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Causal relationships in king's littleneck clam fisheries (*Ameghinomya antiqua*, P.P. King, 1832), Los Lagos Region, Chile

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Abstract – This study investigates the network of causal relationships in the king's littleneck clam (*Ameghinomya antiqua*) fishery in the southern zone of the Los Lagos Region, Chile, using the Convergent Cross Mapping (CCM) method. The dynamics of the system were analysed based on four time series: abundance indices derived from landings per unit effort (LPUE), the percentage of mega-spawners (Mega) in catches, landings and sea surface temperature (SST) anomalies. The study identified a significant unidirectional causal relationship between landings and landings per unit, and between sea surface temperature and catch per unit effort. A marginally significant one-way causal relationship between landing and mega-spawners was found. A unidirectional causal relationship was also observed from temperature to landings; the extended CCM suggested that landings respond with a lag of 2-4 months to changes on SST. Landings and LPUE were driven by the shared environmental force (sea surface temperature). The results suggested that controlling landings rates can influence management decisions aimed at regulating resource conservation, using a precautionary approach and a target reference value for LPUE. The importance of incorporating indicators such as mega-spawners into management strategies is highlighted, as they can be indicators of the stock's health status. This study improves the comprehension of how environmental and socio-economic factor interact in complex system.

Key words: Causal relationship / convergent cross mapping / clam / sustainability / nonlinear dynamics / time series

1 Introduction

King's littleneck clam fishery is exploited by artisanal fishers whose catches are unloaded principally in the Port of Quellón, Chiloé, where processing plants are located (Fig. 1). The king's littleneck clams are gathered from many fishing sites: in total approximately 90 fishing sites are exploited by 804 artisanal fishers. The average annual landing of king's littleneck clams over the last 19 yr was 7.808 tonnes (Bustos et al., 2022).

King's littleneck clams harvesting is currently subject to a minimum extraction size (55 mm). It constitutes an important commercial and food resource for the population and becomes an alternative resource when major species, such as red sea urchins (*Loxechinus albus*) and red seaweed (*Sarcopeltis skottsbergii*), are out of season (i.e., protected) (Bustos et al., 2022). Thus, king's littleneck clams are considered a 'buffer' resource that allows year-round harvesting activities.

Conventional stock assessment methods have been applied to the king's littleneck clam population in the Los Lagos and Aysén Regions by various researchers (Jerez et al., 1991; Mardones et al., 1918; Canales et al., 2019). Canales et al., (2019) identified a set of management strategies for the fishery based on the results of various stock assessment models. While these studies provide valuable insights, a deeper understanding of the complex interplay between sustainability pillars and clam population dynamics is essential for effective management. Bustos et al. (2022) proposed integrating information from five sustainability pillars (biological, environmental, social, economic, and institutional) to assess the status and trends of king's littleneck clam fisheries. This comprehensive approach is a significant step towards sustainable exploitation, but further research is needed to clarify the causal relationships between the sustainability pillars and the clam population dynamics. Identifying these causal relationships and understanding the population dynamics is crucial for developing effective fishery policy and management recommendations. This knowledge will enable a more precise intervention and ensure the long-term viability of king's littleneck clam fishery and its ecosystem.

The natural and ecological ecosystems that support many fishery systems are nonlinear and complex. An understanding

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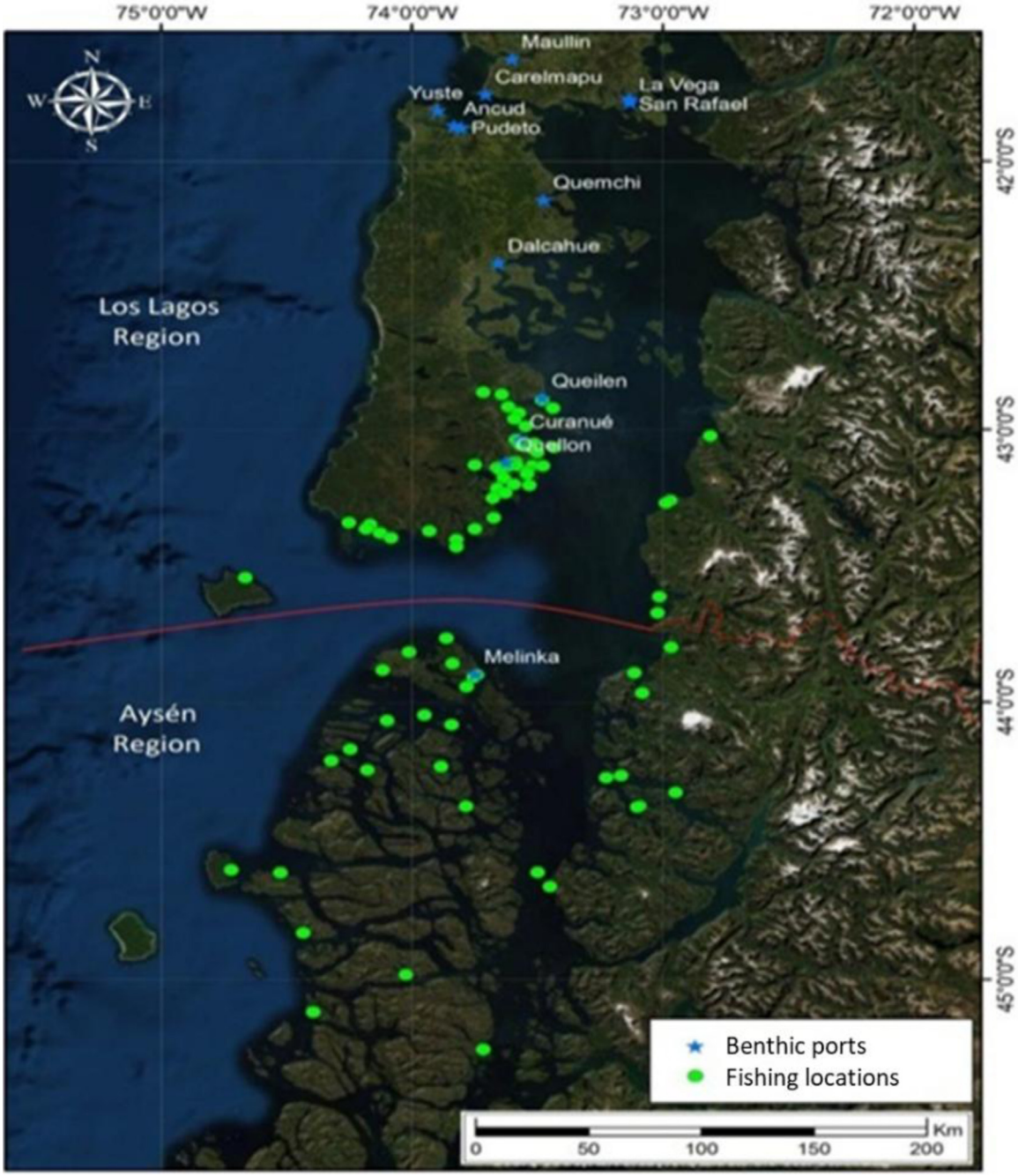

Fig. 1. Map of clam fishing locations from Los Lagos Region, Chile. Google. (n.d.). [Regiones X y XI from Chile]. Retrieved [October 17, 2025], from [https://earth.google.com/web/search/chile+region+X/].

of nonlinear dynamics in fisheries systems is critical when assessing the possibility of unexpected changes in marine populations (Glaser et al., 2014). Sugihara et al. (2012) show how two time series positively coupled for long periods can spontaneously become anticorrelated or decoupled. This effect, called ephemeral or "mirage" correlation, can create problems when fitting models to observational data. Mirage correlations result from a fundamental property of nonlinear dynamical systems known as state dependency (Sugihara et al., 2012; DeAngelis and Yurek, 2015; Chang et al., 2017).

Recently, large-scale time series availability has increased, permitting the development of new methods to infer and quantify potential causal dependencies without intervening in the Earth systems (Runge et al., 2019). These new observational data-based methods do not replicate interventional experiments in the system (because not involve the direct manipulation of variables). Granger (1969) was one of the first authors to address the issue of causality in time series. Mirshojaeian and Kaneko (2012) used the Granger causality model to analyse causality among sustainability pillars (economic, social, environmental and institutional) in coun-

tries both globally and regionally (OECD and non-OECD). The Granger causality model mainly focuses on linear models and considers a stochastic time series and strong coupling, which is unusual in environmental and ecological systems (Sugihara at al., 2012). Among the methods that use causal models, we highlight the convergent cross-mapping (CCM) method. This methodological approach to analyse the causality of deterministic nonlinear dynamic systems from observational time series was developed by Sugihara et al. (2012) and builds on Takens' delay embedding theorem (Takens 1981). Sugihara et al. (2012) used CCM to analyse the causal relationships between sardine landings, anchovy landings and the sea surface temperatures measured in the Californian Current ecosystem and established that sea surface temperature was a common driver of sardine and anchovy landings. CCM has been applied to real-world situations such as the classic prey–predator problem in ecology (Sugihara et al., 2012; Ye et al., 2015b). Van Nes et al. (2015) analysed the effects of insolation, temperature and greenhouse gasses (CO_2 and CH_4) that could be inferred from the Vostok ice core 1. Deyle et al. (2016) applied CCM to species abundance in the Baltic Sea mesocosm time series to further validate the causal relationships between species. Deyle et al. (2016b) used CCM to test alternative hypotheses about the global environmental drivers of influenza outbreaks using country-level epidemic time series. Over the last few years, novel approaches and techniques have broadened the spectrum of application in relation to aquatic ecosystems (Chang et al., 2020; Wang et al., 2020) and ecology (Chang et al., 2021). Recently, Akia et al. (2023) analysed the regional management of tuna stocks based on the causal relationship between one stock and its components belonging temporally to local Exclusive Economic Zones.

This study investigates the causal relationship in benthic clam fisheries using time series analysis and Convergent Cross-Mapping (CCM) (Sugihara et al., 2012). Our focus is on three pillars of sustainable development; i) the bio-ecological pillar, represented by the natural resource subsystem, assessed through abundance indices derived from landings per unit effort (LPUE) and the proportion of mega-spawners in catches, ii) the socio-ecological pillar, represented by the human system, assessed through landings and iii) the environmental pillar, represented by the climatic subsystem assessed by sea surface temperature (SST). Thus, we analysed the dynamical system of the clam fishery using four time series, LPUE, mega-spawner percentage, landings and SST. Landings per unit of effort reflects variation in exploitable biomass. Mega-spawner (clams with larger sizes classes at or above 64 mm in catch) percentage indicates the exploitation pressure on older age classes (Froese, 2004). It serves as a key indicator of stock health, where a percentage below 20% potentially suggests overexploitation (Froese, 2004). Landings reflect human intervention and integrate social, economic, and institutional factors. SST is a key indicator of climatic change.

By identifying the causal structure emerging from these time series, this study aims to understand the interplay between natural, human and environmental systems in the context of clam fisheries. This knowledge is crucial for developing effective management strategies that promote both environmental and ecological sustainability, and socio-economic well-being.

1.1 Causality and CCM

Granger causality (GC), which measures causality by assessing predictability, is one of the most popular measures to identify the causality influences on time series. The variable X is said to 'Granger cause' Y if the predictability of Y declines when X is removed from the universe of all possible causative variables U (Sugihara at al., 2012). According to this approach, X causes Y if it can predict Y . The separability presumption that is implicit in this approach is appropriate mainly for stochastic or linear systems (Sugihara et al., 2012) but not for dynamical systems, as the X variable in these systems cannot be removed. In dynamical systems, time series variables are causally related if they are coupled (i.e., perturbing one variable perturbs the other) and belong to the same dynamic system (Sugihara et al., 2012). Granger causality does not always account for causality in deterministic nonlinear systems, especially with weak or moderate coupling of time series, which frequently occurs in natural or ecological systems (Sugihara et al., 2012).

Unlike the Granger causality approach, CCM is designed to identify and quantify weak to moderate causalities (Sugihara et al., 2012). It is based on state space reconstruction (SSR) using lag coordinates. Its key concept is that if two time series variables X and Y are part of the same dynamical system, then the current signature of the variable X can be predicted from the time lag embedding dimension of the variable Y . The CCM method is independent of a predictive model's performance; it uses the convergence property (cross-mapped estimates) to distinguish causation from simple correlation (Sugihara et al., 2012; Chang et al., 2017; Tsonis et al., 2018). For more detailed information about CCM, see Sugihara et al., (2012).

2 Materials and methods

2.1 Study area and data collection

King's littleneck clams can be found along the Pacific coast from Callao, Peru, to around the Strait of Magellan and on the Atlantic coast from the Strait of Magellan to 34° south (Mollusca Base, *Venus antiqua* P.P. King, 1832). In this study, we include four monthly time series of 174 points between 2004 and 2018 in the southern zone of the Los Lagos Region (Fig. 1). These are: landings, calculated as monthly landings in tons (Data Sources: Official statistics on catch levels by species from Sernapesca (series of 20 yr, 2000–2019)), mega-spawners, calculated as the percentage of clams at or above 64 mm length in catch (mega-spawners include clams of a size larger than optimum length in catch, which in this fishery range above 55 and under 64 mm), and non-standardized landings per unit effort, obtained as the ratio between landings in kg and effort in diving hours. In this small-scale fishery for clams caught manually using semi-autonomous "hookah" diving, landings and effort are monitored monthly. Given the high selectivity of this hand fishing method, landing and catch can be considered similar and therefore, LPUE (landing per unit effort, kg/diving hour) was used as an alternative to CPUE (Data sources: Followup studies undertaken by the Fisheries Promotion Institute, IFOP among seafloor fisheries (series of 24 yr, 1996–2019)). Sea surface temperature (SST, °C), calculated as the Sea Surface Temperature (SST) anomalies

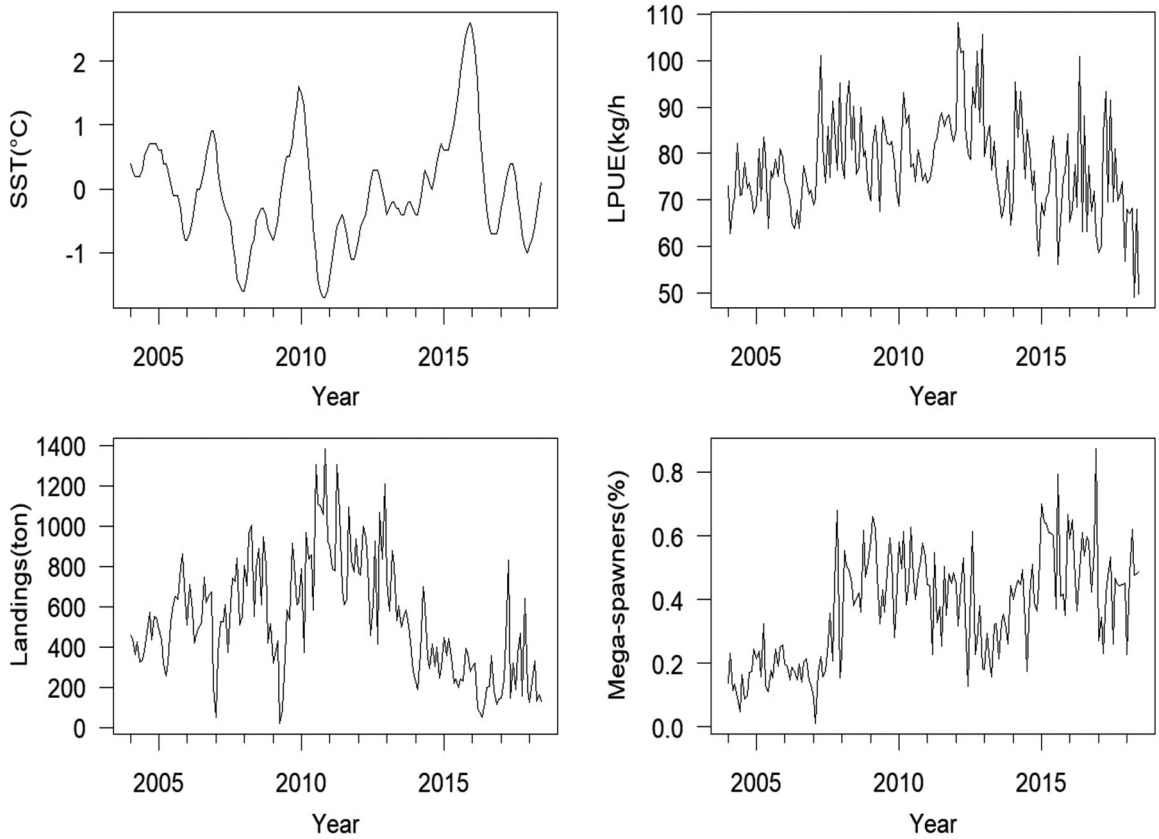

Fig. 2. Monthly fluctuations of the original time series per indicator (Sea surface temperature (SST) anomalies, nominal landings per unit effort (LPUE), landings and mega-spawners in catch between January 2004 and June 2018 (a total of 174 points was included in the library size).

focussing on Niño. 3.4 index Region (5N-5S, 170W-120W) Record from NOAA ERSSTv5 (Huang et al., 2017) series 1886-2018). The original time series are shown in Figure 2.

Seasonality is present in monthly time series data. Importantly, synchrony between paired variables due to seasonality can lead to overestimated CCM skill (Sugihara et al., 2012). The procedures for data transformation employed by each time series adhere to the approach suggested by Chang et al. (2020). Each time series was de-trended (linear regression was used to remove the effects of a linear time trend, de-seasonalised, and then normalised.

2.2 The CCM algorithm

The CCM algorithm was developed by Sugihara et al., (2012) to test causation between two time-series variables in a dynamic system. Two time-series variables (X and Y) are causally linked if they interact in the same dynamical system; in other words, they share a common attractor manifold M (multidimensional attractor, Sugihara et al., 2012). The algorithm is based on the nonlinear state space reconstruction taken from Takens' theorem. A D-dimensional system can be reconstructed from the lag of a one-dimensional time series. According to Takens' delay embedding theorem, the system manifold reconstructed based on variable X (time series) gives a 1:1 map to the original system. This method uses the E (embedding dimension) time-lagged values of X (time lags 0, τ, 2 τ, ... $(E-1)\ \tau$), as coordinate axes to reconstruct the shadow attractor manifold Mx (see in supplementary material for Sugihara et al., (2012)), where τ is the lag for the choice E. E is determined empirically by applying Simplex Projections (Sugihara and May 1990; Glaser et al., 2014; Chang et al., 2017) to the original X and Y series and choosing the optimum E (optimal embedding dimensions). E is a measure of the complexity of the system (number of degrees of freedom of the system). According to the Whitney embedding theorem (Whitney 1936), the real system dimensionality D of the system does not necessarily coincide with the estimate of E, where $D \leq E < 2D+1$.

If variable X influences Y, then causality is established when the state of the causal variable X can be recovered from the time series history of Y (Sugihara et al., 2012; Tsonis et al. 2018). CCM is measuring the extent to which the historical records of Y values can estimate the states of X (cross-mapping of Y by using My; X/My) or vici versa (cros-smapping of X by using Mx; Y/Mx). The CCM algorithm determines the correspondence between the state Y(t) and its contemporary X(t) using simplex projection (based on nearest neighbours forecasting in the state space in the library set (Sugihara and May 1990; Hsieh at al., 2005; Sugihara et al., 2012; Deyle et al., 2013). The Pearson correlation coefficient ($\rho(L)$) or the mean absolute error (MAE) between the observed and expected values is used as an indicator of 'cross- map skill'. The correlation coefficient is examined using increasing data length L (known as 'library length'). Other performance metrics can be used as alternatives to the local nearest

neighbour method using ranks of pairwise distances between all-time points in each reconstruction (Breston et al., 2021).

CCM performance depends on estimation parameters such as E, the time lag (τ) and library length. The minimum library length that Sugihara et al. 2012 suggest is in the order of 30 sequential observations. New methods have been developed to estimate these interactions from time series with shorter library lengths (Breston et al., 2021; Ma et al., 2014; Zhang et al., 2017; Clark et al., 2015).

The stages of the analysis process are: 1) Reduce the effects of short-term autocorrelation, making the series stationary. 2) De-seasonalise each time series to remove short-term synchrony between pairs of time series (Deyle et al., 2016b) 3) Standardise each of the time series. 4) Identify the optimal embedding dimension (E) using the simplex projection method (Sugihara and May 1990; Hsieh et al., 2005) 5) Distinguish the nonlinearity of the system from the linear stochastic system and determine the degree of state dependency (θ) by S-map analysis Sugihara (1994). 6) Identify the network of causal relationships in benthic king's littleneck clam fisheries. The R package rEDM for Empirical Dynamic Modelling (EDM) and Convergent Cross Mapping (CCM) was used in the analysis. EDM is a non-parametric framework for modelling nonlinear dynamic systems (Ye et al., 2016).

To evaluate convergence in cross-mapping, the state space is constructed using different library lengths (L) subsampled randomly from time series. This process starts from minimal library length, L_o, which is equal to the embedding dimension (E), and continues to maximal library length, L_{max}, which is equal to the whole length of the time series, using increments of the library length in r steps (L_o, L_o+r, L_o+2r, ..., L) (Chang et al., 2017). To quantify convergence, we computed the cross-map skill over 100 random subsamples with replacement of time series. For this analysis, we used 33 library vectors L ranging from 6 to 170 (steps of r = 5). We checked the convergence of the CCM adjustment using two criteria: (1) Testing the existence of a significant increase in the $\rho(L)$ trend with Kendall's test. (2) Testing whether the increase ($\Delta\ \rho(L)=\rho(L_{max})-\rho(L_o)$) showed significant improvement in $\rho(L_o)$ with Fischer's $\Delta\ \rho(L)\ Z$ test.

Considering different lags for cross-mapping we identified various time-delayed interactions using the extended CCM analysis of the time series (Ye et al., 2015b).

3 Results

3.1 Structure of clam fishery and CPUE

The de-trended, de-seasonalised, and normalised time series maintain the variability of original time series (Fig. 3). Two parameters, nonlinearity (θ) and E embedding dimension (time-lagged values) were identified for each time series using the S-map analysis and the simplex projection method, respectively (Tab. 1). The optimal embedding dimension (E) selected for the time series ranged from 2 to 4 . The embedding dimension provides an index of the complexity of the system that, in this case, is consistent with an attractor dimension of D=2−3(D ≤ E<2 D+1). The parameter θ controls the degree of state of a nonlinearity dynamical system, the four-time series (mega-spawners, landings per unit effort, landings and sea surface temperature) are dependent on ecosystem state (1 ≤ θ ≤ 7). The state dependency was quantified by S-map analysis.

3.2 CCM

Cross-mapping convergence was achieved for two out of four time-series pairs within the maximum available time series length (Fig. 4). The causality relationships were calculated assuming instantaneous effect (lag =0), between pairs of time series. The correlation ρ(L) was significant for four indicators suggesting causality (Tab. 2). The four pairs are: LPUE: landings, LPUE: SST, landings: SST and mega-spawners: landings. To test significant increasing trend in ρ(L), we applied Kendall's τ test, which confirmed statistical significance (p<0.0001) for all series combination and to test significance of the improvement in $\rho(L)$ we applied Fischer's Δ ρ(L) Z test (Tab. 3). These results enabled us to infer a network of causal relationships (Fig. 5). CCM identified unidirectional instantaneous (time lag =0) causal relationships between landings and catch per unit effort (Landings → LPUE) and between sea surface temperature and catch per unit effort (SST → LPUE). The unidirectional causal relationships Landings → LPUE (p=0.0401) and SST → LPUE (p=0.0228) show significant convergence. While the unidirectional causal relationship SST → Landings (p=0.0721) and Landings → Mega-spawners (p=0.0968) showed marginally significant convergence (p<0.1). There was no significant evidence indicating that landings per unit effort (LPUE) and the sea surface temperature (SST) had causal-effect on mega-spawners.

Based on the identified causal relationships, an optimal time lag (monthly steps) was determined using the extended convergent cross mapping (CCM) method (Ye et al., 2015). The analysis of the extended CCM, specifically for mega-spawners cross mapping to landings variables (notation, mega-spawners: landings), suggests that the proportion of mega-spawners affects future values of landings (l=2>0) (see Fig. 6). While this result was statistically significant (p=0.0075) in the extended CCM analysis, it is important to approach the interpretation with caution. Specifically, future values of one process cannot influence the past values of another. Based in these results, the optimal time lag for the causal relationships (mega-spawners: landings) was assuming instantaneous effect (lag =0).

The extended convergent cross mapping analysis indicated that changes in temperature did not influence landings until two to four months later (Fig. 6), with a maximum level of correlation ρ(L) for three-months lag (l=−3, p=0.0262, ρ(L) =0.4012). This finding suggests that the interaction effect with a lag is greater than the effect of temperature on landings without any lag (l=0, p=0.0721, ρ(L)=0.3524).

4 Discussion

An ecosystem approach to fisheries management is widely accepted (Garcia and Cochrane, 2005). Nonetheless, several obstacles persist in its practical implementation, especially in developing countries. Within this context, our study aims to mitigate the management challenges faced by clam fisheries in the southern zone of the Los Lagos Region. By analysing the

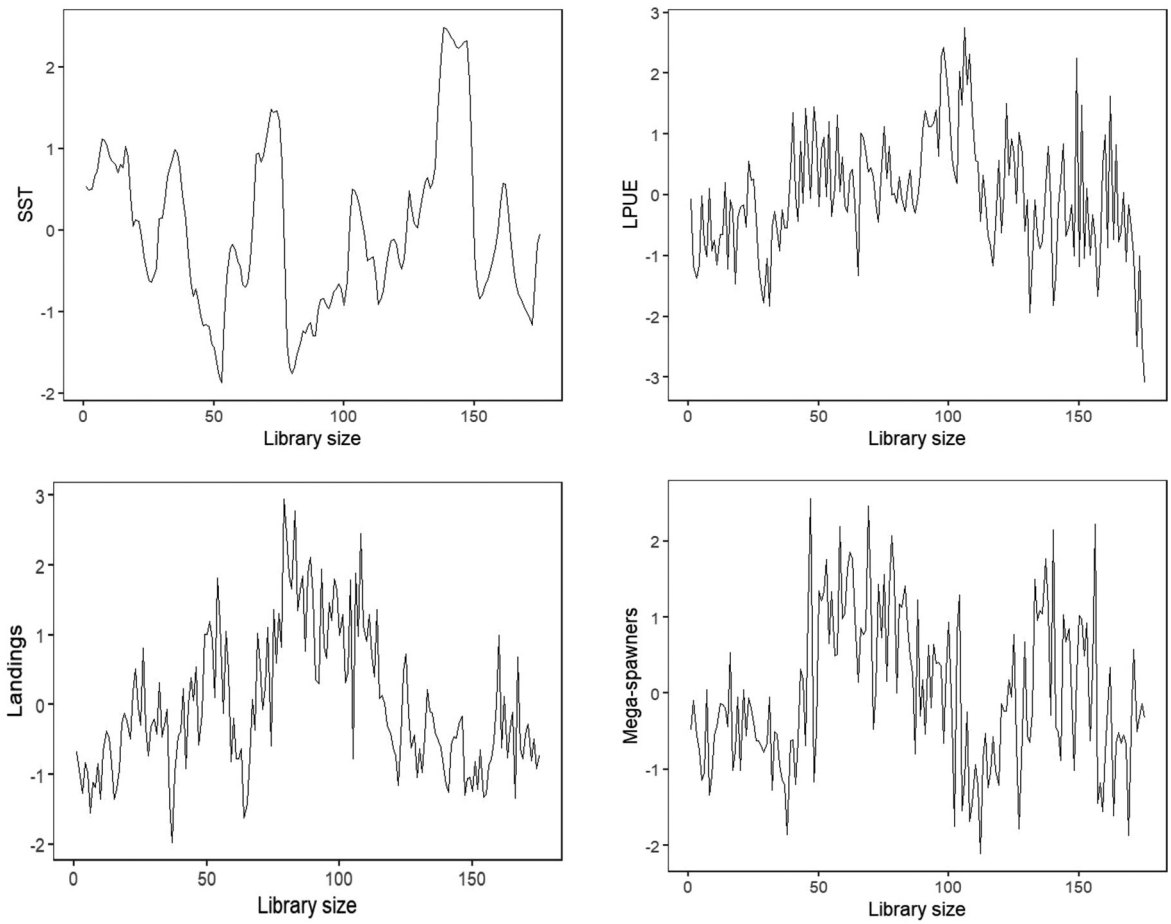

Fig. 3. Monthly fluctuations of de-seasonalised and normalised time series per indicator between January 2004 and June 2018 (a total of 174 points was included in the library size).

Table 1. CCM results for clam fishery time series in Chile. The embedding dimensions (E) was determined by simplex projection; E is a measure of the complexity of the system (number of degrees of freedom of the system). The nonlinearity of the system was determined by S-map; parameter θ is a measure of the degree of state dependency. For linear stochastics systems, θ=0, for nonlinear dynamical systems θ>0.

	E	θ
Mega-spawners	2	7
CPUE	4	4
Landings	4	1
SST	2	2

history (time series) of four indicators of King's Littleneck clam fisheries, we were able to identify the causality network linking three pillars of sustainable development; the bio-ecological pillar represented by catch per unit effort as abundance index and the proportion of mega-spawners in the catch, the socio-ecological pillar represented by landings and the environmental pillar (climatic subsystem) represented by sea surface temperature.

Structure of fishery. System dimensionality and nonlinear dynamics characterised the structure of the clam fishery. This system contains few driving variables, the optimal embedding dimension (E) identified in this study for the Chilean clam fishery ranged from 2 to 4, suggesting simple models may describe this system adequately. The embedding dimension is an indicator of the complexity of the system defined as the number of independent variables needed to reconstruct the original dynamics. Landings per unit effort, mega-spawners (resource system) and sea surface temperature (environmental system) had lower dimensionality than landings (human system), with embedding dimension of 2, 2, 2 and 4, respectively. This result confirms the studies of Glaser et al. (2014) (who compared over 200 time series from marine fisheries), showing evidence of higher dimensionality in landing time series relative to the abundance estimates from the same species/stocks.

The detection of non-linearity in the studied time series suggests that the observed behaviour was state-dependent, therefore, cannot be modelled linearly (the time series displayed nonlinear dynamics, θ>0). In our study, the landing time series had a lower nonlinearity (θ=1) relative to sea surface temperature (θ=2), catch per unit effort (θ=3) and the proportion of mega-spawners (θ=7). The magnitude of θ determines the weightings given to nearest neighbours that are

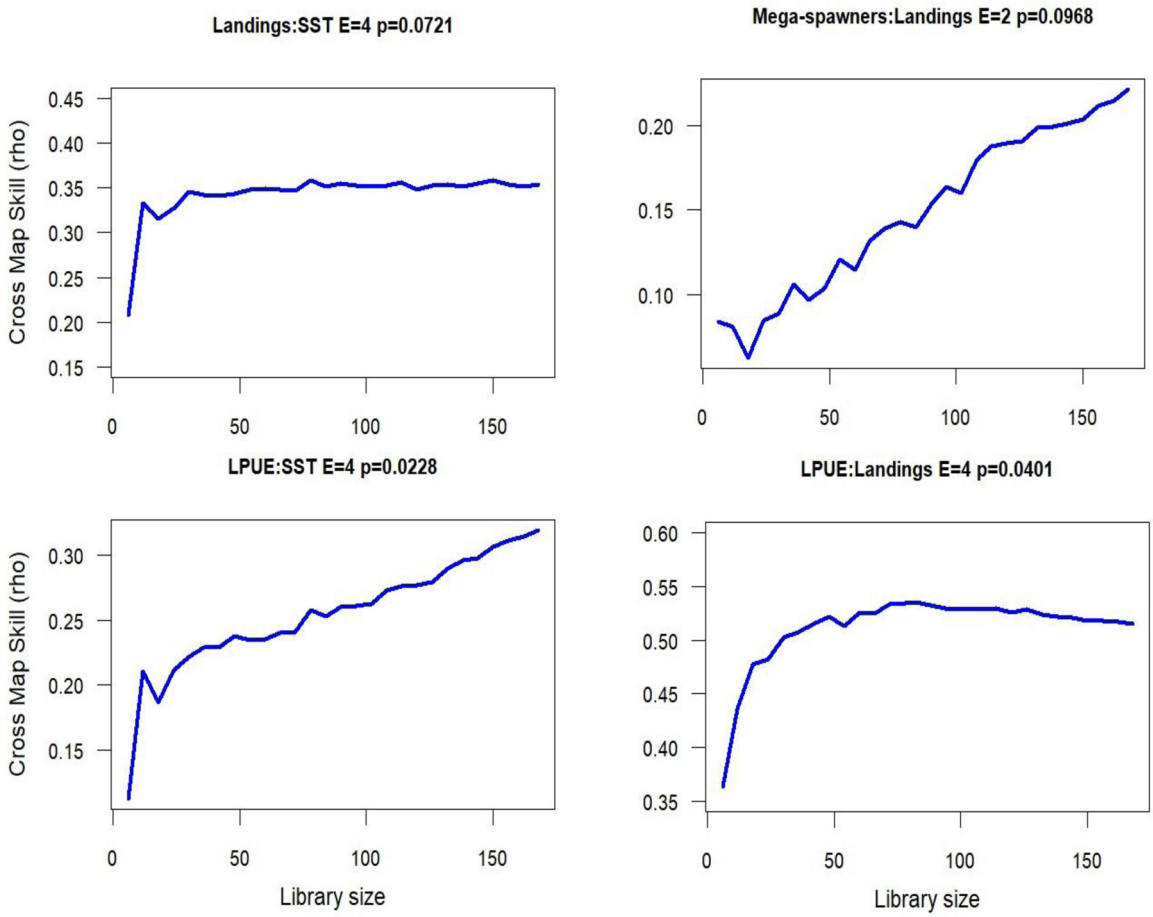

Fig. 4. Level of convergence for X cross mapping to Y variables (notation, X: Y). Was included: embedding dimension (E) and p-value in $\rho(L)$.

Table 2. Cross-mapping prediction skill $\rho(L)$ between indicators of sustainable development in Chilean clam fishery. If influences are quantified from target (row), X, to the source variables (predictor), Y, then X causally influences Y . Significant cross-mapping (**: p <0.05) and marginal cross-mapping significance (*: p<0.1) are indicated in bold. Crossmapping prediction skill less than 0 means there is no prediction skill.

	Mega-spawners	LPUE	Landings	SST
Mega-spawners		0.1567	0.2316	0.1237
LPUE	0.3446		0.3447	0.0133
Landings	**0.2165***	**0.5152****		0.3311
SST	–0.0077	**0.3194****	**0.3524***	

Table 3. Skill metrics for Convergent cross-mapping results for Chilean Camila clam fishery time series; X: Y indicates that Y causes X . $\rho(L)$ is the cross-mapping ability at the maximal library length. Δ ρ(L) is the improvement in $\rho(L)$ obtained as the increment between the cross-mapping ability at the maximal library length and the minimal library length. P -values for Fischer's Δ ρ(L) Z test.

Causality CCM	ρ(L)	Δ ρ(L)	p-value
CPUE: Landings	0.5152	0.1517	0.0401
CPUE: SST	0.3194	0.1641	0.0228
Landings: SST	0.3524	0.1451	0.0721
Mega-spawners: Landings	0.2176	0.1369	0.0968

used to make predictions (S-map model) in the state spaces (Glaser et al. 2011). A parameter θ=0 gives a global linear map and increasing values of θ correspond to increasingly local or nonlinear mappings. When θ increases, the forecasts rely more strongly on the values in the temporally close neighbourhood of the library vectors (Glaser et al. 2011). The identified nonlinear dynamics in the clam fisheries may limit the time horizon of predictions. In the case of nonlinear dynamics, Glaser et al. (2014) recommended only short-term predictions, at most 1−2 yr, providing the correct models were applied. This recommendation must be taken into consideration when making predictions based on models with nonlinear dynamics as the "mirage" effect can create problems fitting models to observational data.

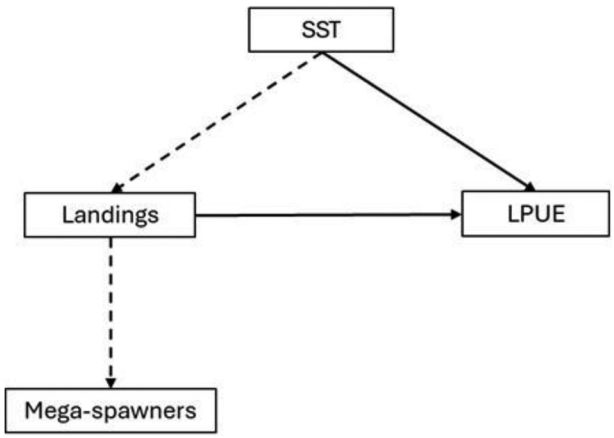

Fig. 5. The panel shows summarized the interaction network the indicators relationships for clam fishery. The black arrows solid represents a statistically significant ($p<0.05$) and the dotted line arrow represents a marginal significance ($p<0.1$) causal relationship convergence in CCM.

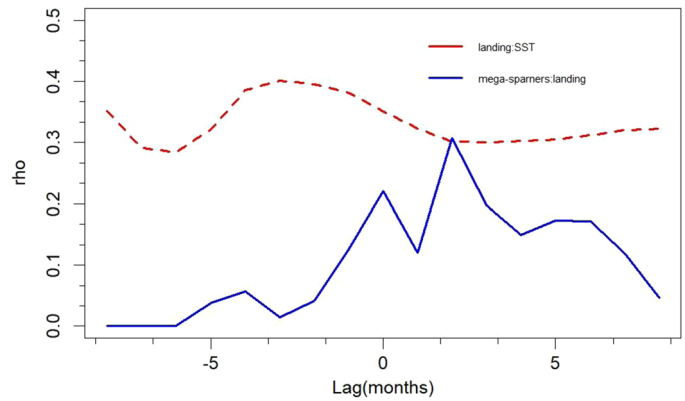

Fig. 6. Notation "X: Y" (effect of Y on X) refers to using X and its lags to cross-map to Y variable with time lag l. Plots show mean-cross map skill (rho value) over 100 random libraries. The sea surface temperatures have delayed effects on landings with an optimal CCM lag ranged from –2 to –4 months (landings: SST). The landings indicator is useful for directly predicting the mega-spawners, with an optimal CCM lag of 2 months (mega-spawners: landings).

Causal relationships. A significant unidirectional causal relationship was found between clam landings and corresponding catch per unit, and between sea surface temperature and landings per unit effort. The driving variables landings and SST acted instantaneously without time lag (l=0) on LPUE. A weak ($p<0.1$) one-way causal relationship between temperature and landings, and between landing and the proportion of mega-spawners was also identified. The time series analysis of SST and landings revealed a unidirectional causal relationship, with an optimal lag ranging between –2 and –4 months. Deyle et al. (2016) suggested that understanding the time delays in causality can provide valuable insights into management scenarios. With S-maps method and using partial derivatives it is possible to calculate time-varying interaction intensities, in this case, ∂ landings(t+1/∂ SST(t) represents the influence of SST on landings in the model. The partial derivatives define the sign or interspecific interaction of the SST has on the landings (Deyle et al. 2016; Chang et al., 2017). This analysis did not incorporate in the study.

The inclusion of sea surface temperature anomalies in the analysis is crucial for understanding the impact of climate change on fishing yields. In the southern Pacific, particularly in the southern austral region of Chile, climate change significantly impacts ocean temperatures. This warming trend has driven marine farming species, such as salmon, to migrate towards colder waters. Landings and LPUE were both driven by sea surface temperature. Ecological systems are often affected by an external force, e,g., temperature (Hoyle et al., 2024).

The health of a fish stock is often reflected) the level of landings. In this case, controlling landings (a key driver) of the fishery would be a suitable management measure for the conservation of the resource. Given the causal relationship between landings and landing per unit effort, which measures stock health, a target reference value for LPUE could be defined for management. The results suggest that regulating landing rates, measures as landings per unit of effort (LPUE), may enhance management decisions aimed at conserving this resource, using a precautionary approach and a target reference value for LPUE. A possible criterion could be to use a reference LPUE to 40% of LPUEo (target = LPUEo) (Canales et al. 2019). For the Chilean clam fishery there exists currently no management regulation based on landing limits, only a minimum size limit of 55 mm. While landings data is an important input for stock assessment models, disaggregating the landings data into indices (Froese 2004) such as the proportion of mega-spawners, optimal catch size, and percentages below the minimum size, can provide additional insights into the structure and health of the fish stock. Incorporating these landings-derived indices, in addition to the overall landing levels can help complement or establish a more comprehensive assessment of the state of the resource. This information is crucial for fisheries managers to make informed decisions that balance sustainable harvest with conservation goals.

The percentage of mega-spawners (larger, older fish) in the catch is an important indicator of a fishery's sustainability. It plays a key role for the long-term survival and productivity of the population. While mega-spawners are part of the landings, their percentage in the catch can be used as a control variable to assess the health of the stock (Froese 2004). Monitoring the percentage of mega-spawners in the catch provides valuable insights into the exploitation patterns and overall sustainability of a fishery. It helps fishery managers identify potential issues and take corrective actions to ensure the long-term viability of the resource.

If proportional to population abundance, catch per unit effort reflects variations in exploitable biomass over time. When exploiting benthic (seabed) resources, fishermen often sequentially target neighbouring fishing sites, motivated by the search for higher yields and larger catch sizes. As a result, fishing sites are left to "rest" and recover while fishermen target other areas. However, this pattern can lead to a phenomenon called "hyperstability", where the LPUE declines at a slower rate than the actual population size (Canales et al. 2019). In other words,

catch rates may remain stable even as the underlying population is declining. Therefore, to accurately assess the usefulness of a LPUE time series it is important to account for this potential hyperstability effect. Simply looking at LPUE trends alone can be misleading, as the rate of LPUE decline may underestimate the true population decline. Incorporating knowledge of the sequential exploitation of fishing sites and recovery periods is key to interpreting LPUE data for benthic resources. The analysis of catch per unit effort in the southern zone of the Los Lagos Region, the focus of this study (Fig. 1), revealed no significant hyper-stability (Canales et al. 2019). In contrast, significant hyper-stability was observed in the northern zone of the Los Lagos Region, which is outside the scope of this study. These findings support the rationale for employing distinct stock assessment models tailored to each study area and support the validity of using the CPUE time series in this study.

Access to comprehensive information is essential for analysing the status of fisheries. At this stage, it is imperative to expand our understanding of the resource's causality structure to develop effective management strategies. Several environmental conditionssuch as temperature fluctuations, red tide occurrences, changes in fishing zones, and fishing efficiency significantly impact the catchability of fish resources. However, not all these factors have been integrated into the indicators for this study. While this limitation may restrict the current study, it also highlights the need for future research to incorporate these critical aspects. By considering these factors in management strategies and fishery assessments, we can enhance our understanding and improve the sustainability of fisheries.

5 Conclusion

This study revealed the characteristics and causal structures associated with the King's Littleneck clam fisheries in the southern zone of the Los Lagos Region, Chile. The results can be utilized to propose management strategies, optimize resource monitoring and control, enhance predictive models, and identify proxy variables.

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Data availability statement

The research data associated with this article are included in the article.

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