6)	17.2 (10.6/23.9)	2 (0/7.5)	0.4 (0/6)	0.6 (0/2.7)
22	19.9 (13.3/26.6)	7.3 (0/14.8)	2.8 (0/7.7)	0.7 (0/4.5)	15.1 (5.4/24.8)	5.2 (0/17.6)	5.2 (0/18.6)	0.3 (0/8.6)	15.3 (8.7/22)	1.9 (0/7.5)	0.7 (0/6.3)	0.5 (0/2.6)
23	17.1 (10.5/23.8)	6.3 (0/13.8)	2.3 (0/7.3)	1.4 (0/5.2)	12.5 (2.8/22.3)	4.2 (0/16.6)	4 (0/17.5)	0 (0/8.3)	12.2 (5.6/18.9)	0.8 (0/6.4)	0 (0/5.4)	0.5 (0/2.5)

The values in parentheses are lower and upper limits of 95% confidence interval, respectively

Table 5. Performance of the best fit ARIMA model for water salinity prediction The best forecast results for individual rivers and between rivers are highlighted in bold

ID	River/ Station	R^2	NSE	MAE (‰)
1	My Tho river	**0.95**	**0.95**	**1.40**
1.1	Long Hoa	0.46	0.25	**0.67**
1.2	Giao Hoa	**0.68**	**0.64**	1.06
1.3	Loc Thuan	0.42	0.32	1.85
1.4	Binh Dai	**0.66**	0.43	2.06
2	Ham Luong river	0.86	0.85	2.47
2.1	My Hoa	0.00	-2.04	3.51
2.2	Phu Khanh	**0.72**	0.35	2.11
2.3	Son Doc	**0.64**	**0.64**	**1.78**
2.4	An Thuan	**0.65**	**0.57**	2.54
3	Co Chien river	0.79	0.28	3.16
3.1	Nhuan Phu Tan	0.00	-1.85	**0.91**
3.2	Thanh Thoi B	**0.03**	-1.19	1.60
3.3	Huong My	0.00	**-0.55**	2.74
3.4	Ben Trai	0.00	-8.63	6.95
	All stations	0.85	0.82	3.30

Overall, the salinity forecasts in the My Tho and Ham Luong rivers were satisfactory ($R^2 > 0.85$, NSE > 0.8). Although the model can explain 79% of the variability in the observed salinity data, the saltwater forecasts in the Co Chien river were not satisfied because NSE was less than 0.5. Most forecasting models captured well the weekly fluctuations of water salinity, except for My Hoa and Ben Trai stations, which have the lowest NSE and highest MAE (Fig. 3). In these individual cases, predicted salinity concentrations were greatly underestimated at My Hoa station but overestimated at Ben Trai station.

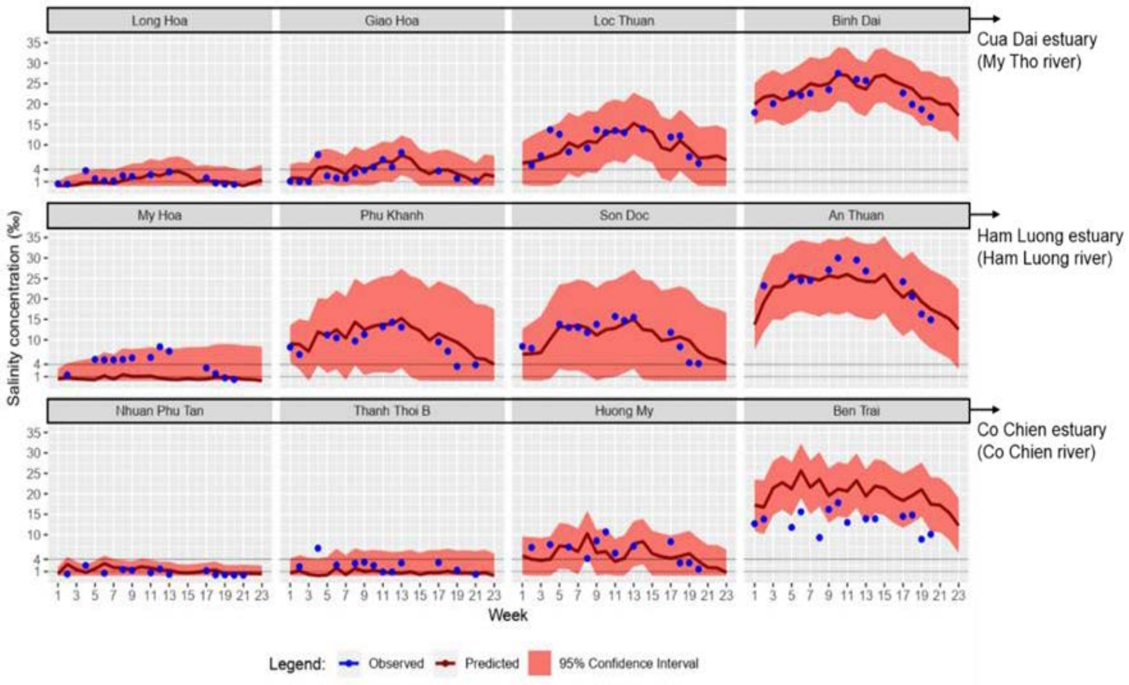

Figure 3. Comparison of observed and predicted salinity during the 2021 dry season in the Mekong river estuaries of Vietnam. The break values of 1‰, 4‰ are assigned according to the saltwater intrusion severity levels of Vietnam (The Prime Minister, 2021)

3.4. Map of saltwater intrusion in the dry season of 2021

The spatial distributions of predicted salinity concentration from week 1 to week 23 of 2021 in the study area using the EBK method are shown in Fig. 4. The salinity season in the My Tho, Ham Luong, and Co Chien rivers is predicted to start at the end of January 2021, rising to the highest level in March before slowly decreasing at the beginning of May. Therefore, three SWI spells are likely to occur in weeks 1-4 (January 1 - January 29), weeks 5-17 (January 29 - April 30), weeks 18-23 (April 30 - June 11). Most rivers and canal networks of Ben Tre province suffer from SWI. Salinization in the second and third spells is considerably more severe than in the first spell, when the 4‰ saline front penetrates up to 41 and 30 kilometers inland, respectively. The deepest SWI is predicted to occur from March 19 - April 16. In this period, the 4‰ saline front reaches the farthest distance of 41 kilometers inland from the sea in the My Tho and Ham Luong rivers, and extends to a maximum distance of 44 kilometers from the Co Chien river mouth. In fact, the SWI regime differs between distributaries because of the significant differences in streamflow.

The forecast map of maximum weekly salinity concentration in the Mekong river estuaries of Vietnam is shown in Fig. 5. The entire river system will be exposed to moderate SWI risk. Freshwater zones with salinity below 0.5‰ will decrease significantly, accounting for 0.73% of the whole area of Ben Tre province.

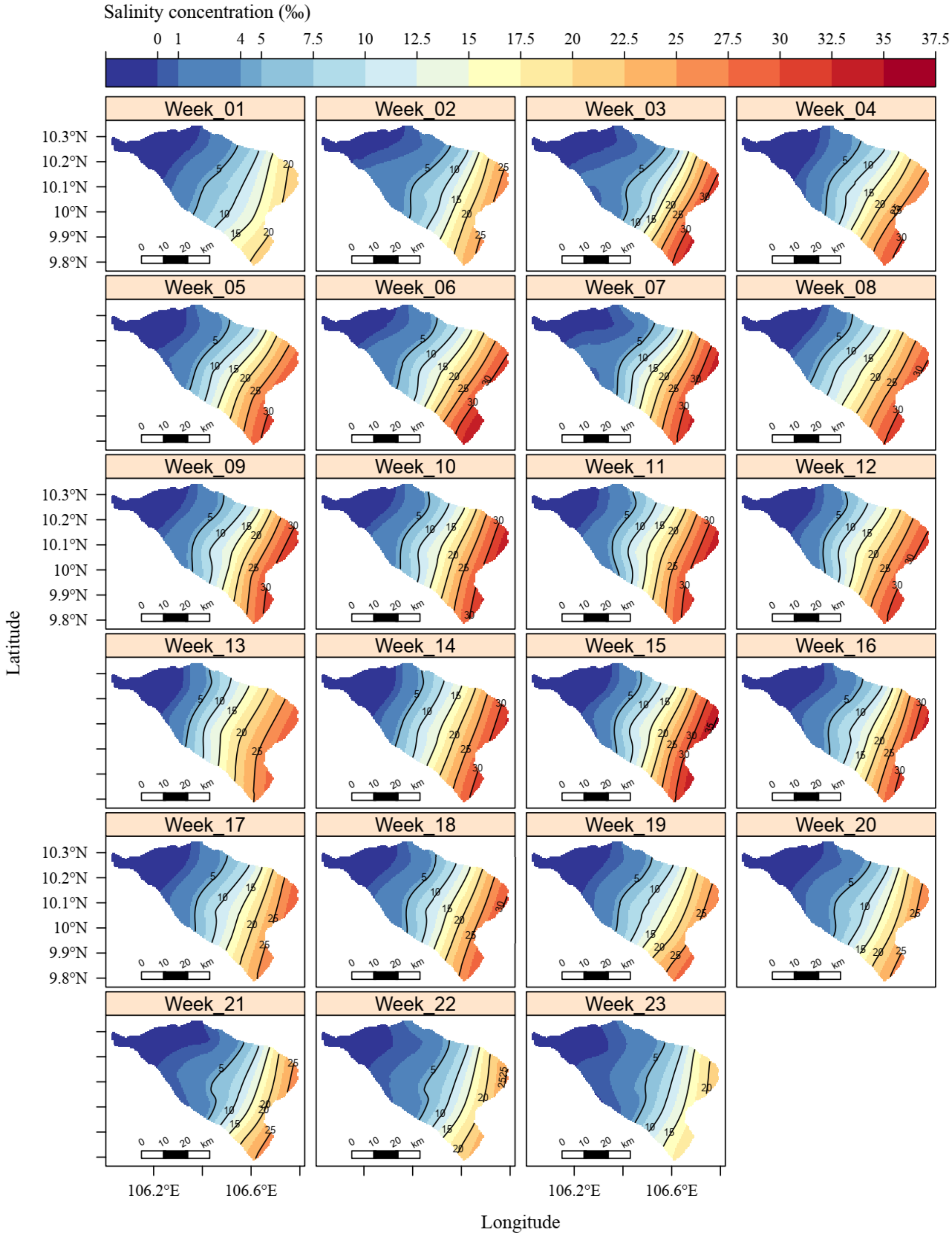

Figure 4. Forecast maps of salinity (‰) from week 1 to week 23 of 2021 in the Mekong river estuaries of Vietnam. The break values of 1‰, 4‰ are assigned according to the saltwater intrusion severity levels of Vietnam (The Prime Minister, 2021)

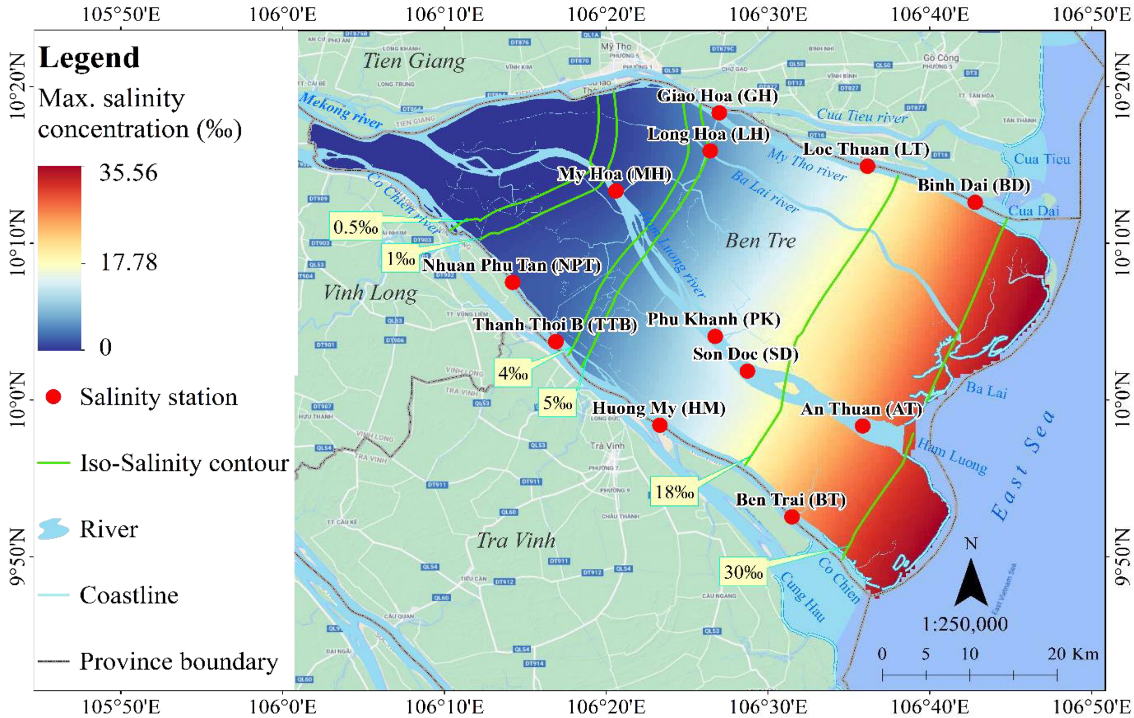

Figure 5. Forecast map of maximum weekly salinity concentration in the Mekong river estuaries of Vietnam. The iso-salinity values are classified according to the classic Venice System (i.e., 0-0.5‰: freshwater, 0.5-5‰: oligohaline, 5-18‰: mesohaline, 18-30‰: polyhalite, 30-40‰: euhaline) and saltwater intrusion severity levels of Vietnam (i.e., 1‰, 4‰) (The Prime Minister, 2021)

4. Conclusions

The risk of SWI occurs annually during the dry season in the Mekong river estuaries of Vietnam. During the past 9 years, from 2012 to 2020, this region has faced the three most severe SWI events occurring in 2013, 2016, and 2020. The variation of annual and monthly salinity tended to increase gradually from the estuary to the mainland. The intensity of SWI was the highest in the Ham Luong river, followed by the Co Chien and My Tho rivers. Moderate SWI risk with 4‰ salinity moving inland from 25 to 50 kilometers occurred most usually in the Ham Luong river with an annual frequency of 88.89% and a monthly frequency of 100%. In the Co Chien river, moderate SWI risk often occurred with an annual and monthly frequency of 77.78% and 66.67%, respectively. Moderate risk of SWI is occasionally recorded in the My Tho river with an annual and monthly frequency of 44.44% and 33.33% in that order.

Simulating and predicting dynamics of the freshwater-saltwater interface is an important element in the appropriate management of coastal aquifers to control or reduce SWI. However, forecasting SWI into the Mekong river estuaries is a major challenge for hydrologists as salinization is governed by complex internal and external drivers while limited monitoring data is available. Using ARIMA models with a single input of water salinity measurements from 2012 to 2020, we have built the best fit models for predicting seasonal water salinity in the My Tho, Ham Luong, and Co Chien rivers. Compared to the weekly salinity observations in 2021, these models predicted very well in the My Tho and Ham Luong rivers but unsatisfactory performance in the Co Chien river.

In the first six months of 2021, SWI was predicted to occur in three spells: January 1 - 29, January 29 - April 30, April 30 - June 11. The deepest SWI was predicted to occur from March 19 – April 16, during which the 4‰ saline front could penetrate the farthest distance of 41, 41, and 44 kilometers inland from the sea through the My Tho, Ham Luong, and Co Chien rivers, respectively. The entire river system was exposed to moderate SWI risk and freshwater zones with salinity below 0.5‰ decreased significantly to only 0.73% of the whole area of Ben Tre province.

The main contribution of this study is that it provides insights into the applicability of ARIMA models for predicting water salinity in complex rivers such as MKD, where it is difficult to develop mathematical models covering entire estuary areas with a variety of physical processes.

The non-stationarity and nonlinearity of water salinity time series may lead to uncertain forecasts of the ARIMA model. To overcome this challenge, it is necessary to integrate the ARIMA model with other models that can capture nonlinear and non-stationary patterns to improve predictive performance.

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