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Spatial and temporal effects improve Bayesian price estimation for the small-scale shrimp fishery in Sergipe State, Brazil

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ABSTRACT

Local shrimp productivity and economic infrastructure may vary among small fishery communities, which can lead to unequal conditions for fishers. Consequently, the domestic market value for shrimp landing can be different and decentralized in space and time. Small-scale fisheries (SSF) have several characteristics, including the spatial and temporal interactions, which add uncertainty to fishery statistics. Bayesian hierarchical models allow parameters to vary on several levels using random effects or other means of randomization, which leads to better estimation of multilevel uncertainty compared to other methods. This study tests the influence of space and time on shrimp production prices in Sergipe State, Brazil, using a Bayesian hierarchical modelling approach. We also tested whether there is a relationship between capture per unit effort and production value. We described landings of *Litopenaeus schmitti* and *Xiphopenaeus kroyeri* in 27 locations in the State of Sergipe between 2010 and 2016. Shrimp production (kg) remained relatively stable (200–300 ton/year). Using the Bayesian approach, we found that prices of both species varied among landing points within and between years, and this variation has spatial and temporal dependence. The model enhanced our understanding of which factors affect price variability in landings. In particular, our models indicated that catch per unit of effort, location, and time affected the price variability in coastal landings within the State of Sergipe. However, the seasonal monthly effects were not as important as the yearly effects, since the variance within years was found to be low. This could indicate that economic activities (tourism) do not play an important role for shrimp prices in this region. Yet, biological factors (abundance and reproduction period) can affect the prices for some locations. Improving the estimates by using methods that can account for the human dimension of fishing activities is paramount in its management, enhancing the decision-making process.

1. Introduction

Shrimp is an important component of global fishery resources with total marine catches tripling in 47 years, reaching 3500.000 tons in 2016, being exploited by both industrial and small-scale fishery (SSF) fleets worldwide (FAO, 2018). SSF activities are essential in economic, social, and cultural functions in many coastal communities around the world (Wyman, 2008; Plagányi et al., 2014; Ramos et al., 2017).

Small-scale shrimp fisheries, in particular in developing countries, are an activity that involves many family members and contributes to reducing poverty and increasing food security (Musiello-Fernandes et al., 2018). Nevertheless, local shrimp productivity and economic infrastructure may vary between small fishery communities, which can lead to unequal conditions for fishermen (Houston et al., 1989). As a result, shrimp landing's domestic market value can be different and decentralized in space and time (Smith and Basurto, 2019).

In the northeastern Brazilian region, shrimp fisheries are mainly based on stocks of groups of Penaeidae family, as seabob shrimp

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Xiphopenaeus kroyeri (Heller, 1862), the white shrimp *Litopenaeus schmitti* (Burkenroad, 1936), and the pink shrimp Farfantepenaeus subtilis (Pérez Farfante, 1967). These species are mostly captured by SSF, which can comprise up to 90% of the catch of the northeastern Brazilian region (Carvalho et al., 2020). For Sergipe State, the annual estimates of first commercialization values are around 16 million USD (Thomé-Souza et al., 2014a, 2014b), with shrimp commercialization reaching 50% of this total. This local fishery plays a fundamental role in socio-environmental and economic aspects (Pinheiro and Martins, 2009; Aragão et al., 2015).

Shrimp fishery fleets exploit many areas along the seacoast, covering a wide range of ecosystems (Ruffino et al., 2016), but markedly exploiting estuarine environments by trawling. The decentralized dynamics of shrimp capture hinders actions aimed at monitoring fishing, leading to few records of quantified or qualified landings. This aspect contributes to the lack of information and practical management actions (Musiello-Fernandes et al., 2018). Consequently, important information, such as the catches composition, revenues, fishing effort, and shrimp price, are limited (Dias-Neto, 2011). An alternative to reverse this situation involves access to local fishers and their ecological knowledge, seeking to understand the spatial and temporal heterogeneity in certain regions (Moreno-Báez et al., 2012).

As a rule, shrimp fishery production records are also uncertain and quite diverse among small fishery communities through time, given their infrastructure development differences. The volume of shrimp caught can influence the shrimp ex-vessel prices, fishing costs, and imports (Houston, 1989; Macho et al., 2013; Villasante et al., 2016). Specifically ex-vessel price is tied to quantity and quality production through catches (Sakai et al., 2010). However, this information is not always available (Musiello-Fernandes et al., 2018), blurring the comprehension on which variables most influence shrimps' price in SSF.

The fishing catch and effort are usually the most feasible variables to be sampled. The ratio between catch and fishing effort, catch per unit effort (CPUE), can reflect the variation in shrimp availability. Hence, it is an appropriate proxy to understand the relationship between price and seasonality (Alizadeh Ashrafi et al., 2020). Yet, the relationship between price and abundance can be unclear (European Parliament, 2011) since the shrimp market does not always follow the demand laws. Besides, the values of first commercialization may be underestimated, taking into account that agents maximize their profits while purchasing a large quantity of the product (Cuervo-Sánchez et al., 2018).

In addition, fishery statistics from SSF are affected by multiple characteristics, especially regarding the spatial and temporal interactions, which increases the uncertainty of the data set, which is poorly estimated with classical statistical methods (Stegmueller, 2013). Conversely, the Bayesian hierarchical models allow varying parameters on several levels by random effects or other means of randomization, which provide a better estimation of multilevel uncertainty. Also, accounting for multilevel uncertainties improves the estimates when testing for relationships with covariates (Snijders, 1996). The Bayesian framework can overcome classical assumptions that are rarely met with this type of data, such as homoscedasticity and equalized treatments (Kruschke, 2013). Improving the estimates by using methods that can account for the human dimension of fishing activities is paramount in its management, enhancing the decision-making process.

Although applying the Bayesian method in fishery sciences and prices is not new (Caskey, 1985; Dalton and Fissel, 2018; Colla-de-Robertis et al., 2019), few studies describe the use of the hierarchical Bayesian models accounting for the effects of time and location on the ex-vessel prices. The most recent studies with price elasticity and demand using hierarchical models are from areas like capital stock, real estate, medical supplements, farms, and land use (Sahu et al., 2014; Ho et al., 2018; Yang et al., 2021; Ling, 2021). Also, few studies explore the impacts of other variables like catch or catch per effort (CPUE) within a multilevel context.

In this sense, this study aims to test the influence of space (several landing ports) and time (2010–2016) on the ex-vessel price of shrimp catches under a Bayesian hierarchical modelling approach. Also, we are testing whether there is a relationship between CPUE and production value. Thus, we intend to offer a straightforward approach to simplifying complex interactions and improving model estimates. To achieve it, we first present all the details about our model, informing how we accounted for the location's effect upon yearly price estimates using six years of small-scale fisheries' daily landings data at 27 harbours in Section 2: Materials and methods. This section also unveils the differences among landing points' prices and the relationship between price and CPUE. The following section presents and discusses results considering spatial and temporal variability in prices and the relationship with the CPUE, showing prospects and caveats to the models. Finally, we underline how the yearly effects influence the prices of both species between landing points and the absence of a relationship between CPUE and prices to the species *X. kroyeri.*

2. Materials and methods

2.1. Study area

The study area comprises the continental shelf of Sergipe State, Brazil, which has approximately 163 km of coastline (Fig. 1) with exposed sandy beaches and high water turbidity (Coelho Dias da Silva et al., 2010). It is the narrowest portion of the continental shelf in the country, ranging between 12 and 34.90 km, with a gentle slope with approximately 50 m depth in the shelf break, which can be considered shallow compared to other areas (Silva et al., 2019). The area has six estuaries, which receive the flow of six large rivers: São Francisco (Brazil's second-longest river), Japaratuba, Sergipe, Vaza-Barris, Piauí-Real, and Itapicuru (Carvalho, 2012; Lima et al., 2017; Lima and Hora Alves, 2017; Albuquerque et al., 2020).

2.2. Data

Landings' data were collected daily from January 2010 to December 2016 at 27 landings sites of small-scale fisheries (Fig. 1). The information collected was obtained directly from the fishers from interviews as logbooks. The ex-vessel price dataset is site-based and is composed by date, landing site, and catch value in Brazil's currency Real (BRL). The catch dataset is individual-based and is composed by date, landing site, days fishing, number of fishermen, and catch in kg. The shrimp species landed in these many harbours were *Litopenaeus schmitti* (white shrimp) and *Xiphopenaeus kroyeri* (Atlantic seabob).

2.3. Statistical analysis

We presented the time-series (2010–2016) of the landings catch (kg) of all sites, for both shrimp species, and highlighted the main landing points.

2.3.1. Modelling the yearly mean price estimates

We used two different models (hierarchical and non-hierarchical) to test the location as a categorical random effect on the price value (BRL/kg) of the both species. One model was a fit that set the price values with a hierarchical structure to account for multilevel uncertainties, while the other model had a non-hierarchical structure.

Specifically, the non-hierarchical model was defined as:

$$W_i \sim N(\mu_i, \tau[Y_i])$$

$$\mu_i = \alpha[Y_i] \tag{1}$$

$$\alpha \sim N(0, 0{\cdot}10E\text{-}6)$$

$$\tau \sim Gamma(0{\cdot}001, 0.001)$$

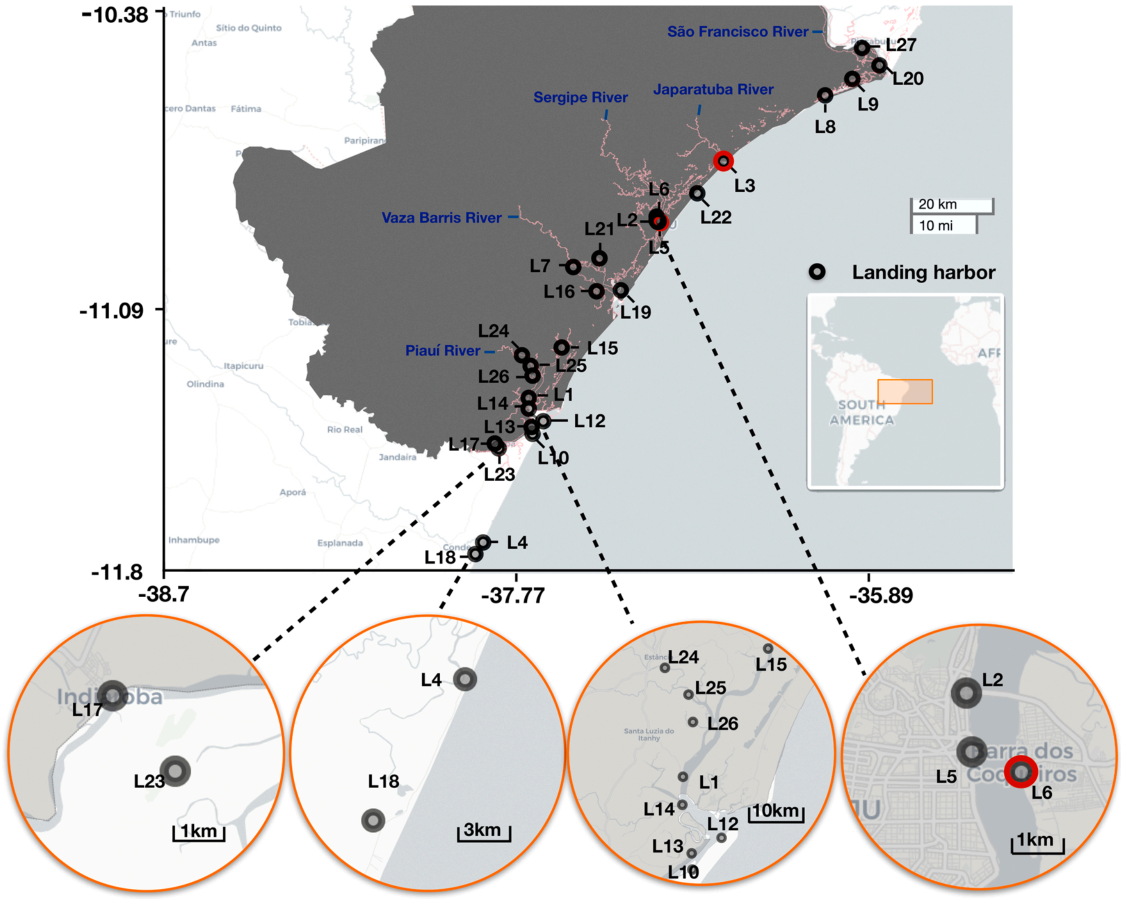

Fig. 1. Map of the study area on Sergipe State (Brazil) with locations of the 27 landing harbors of two shrimp species: *Litopenaeus schmitti* and *Xiphopenaeus kroyeri*. The big-sized landing harbors are highlighted in red. (For interpretation of the references to colour in this figure, the reader is referred to the web version of this article.)

where W_i indicates the error term for i observations with a normal distribution (N) and α specifies the average for each location Y for the parameter μ. Parameter t specifies the precision of the distribution.

The hierarchical model was specified as:

$$W_i \sim N\,(\theta_i,\ \tau\ [Y_i])$$

$$\theta_i = \alpha\ [Y_i] \qquad (2)$$

$$\alpha \sim N\,(\mu,\ t)$$

$$\mu \sim N\,(0,\ 0{\cdot}10E\text{-}6)$$

$$t \sim Gamma(0{\cdot}001,\ 0.001)$$

$$\tau \sim Gamma(0{\cdot}001,\ 0.001)$$

where W_i indicates the error term for i observations with a normal distribution (N) and α specifies the average for each location Y for the parameter θ. The hyperparameters μ and t indicate random variances for the parameter b.

Regarding each year, we only have described the landing sites with data of at least three months, which varied from 5 to 14 for L. *schmitti* and from 2 to 12 for *X. kroyeri* (Table 1). Harbours with less than two months of data (the majority of them) produced poor models that failed to converge. Hence, we only retained the models which diagnostics presented a good fit (German-Rubin criteria = 1). These models were compared using the Watanabe-Akaike information criterion (WAIC) (Watanabe, 2010), which measures the quality of statistical models (Gelman et al., 2014). The models used a Gaussian distribution, and they were fit using Monte Carlo Markov chains (Metropolis-Hasting algorithm) and non-informative priors (Jeffreys, 1961). The hierarchical and non-hierarchical models were tested separately for both shrimp species (L. *schmitti* and *X. kroyeri*).

Table 1
Shrimp landing harbors with enough data to generate reliable results for each year. Two species were analyzed at Sergipe State (Brazil).

	Landing harbors	
Years	*L. schmitti*	*X. kroyeri*
2010	L1, L2, L3, L4, L5, L18	L1, L2, L3, L4, L5, L6, L10, L13, L16, L17, L18
2011	L1, L2, L3, L5, L6, L7, L8, L16	L6, L9, L10, L1, L2, L15, L16, L17, L3, L4, L13, L5
2012	L1, L3, L4, L5, L6, L7, L8, L9, L11, L12, L13	L1, L2, L3, L4, L5, L6, L9, L10, L13, L15, L16, L17
2013	L1, L2, L3, L5, L6, L7, L8, L9, L11, L13, L14	L1, L2, L3, L5, L6, L9, L10, L16
2014	L1, L3, L4, L5, L6, L7, L8, L9, L10, L11, L12, L13, L14, L18	L1, L3, L4, L5
2015	L3, L5, L6, L7, L10, L11	L3, L5
2016	L1, L2, L3, L5, L6, L7, L8, L9, L10, L11, L12, L13, L14, L16, L17	L1, L2, L3, L5

2.3.2. Modelling the probability of differences among landing points prices

For this estimate, only the hierarchical model was fit since this model can account for the random location effect. In this case, the Bayesian probability of difference (analogue to the classical p-value) was computed (Gelman et al., 1996; Kéry and Royle, 2016). This method consisted of using a Boolean variable that counted the number of simulations with a difference among locations of ≥0 or <0. Posterior probabilities with a difference of equal to or higher than 95% posterior probability intervals were considered significant (Gelman et al., 1996; Kruschke, 2013).

2.3.3. Modelling the relationship between price and catch per unit effort

The catch per unit effort (CPUE) was defined as follows:

$$CPUE = \frac{C}{D * N} \tag{3}$$

where C is the total catch for all fisherman in kg; D is the number of days fishing per fishermen; and N is the number of fishermen.

We have divided the locations according to the landing capacity of ports and gear technology of docked fleet: (i) the largest ones, L3 and L5 (40 ton/year ≤ catch ≥15 ton/year for L. *schmitti and* 370 ton/year ≤ catch ≥15 for *X. kroyeri*), which dock only motorized boats, and (ii) the remaining ones considered small-sized harbours (catch < 1 ton/year, for both species) that dock only non-motorized boats and canoes. This context allowed us to analyse, using a hierarchical Bayesian generalized linear model, the relationship between shrimp prices with catch from ports with different capacities and fleet types, location, and time (explanatory variables).

In the model, location and time were considered a categorical random effect, and the catch was considered a fixed effect. In addition, to test whether this model is relevant, we have selected the best subset of explanatory variables following a step-by-step forward addition procedure, including a null model without covariates, using the WAIC. The final model was selected based on the lowest WAIC and contained only relevant predictors (i.e., those predictors with 95% probability of not including zero within its credible interval) (Gelman et al., 1996; Kruschke, 2013).

The hierarchical Bayesian GLM model was specified as:

$$W_i \sim N(\theta_i, \tau)$$

$$\theta_i = \alpha[Y_i, M_i, U_i] + b[Y_i, M_i, U_i] * C \tag{4}$$

$$\alpha_i \sim N(\mu_1, t_1)$$

$$b_i \sim N(\mu_2, t_2)$$

$$\mu_i \sim N(0, 0 \cdot 10E\text{-}6)$$

$$t_i \sim Gamma(0 \cdot 001, 0.001)$$

$$\tau \sim Gamma(0 \cdot 001, 0.001)$$

where W_i indicates the error term for i observations with a normal distribution (N). α specifies the intercept for each location *Y, month M and, year U* for the parameter θ. C is the Catch per unit of effort (CPUE). The hyperparameters μ_i and t_i indicate random variances for the parameter α and b.

2.4. Software and simulations

The parameters were estimated through simulations with 10,000 iterations and 3 chains using the Just Another Gibbs Sampler (JAGS) software (Plummer, 2003) and the "rjags" statistical package (Plummer et al., 2006) through the R software (R Core Team, 2021). In addition, we checked for the success in the convergence using the Gelman-Rubin criterion (Gelman and Rubin, 1992; Brooks and Gelman, 1998; Vats and Knudson, 2021).

3. Results

Shrimp catch dynamics showed variations among years and landing sites. For both species, two landing sites (L3 and L5) had the majority of catch per kg, with landings of *X. kroyeri* being ten times higher than L. *schmitti* (Fig. 2). The high number of landing points (n = 27) brings an irregularity in the landings with very low values (or zero) in the majority of landing points (Figs. 3 and 4).

3.1. Spatial and temporal variability in prices

For L. *schmitti,* the hierarchical model provided better estimates than the non-hierarchical one, with lower WAIC values, for all years (Table 2). However, the credible intervals from the hierarchical models were wider than the non-hierarchical models, thus accounting for more uncertainty in the estimates by considering the temporal and geographical differences.

Shrimp prices between locations of landings were significantly different in all years (Fig. 5). Specifically, the year of 2016 showed the highest number of posterior probabilities of difference equal to or above 95%, with an average of 4.7 significant results per location, indicating that prices between ports differed the most. Likewise, prices contrasted among ports by the years of 2012, 2013, 2014, 2015, 2011, and 2010 with an average of 4, 3.72, 3.53, 1.83, 1.42, and 1 significant result per location, respectively. It is noteworthy that the price's variability within all years can be considered low, ranging from BRL 1.22 in 2011 to BRL 4.29 in 2015.

For *X. kroyeri,* the hierarchical model also provided better estimates than the non-hierarchical model between almost all years with lower WAIC values (Table 3). The unique exception was the year of 2015. Also, like L. *schmitti*, the credible intervals from the hierarchical models were wider than the non-hierarchical models and 2015 was the year with highest standard deviation values and lesser landings for both species.

Prices among locations were significantly different for almost all years (Fig. 6). Again, in 2015, prices were similar among landing points. However, compared to L. *schmitti* species, the price for *X. kroyeri* were more similar among landing ports, presenting lower values of posterior probabilities of difference equal to or above 95% (significant results).

The year of 2011 showed the lowest difference of price between ports and presented the highest number of significant results, with an average of 4.75 significant results per location, followed by the years of 2010, 2013, 2012, 2014, 2015, and 2016 with an average of 4.36, 2.25, 2.12, 1, 0.5, and 0.5 significant results per location, respectively. The price's variability within all the years can be considered low, ranging from BRL 2.66 in 2014 to BRL 0.82 in 2016. The unique exception was 2015 where the variability was considered high (equal to BRL 34).

3.2. Relationship with the CPUE

For L. *schmitti*, the best fit Bayesian model (based on the lowest value of WAIC) included the CPUE fixed effect, the harbour's location, and the random year effects for the big-sized harbours (Table 4). For these harbours, the CPUE presented a negative relationship (posterior mean = -0.014, IC95% [-0.029; 0.005], posterior probability of being < 0= 0.97). For the small-sized harbours, the best fit model included only the location and the random year effects (null model). Hence, there is no relationship between the CPUE and the price for these harbours. Indeed, within this group, only one harbour (L11) presented data for all years (Fig. 3A). Also, it is noteworthy that the month's random effects worsened the fitness of our model.

For *X. kroyeri*, the best fit Bayesian model included only the harbour and random year effects (null model) (Table 4). Hence, there is no relationship between the CPUE and the price for this species. Like with L. *schmitti*, the month's random effects worsened the model's fitness.

4. Discussion

Although many attributes and factors may influence seafood prices, by investigating ex-vessel price formation of two luxury products, white shrimp and seabob shrimp, hierarchical models enhanced our understanding of which factors affect price variability in shrimp landings.

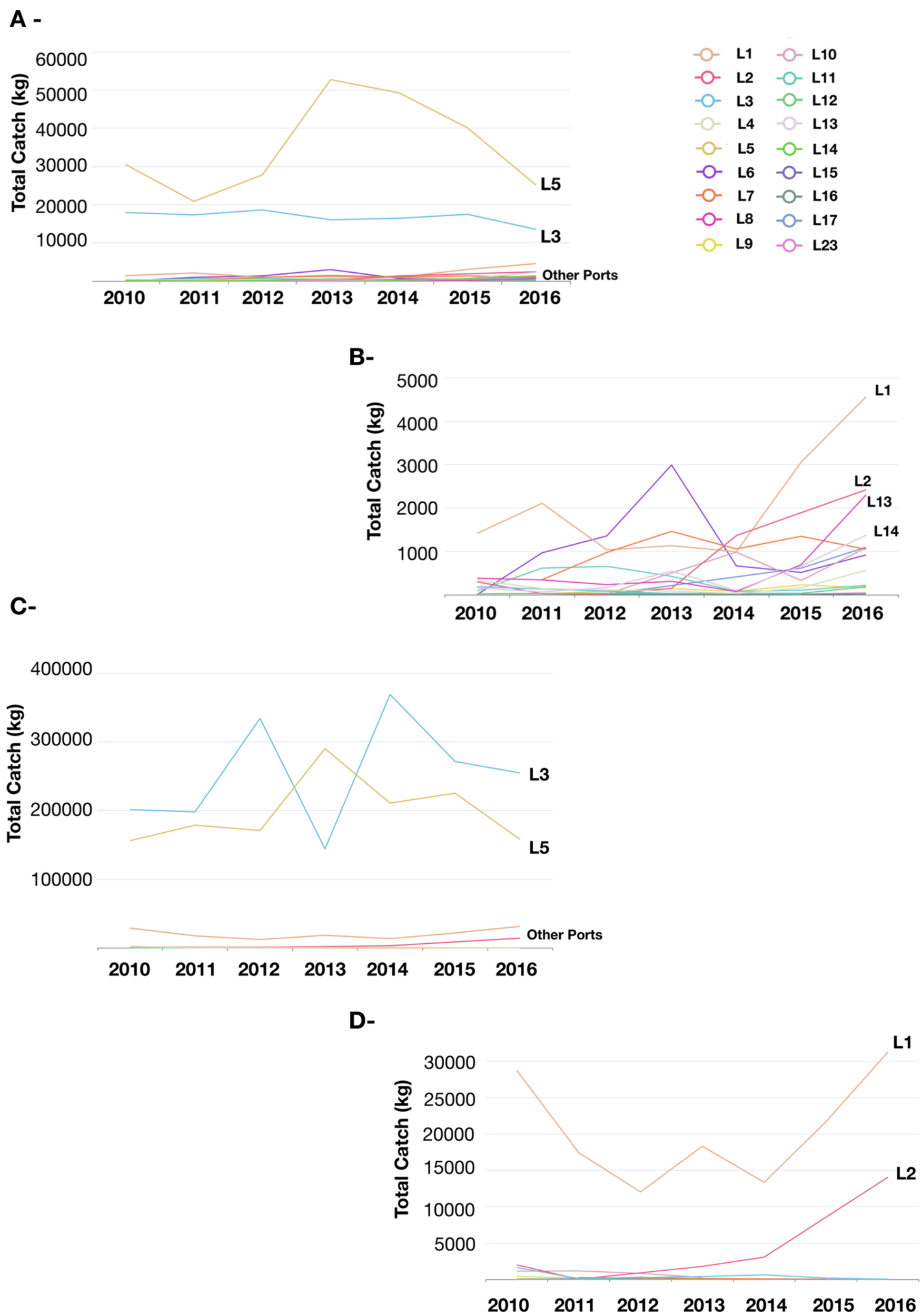

Fig. 2. Annual total catch (kg) for the 27 landing harbors in Sergipe State (Brazil) for L. *schmitti* (A) and *X. kroyeri* (C); and Annual total catch (kg) for the small harbors for L. *schmitti* (B) and *X. kroyeri* (D). The locations of the landing harbors are illustrated in Fig. 1.

Models clearly indicated that shrimp prices were distinct to each species by landing port, within and between the years. For L. *schmitti* big-sized harbours, price variability is yet affected by CPUE coastal landings and according to CPUE. Inspection was carried out from 2010–2016 at 27 landing ports along the coast of Sergipe, the smallest state in the southern part of the northeastern Brazilian coast. During this period, L. *schmitti* yielded from 20 to 50 tons/year while *X. kroyeri* production reached around 150–350 tons/year. Overall production remained reasonably stable in 4 of 27 possible landing points.

4.1. Spatial and temporal variability in prices

The effect of time and space (mainly daily influence) over marine products' price, has increasingly received attention (Guillen and Maynou, 2014). Economically, similar prices among landing sites were expected, since harbours under the same administrative organization (state or municipality) may share similar government subsidy schemes, taxes, and other market rules (Clark and Munro, 2017; Skerritt et al., 2020). For L. *schmitti* and *X. kroyeri* however, the ex-vessel prices presented significant differences among harbours and years in the hierarchical model. It implies that other factors may influence the harbours locally, such as the type of vessel and gears, the size of harbours, the influence of community local leadership, cultural preferences, or some combination thereof (Houston et al., 1989; Grazia Pennino et al., 2016; Carvalho et al., 2020). In addition, fishermen act differently when influenced by institutional, economic, and social incentives (van Putten

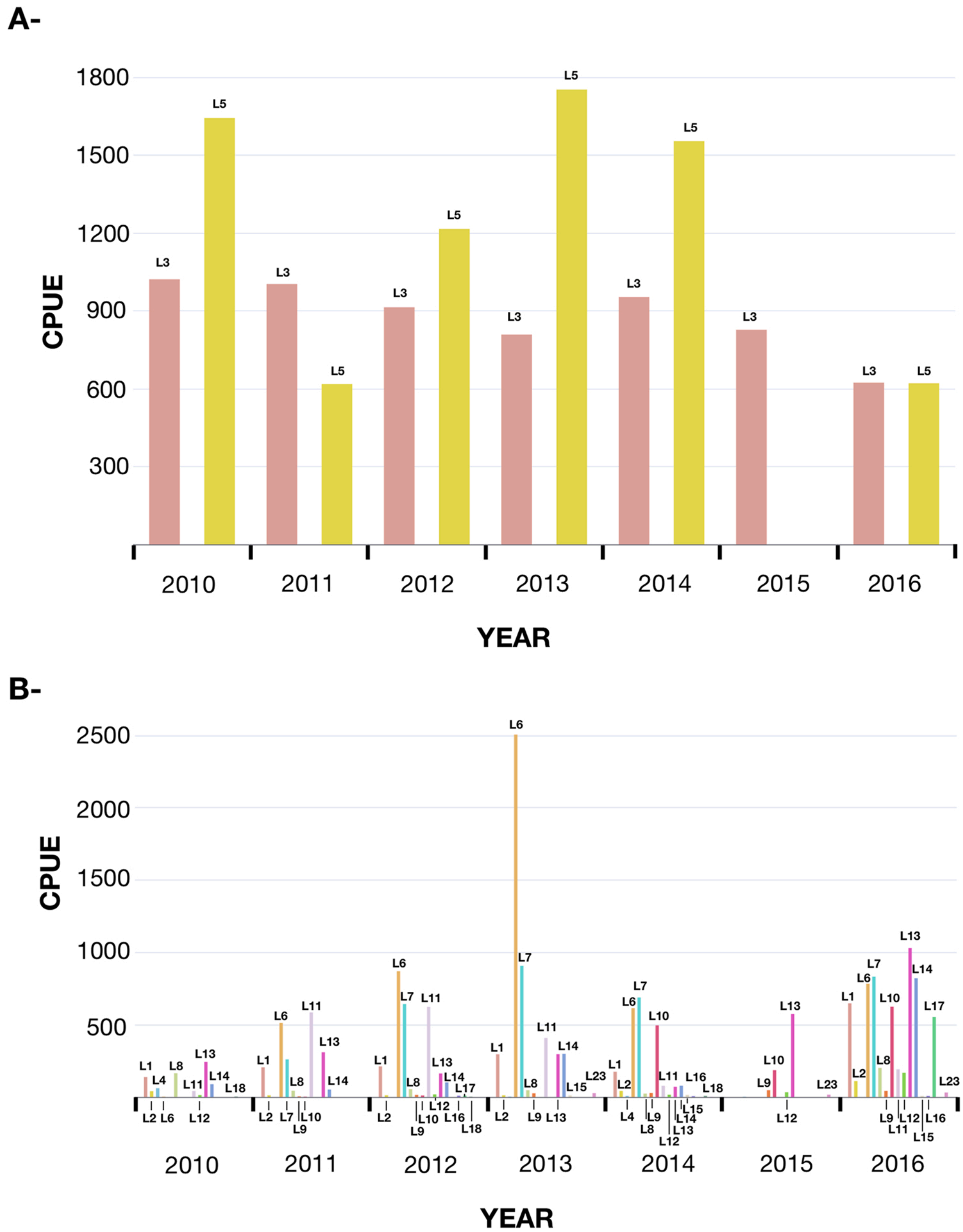

Fig. 3. Estimated CPUE of *Litopenaeus schmitti* for each landing harbors of small (5000 kg >Catch) (A), and big (Catch ≥ 15,000 kg) (B) harbors.

et al., 2012). For example, it has been recognized that a lack of clearly defined property rights in coastal ecosystems has led to unsustainable natural resource use, such as overfishing and consequent biodiversity loss (Ostrom and Hess, 2000). Also, economic (e.g., penalizations illegal, unreported and unregulated fishing [IUU] fishing activities) and market incentives (e.g., eco labeling) are also usually key factors of fish prices, thus determining fishers' vulnerability (Macho et al., 2013; Villasante et al., 2016). Formal institutions are not always able to enforce collectively desirable outcomes in small-scale fisheries, thus social norms (e.g., values and beliefs of people in a social-ecological system) can trigger transformations of social (dis)approval and behaviour of fishers. However, social, economic, and other feedbacks can be intertwined and often difficult to disentangle (Nyborg et al., 2016).

In addition, the ex-vessel price for *X. kroyeri* is more similar among harbours than for L. *schmitti*. *Xiphopenaeus kroyeri* is the most abundant shrimp species of Sergipe, persisting year-round (Thomé-Souza et al., 2012, 2013, 2014b, 2014a; Santos et al., 2017); however, it has a lower commercial value due to the smaller size (Santos et al., 2017). It should be noted that in shrimp trade, price is usually based on categories defined by the size and quantity of shrimp by weight (Smith and Basurto, 2019). Since both factors can affect prices, the combination of high abundance and low commercial value, resulted in more even prices for *X. kroyeri*, (Houston et al., 1989; Geethalakshmi et al., 2009; European Parliament, 2011).

Consideration needs to be given to the fact that tropical small-scale fisheries are frequently developed under patron-client relationships, in which individuals provide fishery credit in exchange for the oncoming catch they are financing (Miñarro et al., 2016; Nunan et al., 2020). In Brazil, this is a common traditional arrangement between fishers and middlemen (Sethi et al., 2010) that entails a cooperative strategy of self-governance (Basurto et al., 2013). Under this bargaining system, the fisher and middlemen become a regular customer to each other (O'Neill et al., 2019), to the point where the relationship evolves into a partnership with the middlemen. In this sense, patron-client relationships are shaped not only by economic collaboration but also by social interaction (Nunan et al., 2020). As a consequence, middlemen develop

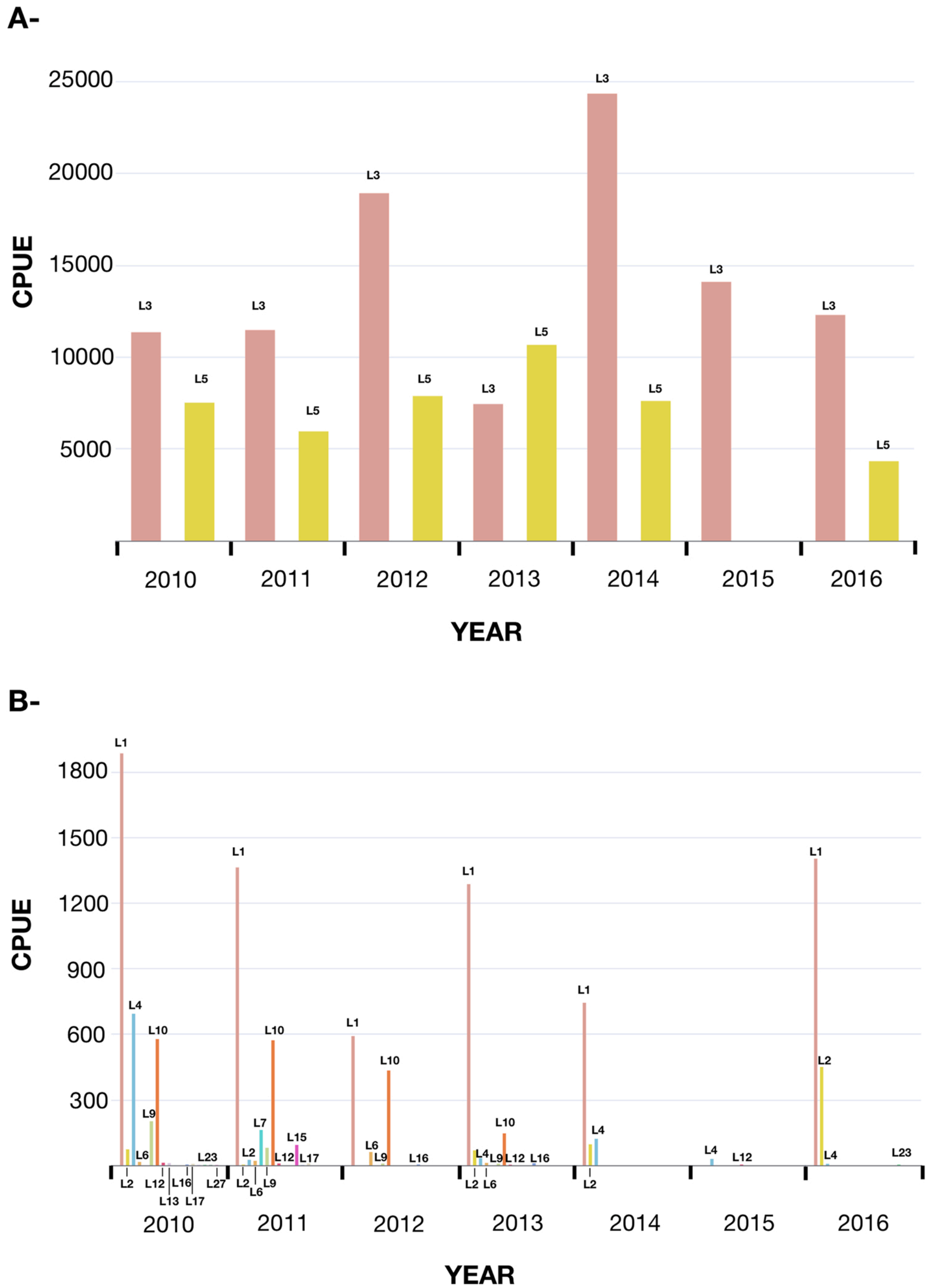

Fig. 4. Estimated CPUE of *Xiphopenaeus kroyeri* for each landing harbors of small (5000 kg >Catch) (A), and big (Catch ≥ 15,000 kg) (B) harbors.

Table 2
Parameter estimates of values (BRL R$/kg) for the Hierarchical and Nonhierarchical Bayesian models of *Litopenaeus schmitti*. Watanabe-Akaike information criterion (WAIC) scores measure goodness-of-fit. Smaller scores (WAIC) represent better models.

	Hierarchical model					Non-hierarchical model				
	Mean	SD	IC 2.5%	IC 97.5%	WAIC	Mean	SD	IC 2.5%	IC 97.5%	WAIC
2010	18.64	1.32	16.06	21.31	309	17.98	0.42	17.15	18.81	388
2011	14.97	1.22	12.57	17.45	190	15.95	0.58	14.80	17.10	346
2012	14.07	1.59	10.93	17.29	398	15.41	0.56	14.32	16.51	550
2013	15.04	1.33	12.45	17.73	307	15.65	0.48	14.70	16.59	612
2014	17.06	1.59	13.93	20.25	535	17.40	0.63	16.18	18.63	659
2015	20.67	4.29	12.35	29.26	107	20.70	1.83	17.08	24.31	141
2016	20.60	1.52	17.61	23.62	514	20.55	0.51	19.56	21.55	1119

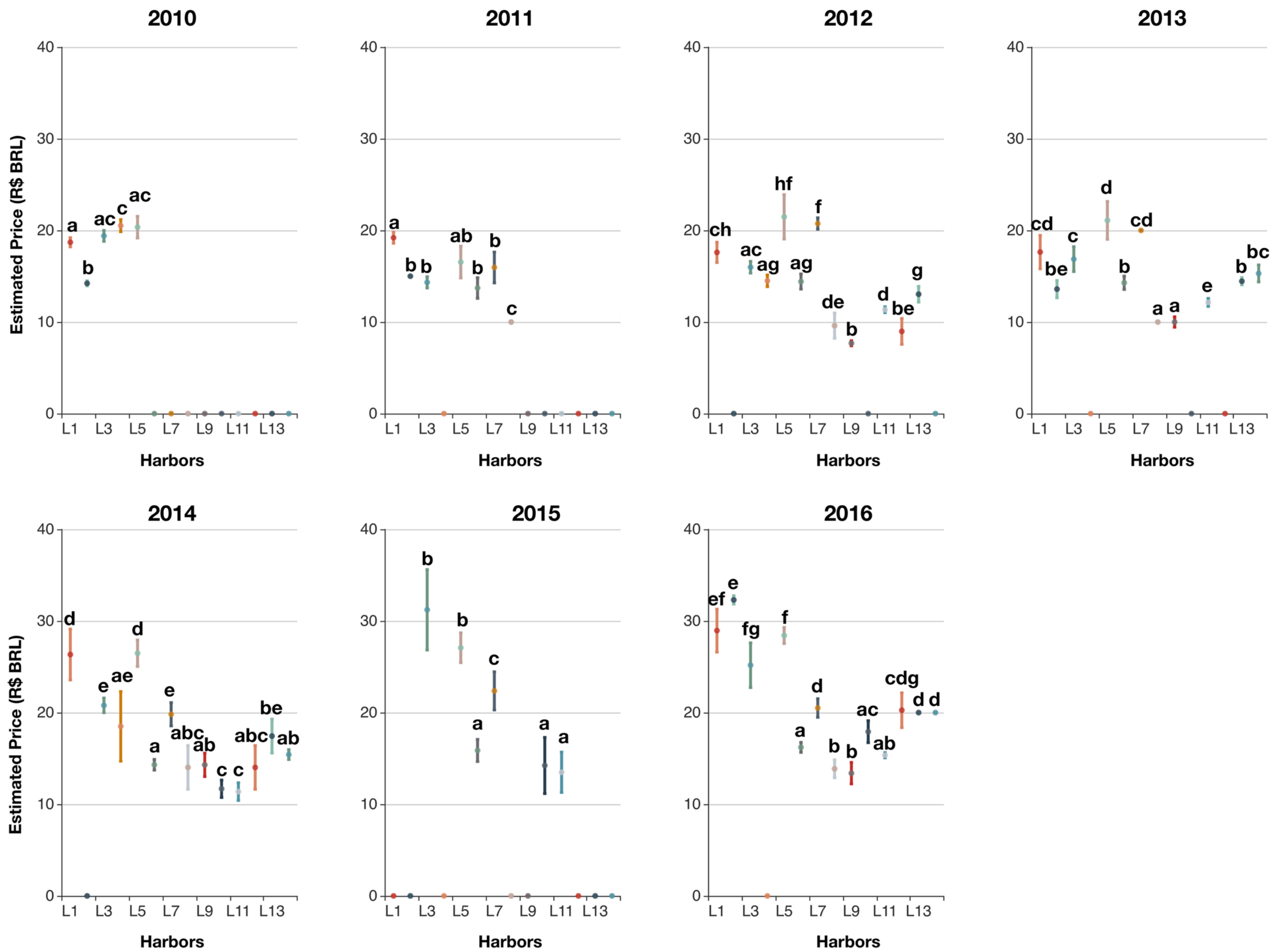

Fig. 5. Yearly mean and standard deviation of estimated price values of *Litopenaeus schmitti* for some landings sites in Sergipe State (Brazil). Landings sites with the same letter have posterior probabilities of difference lower than 95% (non-significant results).

Table 3
Parameter estimates of values (BRL R$/kg) for the Hierarchical and Nonhierarchical Bayesian models of *Xiphopenaeus kroyeri*. Watanabe-Akaike information criterion (WAIC) scores measure goodness-of-fit. Smaller scores (WAIC) represent better models.

	Hierarchical model					Non-hierarchical model				
	Mean	SD	IC 2.5%	IC 97.5%	WAIC	Mean	SD	IC 2.5%	IC 97.5%	WAIC
2010	8.25	1.48	5.33	11.23	153	7.61	0.41	6.82	8.42	708
2011	7.92	1.10	5.76	10.13	192	8.29	0.36	7.57	9.00	617
2012	8.89	1.25	6.38	11.37	245	9.02	0.52	7.99	10.04	334
2013	10.56	2.21	7.44	13.62	206	9.24	0.60	8.08	10.43	266
2014	7.61	2.66	3.01	13.34	123	7.23	0.62	6.04	8.42	152
2015	8.69	34.00	5.15	11.97	27	8.00	0.71	6.51	9.48	24
2016	6.44	0.82	4.84	8.03	123	6.37	0.26	5.85	6.19	131

a fundamental role in fisher livelihoods but also have a degree of power over the price to be paid. This is a trustful arrangement in which fishers get the economic resources for fishing and middlemen get assurance on shrimp provision. In the shrimp fishery assessed here, the patron-client relations represent a bargaining power that likely contributes to keeping ex-vessel prices quite steady through the years.

Notably, monthly seasonal effects were not as determining as the annual effects, although the existing fishing ban period and the restriction to marine tourism could create seasonal monthly patterns for shrimp pricing (Geethalakshmi et al., 2009; Guillen and Maynou, 2014). Evenness in price was also found for *X. kroyeri* in Brazil's Southeast. This pattern results from fisher's behaviour of keeping shrimp in stock, reducing price variation when the shrimp supply is not high (Lopes and Begossi, 2011), and restricting monthly effects over shrimp price. Yet, it is important to consider that yearly effects are more susceptible to external factors like inflation and other global economic issues, which boost yearly price variability and are out of fishers' control.

The hierarchical Bayesian models fit both species' prices better than the non-hierarchical models. It implies that there was a high degree of unexplained uncertainty within each landing site and time (year) of both species. The non-hierarchical model is unable to cope with these uncertainties because it won't consider dependency across time and space. On the other hand, the hierarchical model borrows strength from the likelihood contributions for all the locations and years considering the

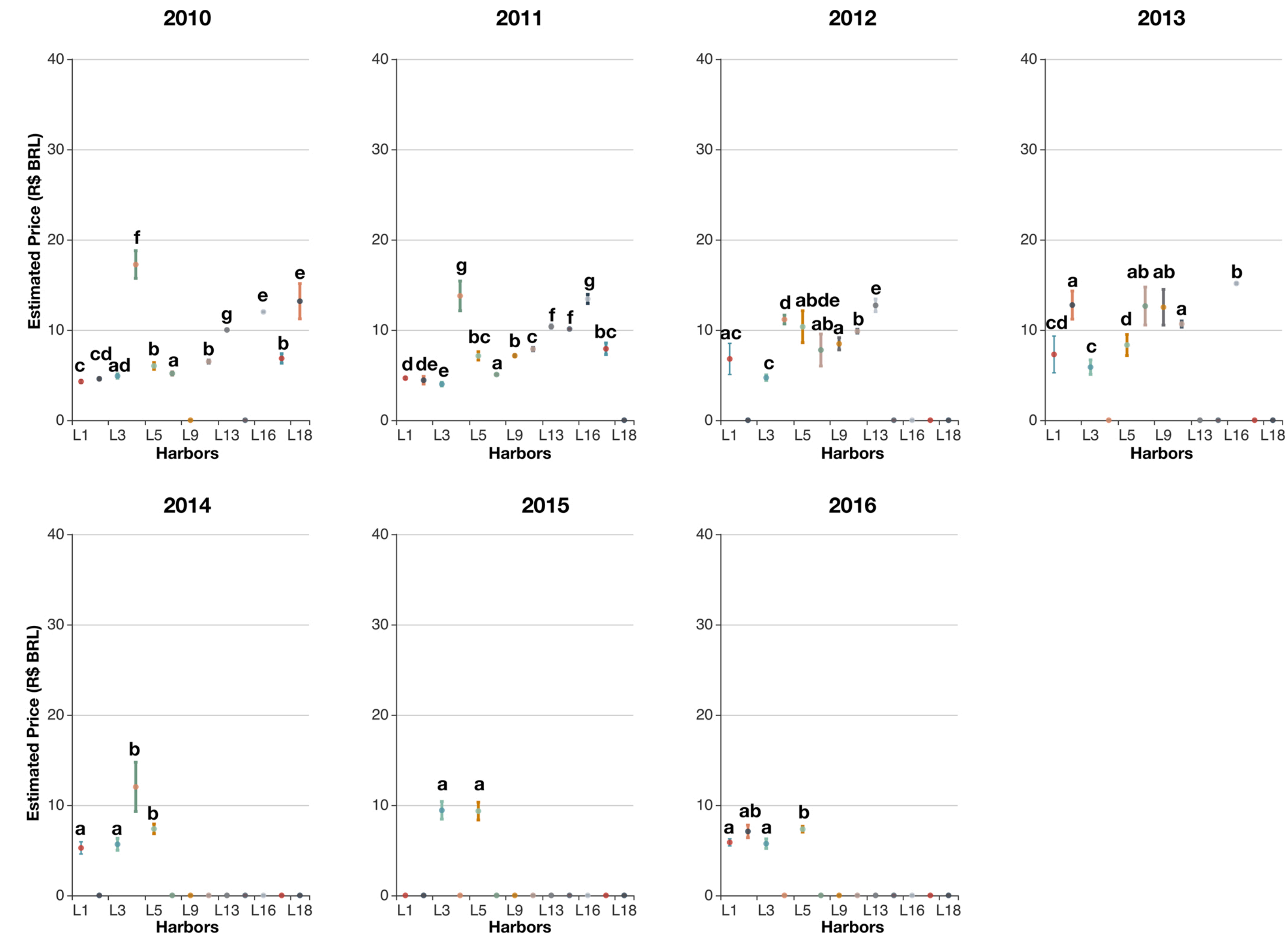

Fig. 6. Yearly mean and standard deviation of estimated price values of *Xiphopenaeus kroyeri* for some landings sites in Sergipe State (Brazil). Landings sites with the same letter have posterior probabilities of difference lower than 95% (non-significant results).

estimate of the hyperparameters, accounting better the unknown variance (Kéry and Royle, 2016). Hence, it improves the precision of our estimates.

4.2. Relationship with CPUE

For both species' landings, the hierarchical Bayesian approach fitted better models for price estimation with spatial-temporal effects (random effects) and CPUE (fixed effect). This model improved the estimates by allowing the slope and intercept to vary according to different conditions of space and time. Thus, better accounting for the unknown variance. Also, the model without random effects would provide misleading conclusions. For example, we would conclude that the relationship between prices and CPUE exists for *X. kroyeri*. Yet, these models presented a worse fit (higher WAIC) than the models with random effects. In the case of the model with random effects, the null model was the best fit (model without the CPUE fixed effect). Hence, likely due to the species' high abundance, small size, and low commercial value (Houston et al., 1989; Santos et al., 2017), there is no relationship between CPUE and price for this species in any harbour.

Concerning the fishery's bioeconomic model, the cost per unit of harvest can be inversely proportional to the species' population density (Sandberg, 2006), given that high stock density leads to higher profitability and less effort. However, high shrimp densities could saturate the markets, making shrimp prices decline and affecting fishing efforts in the opposite direction (Hanneson, 2007; Respondek et al., 2014; Alizadeh Ashrafi et al., 2020). In addition, the lack of relationship between price and CPUE may happen, as observed for *X. kroyeri* in Brazil's Southeast region (Lopes and Begossi, 2011). So, all of these consequences could affect fisher's harvest behaviour unpredictably, especially for a shrimp species that usually has a lower price compared to others, regardless of its density.

For L. *schmitti* landed in big-sized harbours (L3 and L5), the CPUE with location and time as random effects better explained the price estimates. The low posterior mean of the slope hyperparameter (-0.014) showed that it required an increase of at least 71.42 catch per unit of effort to reduce one unit of price, which is in accordance with the price dynamics of shrimp found by other authors (Sardà and Maynou, 1998; Respondek et al., 2014). These two harbours accounted for almost 90% of the whole production of Sergipe. However, the same was not true for the small size harbours. As price (and fishing effort) are negatively affected by shrimp's density (Respondek et al., 2014), fishers from the small-sized harbours use inferior boats and gear technology compared to the big-sized boats. So, the competition forces the price reduction, making the activity less sustainable economically for the small-sized harbours. Indeed, the catch production within the small size harbours was irregular throughout the years. For these harbours, only L11 presented landings in all sampling periods. As a result, productivity does not sustain a regular market, affecting the price fluctuations. Variations in the costs of fisheries (e.g., in fuel prices) could also directly influence product prices (Smith et al., 2017). The fluctuation in the abundance and prices of shrimp also affects competing commodities within the

Table 4
Model comparison for shrimp's price variation in class-size landing harbors at Sergipe State, Brazil (2010–2016). The scores measure goodness-of-fit (Watanabe-Akaike Information Criterion - WAIC). Smaller scores represent better models (in red). CPUE: Catch per effort; RIYEAR: Random intercept of the Year; RSYEAR: Random slope of the Year; RIPORT: Random intercept of the Port; RSPORT: Random slope of the Port; RIMONTH: Random intercept of the Month; RSMONTH: Random slope of the Month.

		WAIC for *L. schmitti*		WAIC for *X. kroyeri*	
Nº	Model	Big Harbors	Small Harbors	Big Harbors	Small Harbors
1	1 + CPUE + RIYEAR + RIMONTH + RIPORT + RSYEAR + RSMONTH +RSPORT	941.6	3160.0	820.2	781.9
2	1 + CPUE + RIYEAR + RIMONTH + RIPORT + RSYEAR +RSPORT	841.6	3025.8	582.9	714.3
3	1 + CPUE + RIYEAR + RIPORT + RSYEAR + RSPORT	660.4	1523.4	506.1	246.3
4	1 + CPUE + RIYEAR + RIPORT + RSYEAR	654.3	1513.5	495.6	241.1
5	1 + CPUE + RIYEAR + RIPORT + RSPORT	677.8	1521.9	499.6	244.0
6	1 + CPUE + RIYEAR + RIPORT	671.9	1510.4	497.4	230.4
7	1 + RIYEAR + RIMONTH + RIPORT	931.2	3149.6	651.6	783.8
8	1 + RIYEAR + RIPORT	696.8	1508.0	495.3	227.6
9	1 + CPUE + RIPORT + RSPORT	798.1	2291.0	576.4	593.4
10	1 + RIPORT	806.9	2293.9	575.0	587.6
11	1 + CPUE + RIYEAR + RSYEAR	750.1	2676.4	541.1	658.2
12	1 + RIYEAR	751.2	2678.8	563.0	663.0
13	1 + CPUE + RIMONTH + RSMONTH	816.6	2818.2	623.5	721.0
14	1 + RIMONTH	812.7	2810.7	625.6	730.3
15	1 + CPUE	809.9	2791.5	623.0	718.9
16	1	811.8	2790.4	631.3	724.7

same value chain (Ankamah-Yeboah and Bronnmann, 2018). Besides, the values of first commercialization may be underestimated, taking into account that agents maximize their own profits while purchasing a large quantity of the product (Cuervo-Sánchez et al., 2018).

4.3. Prospect and caveats to Bayesian hierarchical models

Improving the price estimates for fishing data is crucial to improve decision-making. Bayesian hierarchical modelling approach improved these estimates by accounting for the categorical random effects of time and space. This method does not explicitly model the covariance structure. It only accounts for vertical dependency (between levels), not considering the horizontal dependence (neighbouring effects) like a spatially structured model such as conditional auto-regressive models (CAR) (Cosandey-Godin et al., 2015; Cellmer and Belej, 2019). Although using a categorical proxy is not as precise as CAR, it can still control for spatial or temporal structure in the data that is also matched to the autocorrelation in the data (Silk et al., 2020). Multilevel models should be favoured if there is a clear hierarchical data structure, and the neighbouring effect is not of primary interest (Dasgupta et al., 2014).

Also, our models did not consider the fisher's individual effect because this information was not available in the dataset. However, accounting for this effect can improve the estimates by considering individual biases, values, and morals (Carvalho et al., 2020).

5. Conclusions

We described the landings of L. *schmitti* and *X. kroyeri* in 27 locations in the State of Sergipe (Brazil) between 2010 and 2016. In this period, shrimp production (kg) remained relatively stable (200–300 ton/year in the total). Using the Bayesian approach, we learned that the price of both species varied between landing points within and between years, and this variation seems to show greater spatial and temporal dependence. However, for the temporal dependence, the seasonal monthly effects weren't as important as the yearly effects, since the variance within the years was considered low. It could indicate that economic activities (tourism) do not play an essential role in shrimp prices in this region. Still, biological factors (abundance and reproduction period) can affect the prices for some areas. Using models with random effects we discovered that for *X. kroyeri* there is no relationship between CPUE and prices. Otherwise, this relationship demonstrated that L. *schmitti* has a higher price within Sergipe State.

CRediT authorship contribution statement

Eurico M. Noleto-Filho: Conceptualization, Data curation, Methodology, Formal analysis, Writing – original draft. **Ronaldo Angelini**: Conceptualization, Supervision, Validation, Writing – original draft, Funding acquisition, Resources. **Maria A.L. Lima**: Writing – review & editing. **Sebastián Villasante**: Writing – review & editing, Funding acquisition, Resources. **Mario J.F. Thomé-Souza**: Writing – review & editing, Resources, Data curation. **Adriana R. Carvalho**: Visualization, Supervision, Validation, Writing – original draft, Writing – review & editing. All authors contributed critically to the draft and gave the final approval for publication.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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