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Mapped Aquaculture Land-Cover Dynamics in Coastal Ecuador, 1985–2024: Registry Correspondence, Recent Transitions, and Climatic Context

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Abstract

Reliable aquaculture monitoring requires spatial, administrative, and environmental evidence to be integrated without treating these sources as equivalent. This study characterized mapped aquaculture land-cover dynamics in six coastal provinces of Ecuador from 1985 to 2024, assessed their 2023 correspondence with authorized or concessioned shrimp-farm area, quantified 2023–2024 land-cover transitions, and described climate exposure over a fixed historical aquaculture footprint. Annual MapBiomas Ecuador Collection 3.0 classifications were aggregated by province, canton, and parish; MPCEIP records were harmonized with INEC administrative codes; and CHIRPS v3 precipitation and ERA5-Land temperature were summarized over the union of all pixels mapped as aquaculture at least once during the study period. Mapped class 31 area increased from 58,198.792 ha in 1985 to 138,200.970 ha in 2024, with a maximum of 153,516.642 ha in 2022. In 2023, mapped area represented 74.508% of 202,114.900 ha of authorized or concessioned area, with strong canton-level rank correspondence. Between 2023 and 2024, persistence reached 135,774.430 ha, gross loss 14,816.766 ha, gross gain 2426.130 ha, and net change −12,390.636 ha. Climate exposure was wettest in 1998 and warmest in 2023. Together, the results show that coastal aquaculture development cannot be inferred reliably from a single territorial measure: long-term mapped expansion, administrative extent, recent classification changes, and climate exposure describe complementary but non-equivalent dimensions of the system. This distinction provides a more defensible basis for interpreting aquaculture land-use change and for targeting territorial monitoring and administrative verification.

Keywords: aquaculture; land-cover change; remote sensing; MapBiomas Ecuador; administrative registry; authorized area; climate exposure; CHIRPS; ERA5-Land; Ecuador

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1. Introduction

Aquaculture has become an important component of the global food system, but its expansion has also intensified the need for reliable evidence on spatial development, environmental exposure, production systems, and governance. These dimensions are not represented by a single data source. Satellite classifications describe visible land-cover conditions, administrative registries record legally or institutionally recognized areas, production statistics quantify outputs, and climate products characterize environmental exposure. Treating these measures as equivalent can obscure rather than clarify the development of aquaculture landscapes. An integrated approach must preserve their conceptual differences while examining the relationships among them.

1.1. Aquaculture Expansion and the Coastal Monitoring Challenge

Global aquaculture has expanded substantially over recent decades and now contributes centrally to aquatic-food supply, employment, trade, and food security. This growth has been accompanied by improvements in feeds, production technologies, governance, and resource efficiency, but sustainability concerns remain, particularly in relation to habitat transformation, disease, environmental pressures, and climate vulnerability [1].

Coastal pond aquaculture creates a particular monitoring challenge because its infrastructure occupies extensive and dynamic land–water interfaces. Pond systems may include water surfaces, exposed pond bottoms, embankments, channels, reservoirs, processing areas, and temporarily inactive units. The condition visible in satellite imagery can consequently vary according to operational stage, seasonal water management, maintenance, and image-acquisition conditions, even when the underlying infrastructure remains present.

Earth observation provides an important means of addressing this challenge. Satellite time series permit spatially consistent mapping over large coastal territories and support the identification of pond distribution, historical expansion, persistence, and change [2]. Recent developments combining remote sensing and computer vision have further demonstrated the potential to generate independent and scalable aquaculture estimates, while also emphasizing the need to quantify uncertainty and distinguish remotely inferred information from official production or administrative records [3]. For the present study, this distinction is central because mapped aquaculture is treated as a spatial classification product whose interpretation requires explicit consideration of thematic uncertainty and temporal consistency, rather than as a direct measure of farm activity or production.

Remote-sensing products should not, however, be interpreted as cadastral or regulatory datasets. A pixel classified as aquaculture does not identify the farm operator, species, production intensity, authorization status, or annual output. Likewise, an administratively authorized area does not necessarily correspond to the water-covered or spectrally detectable pond surface observed during a specific year. The two forms of evidence can be compared at compatible territorial levels, but correspondence in area or ranking does not establish farm-level spatial agreement.

In Ecuador, commercial shrimp aquaculture has been associated with extensive changes in coastal and estuarine landscapes since the second half of the twentieth century. An early multitemporal study of the southern Gulf of Guayaquil documented a 16% reduction in mangrove extent and a 27% increase in shrimp-pond development between 1966 and 1982, demonstrating the value of remote sensing for monitoring this transformation at an early stage [4].

Subsequent work extended the historical analysis across Ecuadorian estuaries and showed that aquaculture expansion was an important component of mangrove and estuarine land-cover change. Hamilton and Lovette (2015), using remotely sensed maps at approximately decadal intervals, linked commercial aquaculture development to substantial losses of mangrove-associated carbon stocks [5]. Their findings established a detailed historical basis for understanding the environmental significance of shrimp-pond expansion, while also illustrating the spatial concentration of these transformations in particular estuaries.

The 1999 WSSV crisis remains relevant here primarily because it illustrates the distinction between production shocks and mapped land-cover change. WSSV-associated mortalities were documented in cultured Penaeus vannamei in Ecuador from 1999 [6], but disease dynamics are not analyzed in the present study. Disease history is therefore retained only as contextual evidence that changes in production or farm activity need not produce equivalent changes in mapped pond infrastructure; the corresponding temporal interpretation is addressed in Section 4.1.

Previous Ecuadorian studies have therefore provided strong evidence of historical aquaculture development and its relationship with mangrove conversion. Less attention has been given to integrating an annual national-scale land-cover series with recent administrative records, pixel-level transition accounting, and long-term climate exposure over a constant spatial domain. These components answer different questions but are necessary for distinguishing historical expansion, current administrative correspondence, recent classification changes, and environmental context.

The present study addresses this gap through a multiscale analysis of six provinces in Ecuador's coastal region from 1985 to 2024. Rather than estimating shrimp production or farm-level compliance, it examines the evolution of mapped aquaculture land cover and its relationship with independently derived administrative and climate information.

1.2. From Historical Mapping to Integrated Aquaculture Evidence

Historical remote-sensing studies have established that aquaculture expansion can be reconstructed from changes in coastal land cover. However, mapped pond extent alone cannot describe the administrative, operational, or environmental dimensions of aquaculture. A land-cover product identifies surfaces assigned to a thematic class, whereas an administrative registry represents areas recognized through specific institutional procedures. Climate datasets describe environmental conditions over space and time but do not indicate whether farms were active, productive, authorized, or affected by those conditions.

This distinction is particularly relevant for annual land-cover products. MapBiomas Ecuador Collection 3.0 provides a consistent classification series from 1985 to 2024 and identifies aquaculture as class 31 [7]. The annual structure of the product permits the examination of long-term trajectories and recent transitions using a common legend and processing framework. Nevertheless, class 31 represents mapped aquaculture land cover in general. It does not distinguish shrimp from other aquaculture activities or report production, ownership, legal authorization, stocking status, or farm performance.

Administrative records provide a different form of evidence. The MPCEIP registry identifies regularized shrimp-farming records and their authorized or concessioned areas, but the dataset used in this study does not contain farm polygons or geographic coordinates [8]. Consequently, the registry can be compared with remotely mapped area after harmonization at province or canton level, but individual administrative records cannot be linked spatially to particular MapBiomas pixels. Differences between the two sources may arise from measurement definitions, administrative attribution, temporal alignment, pond condition, thematic classification, or data completeness.

A meaningful comparison must therefore distinguish correspondence from equivalence. Similar rankings across cantons would indicate that both sources identify broadly comparable territories of aquaculture concentration. Equality of hectare totals would be a separate property, and neither rank correspondence nor similarity in magnitude would demonstrate farm-level spatial coincidence. This distinction is essential when administrative data lack the geometries required for direct overlay.

Recent advances in aquaculture remote sensing have increased the ability to map ponds over large territories using dense optical and radar time series [2]. Computer-vision approaches have further expanded the possibility of generating spatially explicit aquaculture estimates independently of conventional administrative reporting [3]. These methods strengthen territorial monitoring, but their outputs remain classifications or model-based inferences and should not be treated as automatic evidence of legal status, operational activity, or production.

Annual area differences also conceal the internal composition of change. A reduction in mapped aquaculture between two years may combine persistent aquaculture pixels,

transitions from class 31 to other classes, and simultaneous gains from other classes into class 31. Pixel-level transition accounting is therefore required to separate gross loss, gross gain, persistence, and net change. This distinction is especially important for pond landscapes, where drainage, refilling, maintenance, exposed sediment, and temporary inactivity may alter the annual spectral state without eliminating the underlying infrastructure [9].

Environmental information introduces a further analytical layer. CHIRPS v3 provides a long-term gridded precipitation record combining satellite and station information [10,11], while ERA5-Land provides spatially and temporally consistent land-surface and near-surface atmospheric variables [12,13]. These products can describe climate exposure over aquaculture-associated territory, but their inclusion does not by itself establish a causal relationship between climate variability and land-cover change.

Climate extraction over a changing annual aquaculture footprint would introduce an additional source of variation because the spatial domain used to calculate climate values would change together with mapped aquaculture extent. A fixed footprint, defined from the union of all pixels mapped as aquaculture during the study period, provides a constant spatial reference for comparing annual precipitation and temperature exposure. This design improves temporal consistency while retaining the limitation that the footprint does not represent active aquaculture in every location and every year.

Integrating land-cover, administrative, transition, and climate data therefore requires explicit measurement boundaries. The value of integration does not arise from merging the sources into a single estimate, but from examining what each source contributes, where their territorial patterns correspond, and where their differences require further investigation.

1.3. Research Gap, Objective, and Contributions

The studies reviewed above address complementary but distinct aspects of aquaculture monitoring. In Ecuador, Terchunian et al. [4] and Hamilton and Lovette [5] reconstructed historical shrimp-pond expansion and its relationship with mangrove and estuarine change using selected multitemporal observations, thereby establishing the long-term land-cover context. More recent remote-sensing research has demonstrated the value of dense optical and radar time series for large-scale pond mapping [2], while computer-vision approaches have focused on generating spatially explicit aquaculture estimates and improving pond delineation [3,14]. These studies provide important evidence on historical change and remote-sensing performance, but they address different analytical questions from the administrative and environmental comparisons developed here. Within the literature examined for this study, the unresolved issue is therefore not the absence of aquaculture mapping itself, but the joint interpretation of a complete annual land-cover trajectory, a temporally matched administrative-area comparison, explicit pixel-level transition accounting, and climate exposure over a fixed spatial domain. The present study brings these components into a common territorial framework while retaining their different measurement meanings rather than treating them as interchangeable estimates.

The primary objective of this study was to characterize the spatial and temporal evolution of mapped aquaculture land cover in six provinces of Ecuador's coastal region between 1985 and 2024, examine its 2023 correspondence with MPCEIP authorized or concessioned areas, quantify the detailed 2023–2024 land-cover transition balance, place this recent transition within the broader 2020–2024 mapped-area trajectory, and describe precipitation and temperature exposure over a fixed aquaculture footprint.

Four research questions guided the analysis:

1. How did MapBiomas class 31 evolve across the study region between 1985 and 2024, and how did the temporal trajectory differ among provinces?

2. To what extent did the 2023 distribution and magnitude of mapped class 31 area correspond with MPCEIP authorized or concessioned shrimp-farm area at province and canton levels?
3. How were recent changes in MapBiomas class 31 expressed through persistence, gross loss, gross gain, and origin or destination classes between 2023 and 2024, and to what extent did class 31 classification states persist or reverse across 2020–2024?
4. How did annual precipitation and temperature conditions vary between 1985 and 2024 over a fixed footprint representing the historical spatial domain of mapped aquaculture?

The four questions are connected through mapped aquaculture land cover as the central analytical reference rather than through a single composite model. Research Question 1 establishes the long-term spatial and temporal trajectory of mapped class 31, while Research Question 3 decomposes its most recent change into persistence, gross loss, gross gain, and transition pathways. Research Question 2 evaluates how the contemporary mapped pattern corresponds with an independently generated administrative measure, thereby testing whether the territorial signal identified by remote sensing is similarly reflected in authorized or concessioned area without assuming equivalence between the two constructs. Research Question 4 provides the environmental context for the historical aquaculture domain using a spatially fixed exposure footprint. The integration is therefore comparative and evidentiary: each component addresses a different dimension of the same territorial system, and their combined interpretation defines both areas of convergence and the limits of inference from any single source.

The study makes four empirical contributions. First, it reconstructs a complete annual aquaculture land-cover trajectory for the coastal study region over four decades, extending previous Ecuadorian assessments based on selected historical dates. Second, it quantifies how the contemporary geography of mapped aquaculture corresponds with, but does not reproduce, the geography and magnitude of administratively authorized or concessioned shrimp-farm area. Third, it shows that recent net change cannot be interpreted adequately from annual area totals alone because persistence, gross loss, gross gain, and bidirectional transitions between aquaculture and other land-cover states occur simultaneously. Fourth, it provides a temporally consistent environmental baseline by describing climate exposure over a fixed historical aquaculture footprint rather than over a spatial domain that changes each year.

Taken together, these contributions show that aquaculture development is represented differently by land-cover classifications, administrative records, annual transition states, and environmental exposure. The scientific value of integrating these sources therefore lies not in producing a single combined estimate, but in identifying where independent forms of evidence converge, where they diverge, and what can legitimately be inferred from each. This provides a stronger basis for interpreting coastal aquaculture development and land-use change, while also defining the evidentiary limits that should precede regulatory or environmental conclusions.

2. Materials and Methods

This study combined multitemporal land-cover mapping, administrative registry analysis, land-cover transition assessment, and climate-exposure characterization to examine aquaculture dynamics across six provinces in Ecuador's coastal study region between 1985 and 2024. MapBiomas Ecuador Collection 3.0 was used to quantify the annual extent of mapped aquaculture land cover and to identify pixel-level transitions between 2023 and 2024. The 2023 MPCEIP administrative registry was used to characterize authorized or concessioned shrimp-farm area and to assess its correspondence with mapped class

31 area at provincial and canton levels. Harmonized 2022 INEC administrative boundaries provided the common spatial framework for aggregation and reconciliation. Long-term precipitation and temperature exposure were derived from CHIRPS v3 and ERA5-Land, respectively, using a fixed aquaculture footprint defined as the union of all pixels classified as aquaculture at least once during 1985–2024. These components were treated as distinct analytical constructs: mapped aquaculture land cover, authorized administrative area, and climate exposure were not interpreted as interchangeable measures, and the analysis was descriptive rather than causal.

2.1. Study Design and Analytical Scope

The research was designed as a retrospective, multiscale geospatial and administrative study covering the period from 1985 to 2024. The study area comprised El Oro, Esmeraldas, Guayas, Los Ríos, Manabí, and Santa Elena, which together formed the analytical region considered in this research. Figure 1 presents the study area and the administrative units used in the analysis. The design combined annual land-cover information, administrative registry data, pixel-level transition estimates, and gridded climate data within a common territorial framework.

The analysis was organized into four complementary components. First, the annual extent of MapBiomas class 31 was quantified at the provincial level for the complete 1985–2024 period to characterize long-term changes in mapped aquaculture land cover. Second, the 2023 MapBiomas area was compared with the authorized or concessioned area recorded in the MPCEIP registry. This comparison was conducted at provincial and canton levels after reconciling the administrative identifiers contained in the registry with the harmonized INEC geographic framework. Third, pixel-level transitions between 2023 and 2024 were assessed to distinguish persistence, gross loss, gross gain, and net change in class 31. Fourth, annual precipitation and temperature exposure were summarized over a fixed spatial footprint representing the union of all pixels mapped as class 31 at least once between 1985 and 2024, providing a temporally consistent environmental context rather than explanatory predictors of mapped land-cover change

Different spatial units were used according to the analytical objective. Province was the principal unit for the long-term land-cover and climate series. Canton was used for the detailed correspondence analysis between MPCEIP authorized area and MapBiomas class 31 area. Parish was used for the transition analysis because it provided a finer administrative unit for aggregating pixel-level changes while maintaining compatibility with the INEC boundary framework. Cross-level checks were conducted to verify that parish-derived and canton-derived totals reproduced the corresponding provincial estimates within negligible numerical differences.

The three principal measures used in the study were treated as conceptually distinct. MapBiomas class 31 represented mapped aquaculture land cover, whereas the MPCEIP registry represented administratively authorized or concessioned shrimp-farm area. The fixed footprint used for climate extraction represented a constant spatial sampling domain derived from the multiyear land-cover series. Accordingly, differences between mapped and authorized areas were interpreted as source-to-source correspondence or divergence and not as evidence of illegality, omission, abandonment, operational inactivity, or physical farm closure. Similarly, precipitation and temperature were examined as exposure variables and were not used to infer causal effects on land-cover change.

The analytical design was therefore descriptive and comparative. It was intended to document temporal trajectories, spatial correspondence, recent land-cover transitions, and climatic exposure without estimating causal relationships. Table 1 summarizes the

data sources, temporal coverage, spatial units, principal variables, analytical roles, and interpretation constraints applied throughout the study.

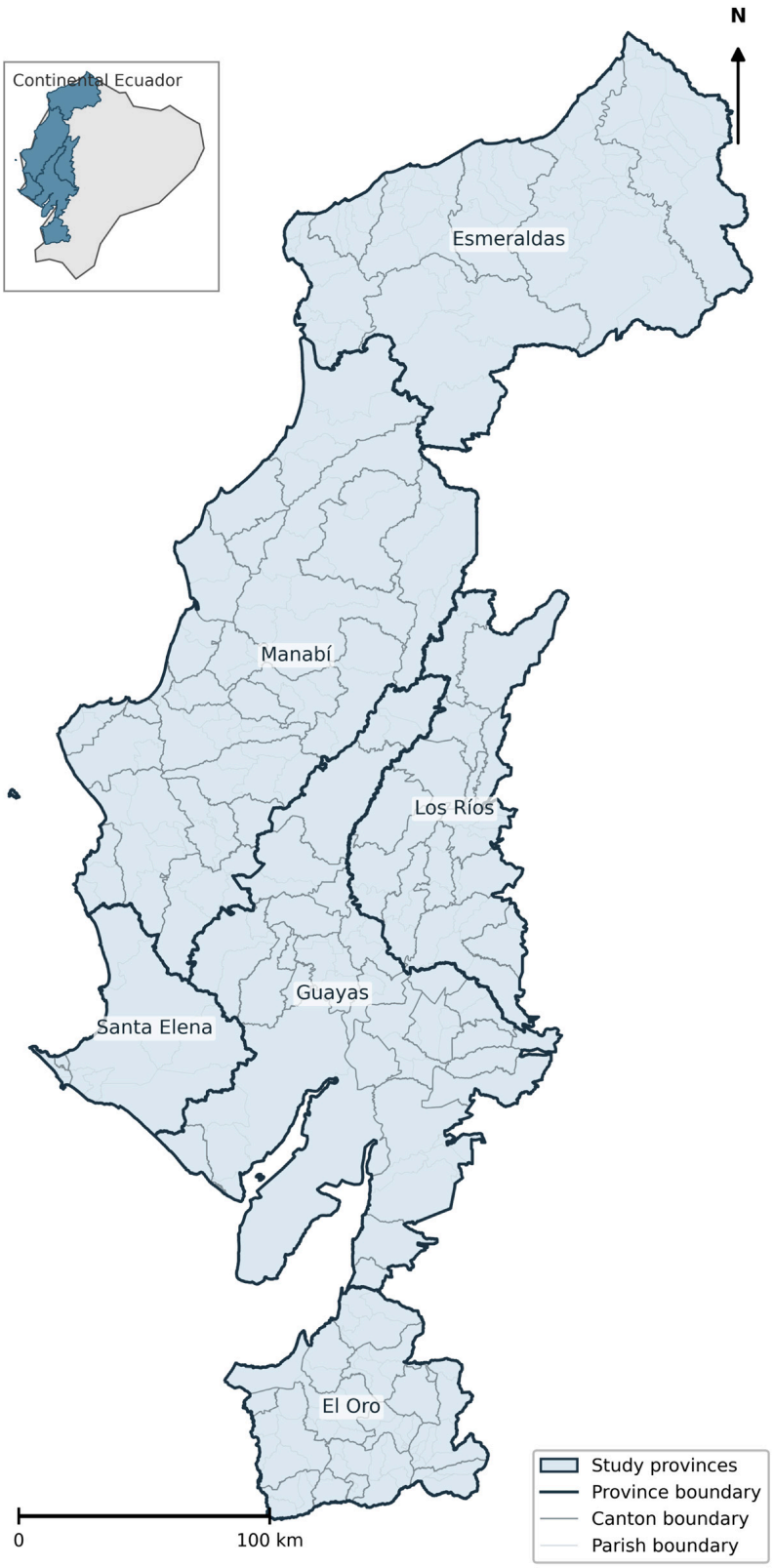

Figure 1. Study area and harmonized administrative units used in the analysis. The coastal analytical region comprises El Oro, Esmeraldas, Guayas, Los Ríos, Manabí, and Santa Elena, Ecuador, and includes 84 cantons and 301 parishes according to the harmonized 2022 INEC administrative framework. The inset locates the study region within continental Ecuador.

Table 1. Data sources, analytical constructs, roles, and interpretation constraints used in the study.

Data Source or Construct	Temporal Coverage Used	Native Spatial Resolution or Unit	Measurement Construct	Analytical Role	Principal Interpretation Constraint
MapBiomas Ecuador Collection 3.0 [7]	1985–2024	30 m annual land-cover classification	Mapped aquaculture land cover, defined as class 31 area	Estimation of annual provincial trajectories, 2022–2024 parish areas, 2023 canton areas, and 2023–2024 pixel-level transitions	Does not directly represent shrimp production, farm activity, legal authorization, species composition, or number of farms
MPCEIP administrative registry [8]	dataset updated 16 June 2023	Administrative records with authorized area and textual location; no farm geometries	Authorized or concessioned shrimp-farm area	Province- and canton-level comparison with MapBiomas class 31 area	Authorized area is not equivalent to mapped, occupied, cultivated, water-covered, or operational area
INEC administrative boundaries [15]	2022 framework	Province, canton, and parish polygons	Harmonized administrative framework	Standardization of territorial identifiers and spatial aggregation of registry and remotely sensed results	Administrative harmonization does not establish the physical location of individual farms
CHIRPS v3 [10,11]	1985–2024	0.05° gridded precipitation	Annual precipitation exposure over the fixed aquaculture footprint	Long-term climatic characterization and calculation of annual precipitation anomalies	Represents gridded precipitation estimates rather than direct measurements at aquaculture facilities
ERA5-Land [12,13]	1985–2024	0.1° grid; approximately 9 km native resolution	Annual mean 2 m air-temperature exposure over the fixed aquaculture footprint	Long-term climatic characterization and calculation of annual temperature anomalies	Represents atmospheric reanalysis estimates, not pond-water temperature or farm-level measurements
Fixed aquaculture footprint	Derived from the 1985–2024 MapBiomas series	Union of all 30 m pixels classified as class 31 at least once	Constant historical aquaculture exposure domain	Maintains the same spatial sampling domain for climate extraction across all years	Does not represent active or mapped aquaculture area in every location and every year

Note: MPCEIP, Ministerio de Producción, Comercio Exterior, Inversiones y Pesca; INEC, Instituto Nacional de Estadística y Censos; CHIRPS v3, Climate Hazards Center Infrared Precipitation with Stations, Version 3. The data sources represent distinct analytical constructs. Mapped aquaculture land cover, authorized or concessioned area, and climate exposure were not treated as interchangeable measurements. Native spatial resolution refers to the original source product; no climate variable was interpreted as a 30 m meteorological observation.

2.2. Data Sources and Measurement Constructs

The analytical database integrated five primary data sources and one derived spatial construct, as summarized in Table 1. The primary sources comprised annual land-cover maps, an administrative aquaculture registry, official administrative boundaries, gridded precipitation data, and land-surface temperature reanalysis. The derived construct was a temporally fixed aquaculture footprint created specifically for the climate-exposure analysis. Each source was retained in its original conceptual domain, and no variable from one source was treated as a direct substitute for a variable obtained from another.

Annual land-cover information was obtained from MapBiomas Ecuador Collection 3.0, which provides 30 m annual land-cover and land-use classifications for Ecuador from 1985 to 2024. The analysis used class 31, formally labelled Aquaculture in the MapBiomas Ecuador legend [7]. In this study, class 31 was operationalized as mapped aquaculture land cover, measured in hectares after pixel-area calculation. It was not interpreted as a direct measure of aquaculture production, operational status, legal authorization, number of farms, or species composition. In particular, although the analysis focused on coastal provinces with extensive shrimp-farming activity, class 31 was not automatically reclassified as shrimp aquaculture because the MapBiomas legend identifies the broader land-cover category of aquaculture. MapBiomas Ecuador Collection 3.0 covers 1985–2024 at 30 m resolution, and its official methodological documentation explicitly identifies aquaculture as

class 31. The annual MapBiomas classifications do not represent single-date observations. Collection 3.0 constructs annual mosaics from multiple Landsat observations selected within year-specific temporal windows after image-quality screening. The 2023 class 31 estimate should therefore be interpreted as an annual classification product rather than as aquaculture extent observed on a particular date.

Administrative information was obtained from the MPCEIP dataset of regularized shrimp farms identified by the source as the 2023 registry [8]. The public dataset portal provides the file MPCEIP_DATOS CAMARONERA_2023.csv and reports 16 June 2023 as the dataset update date. The available metadata do not provide a single observation date for each administrative record; therefore, the registry was interpreted as a 2023 administrative snapshot rather than as a measurement corresponding to a specific day of that year. The analytical fields used from this registry included the recorded administrative location, ministerial agreement information, and authorized area expressed in hectares. The variable authorized_area_ha was interpreted as the area authorized or concessioned through the corresponding administrative instrument. Registry rows represented administrative records and did not contain farm geometries. Consequently, the registry could be aggregated by standardized province and canton, but it could not be spatially intersected with individual MapBiomas polygons or pixels. The registry-derived construct was therefore termed authorized/concessioned shrimp-farm area, rather than mapped, occupied, cultivated, or operational area.

The common territorial framework was derived from the 2022 geographic boundaries and standardized administrative codes of the Instituto Nacional de Estadística y Censos [15]. The harmonized study framework contained six provinces, 84 cantons, and 301 parishes. These boundaries were used to standardize registry locations and aggregate the remotely sensed results at comparable administrative levels. Administrative harmonization did not imply that the registry contained spatially explicit farm boundaries; it provided only a consistent geographic classification for summarization and comparison. INEC provides the official national, provincial, and cantonal geostatistical frameworks and the standardized geographic coding structure used by Ecuadorian public institutions.

Precipitation exposure was characterized using the Climate Hazards Center Infrared Precipitation with Stations, Version 3 (CHIRPS v3), a 0.05° gridded precipitation product combining satellite-based thermal-infrared estimates with in situ station observations [10,11]. The study used annual precipitation accumulated over the aquaculture footprint for each year from 1985 to 2024. CHIRPS values were treated as gridded precipitation estimates and not as exact observations from meteorological stations located within aquaculture areas. The specific CHIRPS v3 dataset has its own repository DOI, while its current methodology is documented in a peer-reviewed Scientific Data article.

Temperature exposure was obtained from ERA5-Land, the land component of the ERA5 reanalysis. ERA5-Land provides hourly land-surface and near-surface atmospheric variables on a regular 0.1° grid, with a native resolution of approximately 9 km [12,13]. The variable used in this study was 2 m air temperature, subsequently aggregated to annual mean exposure over the fixed aquaculture footprint. ERA5-Land values were interpreted as model-based reanalysis estimates influenced indirectly by observations through the ERA5 atmospheric forcing, rather than as direct measurements at farm locations.

The fixed aquaculture footprint was derived from the MapBiomas time series and was defined as the spatial union of all pixels classified as class 31 at least once between 1985 and 2024. Unlike the annual mapped-area series, this footprint remained spatially constant across all years of the climate analysis. Its purpose was to maintain a consistent sampling domain so that changes in annual precipitation and temperature summaries would not be mechanically driven by changes in the extent or location of the annual class 31 map. The

footprint was therefore a study-derived exposure domain and was not interpreted as the area occupied by active aquaculture in every year.

Together, these sources generated three principal measurement domains: mapped aquaculture land cover, authorized/concessioned shrimp-farm area, and climate exposure over a fixed aquaculture footprint. Their definitions, temporal coverage, spatial resolution, analytical roles, and interpretation constraints are presented in Table 1. The procedures used to harmonize, extract, aggregate, compare, and validate these data are detailed in Sections 2.3–2.9.

2.3. Study Area and Administrative Harmonization

The study used a purposively defined six-province coastal analytical framework comprising El Oro, Esmeraldas, Guayas, Los Ríos, Manabí, and Santa Elena. The framework was not defined by the presence of a positive MapBiomas class 31 footprint and was not intended to represent an exhaustive coverage of every province associated with Ecuador's broader coastal region. The six provinces constituted the territorial scope used to harmonize the MPCEIP shrimp-farm registry with the INEC administrative framework and to maintain a consistent spatial domain across the study components. Los Ríos was therefore retained because it formed part of the administrative and registry framework, even though no MapBiomas class 31 footprint was identified there during 1985–2024. Provinces outside this predefined six-province framework were not included in the land-cover, administrative correspondence, transition, or climate analyses. Using the 2022 INEC administrative structure, the final study framework comprised 6 provinces, 84 cantons, and 301 parishes. Figure 1 shows the spatial extent of this analytical region and the administrative units used for data aggregation.

Official province, canton, and parish boundaries were assembled in a harmonized geospatial database. The provincial files were checked for geometry validity, coordinate reference system consistency, duplicated identifiers, and completeness of the administrative hierarchy. All spatial layers were standardized to a common geographic reference system before being used for area extraction and aggregation. The final administrative database preserved the official INEC codes and names for each province, canton, and parish.

Because the MPCEIP registry contained textual administrative locations but no farm geometries, province and canton names were standardized against the 2022 INEC hierarchy. Exact matches were accepted directly, while non-exact records were reviewed against province–canton combinations and the original registry wording. All 3269 records were reconciled to standardized province and canton codes, representing 202,114.90 ha of authorized or concessioned area. This administrative coding provides a consistent aggregation framework but does not independently validate the physical location of individual farms.

Parish boundaries were used only for MapBiomas extraction and transition aggregation. The MPCEIP comparison was restricted to province and canton levels because parish text was insufficiently consistent and the registry lacked coordinates or farm polygons. The complete harmonization crosswalk, including the Sosote code correction, is provided in the Zenodo analytical package [16].

2.4. MapBiomas Land-Cover Extraction and Temporal Metrics

Annual aquaculture land cover was extracted from MapBiomas Ecuador Collection 3.0 using Google Earth Engine, a cloud-based platform for large-scale geospatial processing [17]. The source asset was projects/mapbiomas-public/assets/ecuador/lulc/collection3/mapbiomas_ecuador_collection3_coverage_v3, which contains one annual classification band for each year from 1985 to 2024. The analysis was restricted to class 31, identified in the MapBiomas Ecuador legend as aquaculture [7]. Google Earth Engine provides an

integrated environment for accessing and processing large geospatial datasets without requiring local storage of the complete source archive.

For each annual band, a binary mask was created by retaining pixels classified as class 31. Pixel area was calculated in square metres using the Earth Engine pixel-area image and converted to hectares by dividing by 10,000. The resulting masked area image was spatially summarized within the harmonized administrative boundaries. The thematic classification values were not interpolated, smoothed, or converted into another aquaculture subclass during extraction.

The complete annual series was extracted independently for the six study provinces from 1985 to 2024, producing 240 province–year observations. The regional series was subsequently calculated as the sum of the six provincial estimates for each year. This procedure preserved the provincial results as the primary extraction level and avoided estimating the regional total from a separately generalized study-area geometry.

Subprovincial extraction was conducted for all 301 parishes for 2022, 2023, and 2024. These years were selected to support the recent-change analysis, the 2023 administrative-registry comparison, and cross-level validation. Parish estimates were aggregated through their standardized INEC identifiers to obtain canton-level and province-level totals. The 2023 canton values used in the MPCEIP–MapBiomas comparison were therefore derived from the sum of the corresponding parish estimates rather than from an independent canton extraction.

The annual land-cover series was characterized using absolute area, interannual absolute change, interannual percentage change, and cumulative change relative to 1985. For province or region i, the absolute annual change between years $t-1$ and t was calculated as:

$$\Delta A_{i,t} = A_{i,t} - A_{i,t-1} \tag{1}$$

where $A_{i,t}$ is the mapped class 31 area in hectares during year t. The corresponding percentage change was calculated as:

$$\Delta A_{(i,t)(\%)} = \left(\frac{A_{i,t} - A_{i,t-1}}{A_{i,t-1}} \right) \times 100 \tag{2}$$

Provided that the area in the preceding year was greater than zero. Cumulative change between 1985 and 2024 was calculated using the same formulation, with 1985 as the reference year.

The 1985–2024 regional series was additionally evaluated for a monotonic temporal trend using the modified Mann–Kendall test of Hamed and Rao, which adjusts the variance of the test statistic for serial autocorrelation [18]. Trend magnitude was estimated using Sen's slope [19], expressed as the median annual change in mapped class 31 area. Statistical significance was assessed using a two-sided $\alpha = 0.05$ threshold. The year with the highest observed mapped extent was identified directly from the unsmoothed annual series. The trend analysis was used to characterize the direction and magnitude of the complete 40-year trajectory and did not replace the original annual observations with fitted values. No breakpoint was inferred solely from the year of maximum observed area.

Cross-level consistency was assessed by comparing parish-derived province totals with the independently extracted provincial totals for the same years. Absolute and relative residuals were used to quantify numerical differences between the two aggregation levels. These differences were expected to be minimal because raster reduction along adjacent administrative boundaries may produce small discrepancies associated with pixel-edge treatment and computational precision. The direct province-level extraction was retained for the historical time series, whereas the parish-derived hierarchy was retained for canton-

and parish-level analyses. Detailed residual definitions and validation results are provided in the Zenodo reproducibility package [16].

Mapped area was interpreted as the surface classified as aquaculture in the annual MapBiomas product. Changes in this area may reflect actual land-cover transitions, changes in pond water conditions, temporary inactivity, exposed substrates, spectral variation, or classification uncertainty. Accordingly, annual decreases were not automatically interpreted as physical pond removal or permanent cessation of aquaculture activity.

2.5. Administrative Registry Aggregation and Canton-Level Correspondence Analysis

The 2023 MPCEIP registry was aggregated by standardized INEC province and canton codes and compared cross-sectionally with the 2023 MapBiomas class 31 area. Because the registry did not contain farm polygons or coordinates, the analysis assessed territorial correspondence between independently derived measures rather than farm-level spatial agreement.

For each canton, the analysis calculated the signed difference between authorized or concessioned area and mapped area, the MapBiomas-to-authorized-area ratio, and one of four source-presence categories: BOTH_PRESENT, REGISTRY_ONLY, MAPBIOMAS_ONLY, or NEITHER_PRESENT. Spearman's rank correlation was calculated for all active cantons and separately for cantons with positive values in both sources, using a two-sided $\alpha = 0.05$ threshold. These statistics were interpreted as measures of magnitude and rank correspondence, not as evidence that the datasets represented the same legal, spatial, or operational construct.

For visualization, authorized and mapped areas were displayed on $\log_{10}(x + 1)$ axes with a 1:1 reference line, and the largest positive canton-level differences were summarized together with their concentration among the two, five, and ten largest values. Full metric definitions, equations, and validation checks are provided in the Zenodo analytical package [16].

2.6. Pixel-Level Land-Cover Transition Analysis, 2023–2024

The 2023 and 2024 MapBiomas classifications were compared at pixel level, retaining transitions in which class 31 occurred in at least one of the two years. Pixels were classified as persistence (31→31), gross loss (31→other classes), or gross gain (other classes→31), and areas were aggregated by parish and subsequently by canton, province, and the six-province region.

Net change was calculated as gross gain minus gross loss, the persistence rate as the proportion of 2023 class 31 area remaining in class 31 in 2024, and gross-loss and gross-gain composition according to destination and origin classes, respectively. Internal consistency was verified by confirming that persistence plus gross loss reproduced the 2023 mapped area and persistence plus gross gain reproduced the 2024 mapped area. The full equations and validation identities are provided in the Zenodo analytical package [16].

Transitions were interpreted as changes between annual classification states. A change from class 31 to another class did not, by itself, demonstrate pond removal, abandonment, permanent cessation of production, or ecological restoration; likewise, entry into class 31 was not assumed to represent newly constructed or newly authorized aquaculture. This interpretative constraint was retained for all destination and origin classes.

2.7. Fixed-Footprint Climate Context Analysis

Long-term climate exposure was characterized over a fixed aquaculture footprint defined as the union of all pixels classified as MapBiomas class 31 at least once between 1985 and 2024. This constant domain was used to avoid changing the spatial sampling

area together with annual mapped aquaculture extent. Los Ríos did not contain a class 31 footprint and therefore did not contribute to the climate summaries.

Annual precipitation was derived from CHIRPS v3 [10,11] and annual mean 2 m air temperature from ERA5-Land [12,13]. Climate values were summarized as area-weighted means over the fixed footprint while preserving the native resolution of each climate product. Limited coastal gaps in ERA5-Land were completed using bilinear interpolation restricted to a one-cell neighbourhood; coverage was retained as a diagnostic. Regional exposure was obtained by area-weighted aggregation of provincial values, and annual precipitation and temperature anomalies were expressed relative to their 1985–2024 means. Detailed equations and the interpolation diagnostic are provided in the Zenodo analytical package [16].

2.8. Validation and Quality-Assurance Procedures

Validation assessed administrative coding completeness, cross-level aggregation consistency, transition accounting identities, climate-data completeness and coverage, and consistency of the reported analytical outputs. These checks evaluated internal consistency and reproducibility rather than independent thematic accuracy of the source products. Detailed validation tables, diagnostics, and audit information are provided in the Zenodo analytical package [16].

2.9. Software and Reproducibility

Geospatial extraction and raster-based calculations were conducted in Google Earth Engine, whereas data cleaning, administrative reconciliation, statistical analysis, validation, and figure preparation were conducted in Python (version 3.13.5). The study-generated analytical outputs and supporting documentation have been deposited in Zenodo as a versioned reproducibility package [16].

The Zenodo package contains derived and aggregated analytical tables, validation logs, publication figures, administrative crosswalks, manuscript-support files, source-licence documentation, and checksums. It supports verification of the reported values and evidence tracing, but it is not a complete end-to-end computational reproduction environment because complete raw source archives, the raw record-level MPCEIP file, executable scripts or notebooks, and a containerized computing environment are not included. Original MapBiomas Ecuador, MPCEIP, INEC, CHIRPS v3, and ERA5-Land products remain available from their respective providers and should be cited independently.

3. Results

The results are presented according to the four analytical components defined in the study design. First, the long-term evolution of mapped aquaculture land cover is examined at regional and provincial levels for 1985–2024. Second, the 2023 MapBiomas class 31 estimates are compared with the authorized or concessioned areas recorded in the MPCEIP registry. Third, the persistence, gross loss, gross gain, and destination or origin classes associated with the 2023–2024 transition are quantified. Finally, precipitation and temperature exposure are described over the fixed aquaculture footprint. All reported values derive from the validated analytical tables described in Section 2.8.

3.1. Long-Term Evolution of Mapped Aquaculture Land Cover, 1985–2024

Mapped aquaculture land cover across the six-province study region increased substantially over the 40-year period. The regional class 31 area expanded from 58,198.792 ha in 1985 to 138,200.970 ha in 2024, representing a net increase of 80,002.178 ha, or 137.464% relative to the initial year.

The formal trend analysis confirmed a significant positive monotonic trend in regional mapped class 31 area over 1985–2024 (modified Mann–Kendall $\tau = 0.910$, $z = 4.962$, $p < 0.001$). Sen's slope indicated a median increase of 2460.810 ha year^{-1} (95% CI: 2270.329–2648.624 ha year^{-1}). This result supports the interpretation of long-term mapped expansion while allowing substantial interannual variation within the overall trajectory.

The temporal trajectory was not characterized by uninterrupted annual growth. The highest numerical value in the annual series occurred in 2022, with 153,516.642 ha; however, this was only 0.305 ha (0.0002%) above the 2021 value of 153,516.337 ha. The two years are therefore interpreted as a near-identical high plateau rather than as evidence of a distinct statistical breakpoint in 2022. Mapped area subsequently declined to 150,591.587 ha in 2023 and to 138,200.970 ha in 2024. The 2023–2024 change corresponded to a reduction of 12,390.617 ha, equivalent to 8.228% of the mapped area recorded in 2023.

These values indicate that the 2024 mapped extent remained substantially higher than the 1985 baseline despite the marked decline observed after the 2022 maximum. The long-term trajectory should therefore be distinguished from the most recent interannual change: the complete period shows a strong net expansion, whereas the final interval shows a pronounced reduction in the area classified as class 31. Within the more recent 2020–2024 period, mapped class 31 area increased from 151,903.356 ha in 2020 to 153,516.337 ha in 2021 and remained virtually unchanged in 2022 at 153,516.642 ha. It then declined to 150,591.587 ha in 2023 and to 138,200.970 ha in 2024. The pronounced 2023–2024 reduction therefore followed approximately two years of near-maximum mapped extent rather than a continuous decline throughout the 2020–2024 period.

Provincial trajectories showed substantial spatial heterogeneity in both mapped extent and temporal evolution. Figure 2 presents the annual class 31 series for El Oro, Esmeraldas, Guayas, Manabí, and Santa Elena. Los Ríos is not represented as a trajectory because no mapped class 31 footprint was identified in that province during 1985–2024. Its absence from the line plot therefore represents a validated zero mapped footprint rather than missing annual observations.

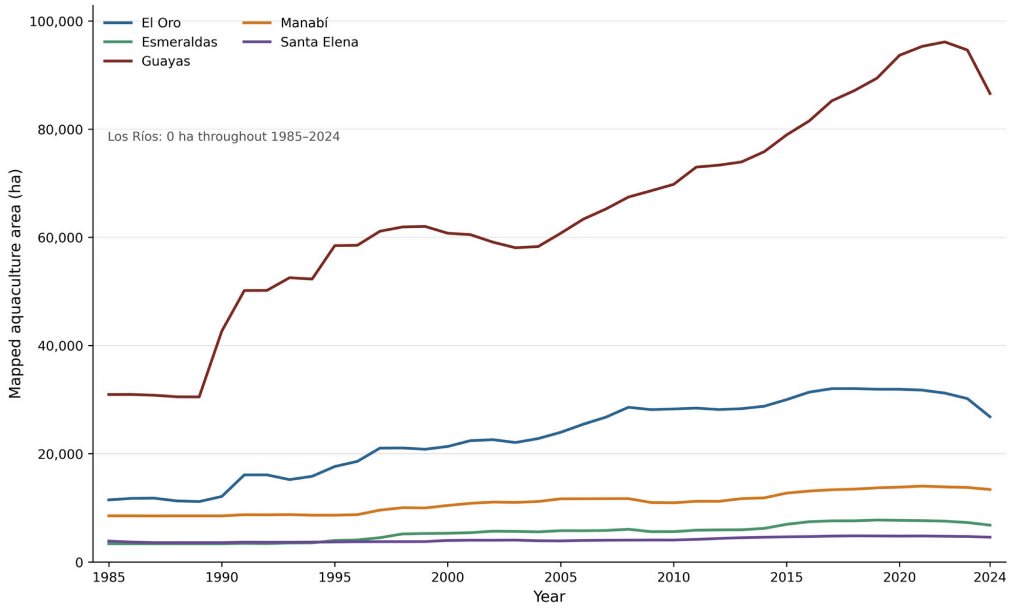

Figure 2. Annual mapped aquaculture land-cover trajectories in El Oro, Esmeraldas, Guayas, Manabí, and Santa Elena, Ecuador, 1985–2024. Values represent MapBiomas Ecuador Collection 3.0 class 31 area in hectares. Los Ríos is not shown because no mapped class 31 footprint was identified during the study period. The series represent annual classification outputs and should not be interpreted directly as aquaculture production or operational farm area.

The regional pattern is also considered together with the long-term precipitation and temperature anomalies in Section 3.6, allowing the 1985 baseline, the 2022 maximum, and the 2024 endpoint to be viewed within the corresponding environmental exposure context.

No smoothing or fitted values were used to replace the annual MapBiomas observations. The modified Mann–Kendall and Sen's slope analyses characterized the complete 1985–2024 trajectory statistically, while the observed year-to-year variation continued to represent differences between successive annual classifications. Consequently, the observed year-to-year variation represents differences between successive MapBiomas annual classifications. These variations may reflect physical land-cover change, changes in pond water conditions or temporary activity, and classification variability; their specific transition composition is examined in Section 3.5.

3.2. Provincial Distribution and Temporal Trajectories

The long-term regional expansion was spatially concentrated, with marked differences in the magnitude and timing of change among provinces. Guayas contained the largest mapped aquaculture area throughout most of the study period and increased from 30,929.940 ha in 1985 to 86,595.193 ha in 2024. This represented an absolute increase of 55,665.253 ha and a relative increase of 179.972%. Guayas alone accounted for 69.580% of the total net regional increase observed between 1985 and 2024.

El Oro had the second-largest mapped area in 2024. Its class 31 extent increased from 11,473.042 ha in 1985 to 26,808.380 ha in 2024, corresponding to an absolute increase of 15,335.338 ha, or 133.664%. El Oro contributed a further 19.169% of the regional net increase.

Manabí increased from 8541.195 ha to 13,390.260 ha over the same period. Its absolute increase of 4849.065 ha represented a relative expansion of 56.773% and contributed 6.061% of the regional net change. Esmeraldas more than doubled its mapped area, increasing from 3383.515 ha in 1985 to 6811.637 ha in 2024. This corresponded to an increase of 3428.122 ha, or 101.318%.

Santa Elena exhibited the smallest long-term absolute and relative increase among provinces with a mapped class 31 footprint. Its area increased from 3871.100 ha in 1985 to 4595.500 ha in 2024, representing an additional 724.400 ha, or 18.713%. No class 31 area was identified in Los Ríos during any year of the 1985–2024 series.

The 2024 regional distribution remained highly concentrated. Guayas represented 62.659% of the mapped class 31 area across the study region, followed by El Oro with 19.398%, Manabí with 9.689%, Esmeraldas with 4.929%, and Santa Elena with 3.325%. Consequently, Guayas and El Oro together accounted for approximately 82.1% of the 2024 mapped aquaculture area. Table 2 summarizes the provincial mapped aquaculture trajectories between 1985 and 2024, including absolute and relative changes and the maximum mapped area recorded in each province.

All five provinces with mapped aquaculture reached their individual maximum before 2024. El Oro and Santa Elena reached their highest mapped extents in 2018, Esmeraldas in 2019, Manabí in 2021, and Guayas in 2022. By 2024, El Oro was 5217.194 ha below its provincial maximum, while Guayas was 9539.986 ha below its 2022 maximum. The corresponding differences were 954.624 ha in Esmeraldas, 615.998 ha in Manabí, and 244.753 ha in Santa Elena.

Despite these reductions from provincial maxima, all five provinces retained a larger mapped class 31 area in 2024 than in 1985. The results therefore show a common long-term direction of expansion, combined with different provincial peak years and different magnitudes of subsequent decline. These province-specific trajectories underpin the more recent transition patterns examined in Section 3.5.

Table 2. Provincial summary of mapped aquaculture land-cover trajectories, 1985–2024.

Province	Area in 1985 (ha)	Area in 2024 (ha)	Absolute Change (ha)	Relative Change (%)	Maximum Area (ha)	Year of Maximum
El Oro	11,473.042	26,808.380	15,335.338	133.664	32,025.574	2018
Esmeraldas	3383.515	6811.637	3428.122	101.318	7766.261	2019
Guayas	30,929.940	86,595.193	55,665.253	179.972	96,135.179	2022
Los Ríos	0.000	0.000	0.000	—	0.000	—
Manabí	8541.195	13,390.260	4849.065	56.773	14,006.258	2021
Santa Elena	3871.100	4595.500	724.400	18.713	4840.253	2018
Six-province total	58,198.792	138,200.970	80,002.178	137.464	153,516.642	2022

Note: Relative change was not calculated for Los Ríos because the mapped class 31 area was zero in the reference year and throughout the study period. Provincial maxima were identified independently from each annual series; therefore, their sum does not necessarily correspond to the regional maximum in a single year.

3.3. Correspondence Between Authorized and Mapped Aquaculture Area in 2023

The 2023 MPCEIP registry contained 3269 harmonized administrative records representing 202,114.900 ha of authorized or concessioned shrimp-farm area across the six-province study region. The corresponding canton-level MapBiomas class 31 total, derived from the harmonized parish hierarchy, was 150,591.195 ha. The mapped area therefore represented 74.508% of the authorized or concessioned area recorded in the registry.

The absolute regional difference between the two independently derived measures was:

$$D_{regional} = 202114.900 - 150591.195 = 51523.705 \text{ ha} \quad (3)$$

This difference represents a comparison between administrative area and mapped land cover. It does not indicate that 51,523.705 ha were omitted by MapBiomas, inactive, abandoned, unauthorized, or physically absent. The two sources describe different constructs and do not share farm-level geometries.

Among the 84 cantons in the harmonized administrative framework, 32 had positive values in both sources. Six cantons had positive authorized or concessioned area but no mapped class 31 area, while three had mapped class 31 area but no authorized area recorded in the harmonized registry. The remaining 43 cantons had zero area in both sources. Table 3 summarizes the main indicators of canton-level correspondence between the MPCEIP authorized or concessioned area and MapBiomas class 31 area in 2023.

The association between the canton rankings of authorized and mapped area was strong. Considering all 41 active cantons, Spearman's rank correlation coefficient was 0.889753, with $p < 0.001$. When the analysis was restricted to the 32 cantons with positive values in both sources, the coefficient increased to 0.929252, also with $p < 0.001$.

These results indicate that cantons with larger authorized or concessioned areas generally also tended to have larger mapped class 31 areas. However, the high rank correlation does not imply equality of magnitude or spatial coincidence between the two sources. A canton may occupy a similar position in both rankings while still presenting a substantial absolute difference in hectares.

Figure 3 displays the canton-level relationship after applying the $\log_{10}(\text{ha} + 1)$ transformation. The vertical displacement from the 1:1 line corresponds to the signed log-scale divergence L_i defined in Section 2.5: values above the line indicate a larger MapBiomas class 31 area, whereas values below the line indicate a larger authorized or concessioned area. Registry-only cantons appear along the horizontal axis, while MapBiomas-only cantons appear along the vertical axis. Because the logarithmic transformation compresses

differences at larger area values, the visual comparison in Figure 3 is interpreted together with the original-scale differences in hectares summarized below and in Figure 4.

Table 3. Canton-level correspondence between MPCEIP authorized or concessioned area and MapBiomas class 31 area, 2023.

Indicator	Value
Number of harmonized registry records	3269
Authorized or concessioned area (ha)	202,114.900
MapBiomas class 31 area (ha)	150,591.195
Absolute difference (ha)	51,523.705
MapBiomas-to-authorized-area ratio	0.745077
MapBiomas area as a percentage of authorized area	74.507716%
Cantons with positive area in both sources	32
Registry-only cantons	6
MapBiomas-only cantons	3
Cantons with zero area in both sources	43
Spearman's ρs all active cantons	0.889753
Spearman's ρs, both-present cantons	0.929252

Note: Active cantons were defined as cantons with a positive area in at least one source. The source-presence categories describe the observed combination of values and do not establish legal, operational, or spatial correspondence.

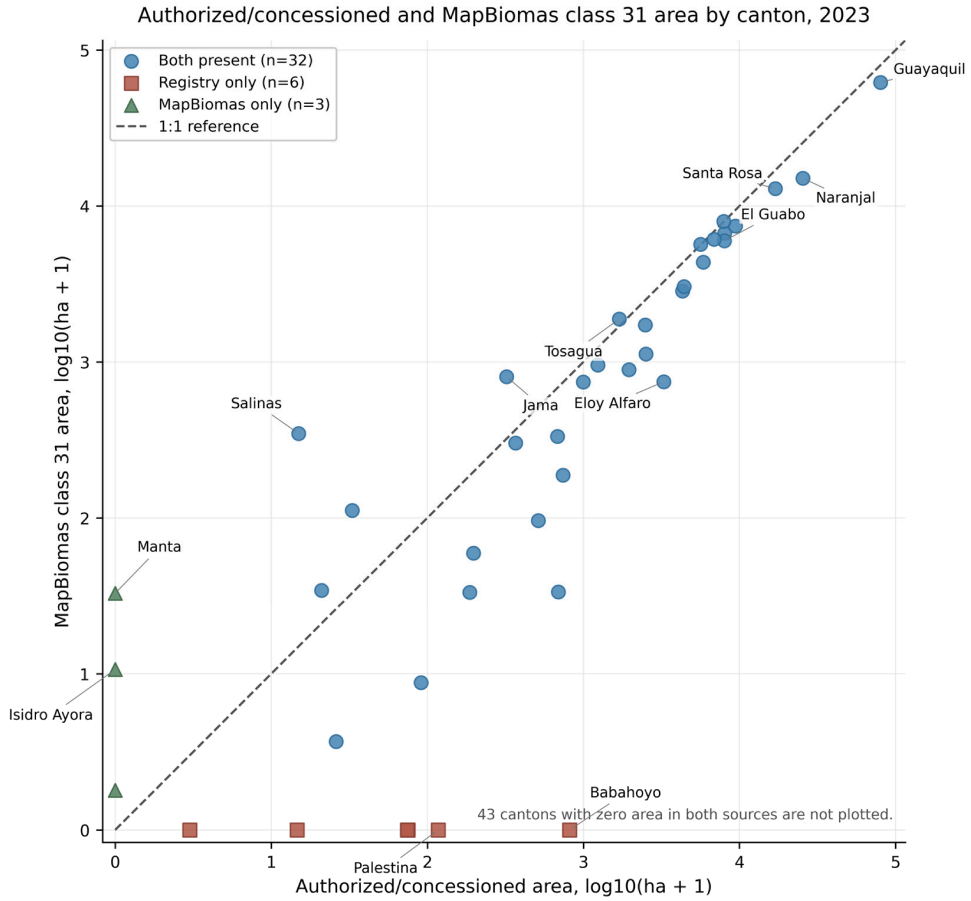

Figure 3. Authorized or concessioned area and MapBiomas class 31 area by canton in 2023, represented as $\log_{10}$(ha + 1). Active cantons are classified as both present, registry only, or MapBiomas only. Cantons with zero area in both sources are omitted from the plotting field. The 1:1 line indicates equality of transformed magnitude; distance from the line represents log-scale magnitude divergence and should not be interpreted as statistical or spatial agreement between the two sources.

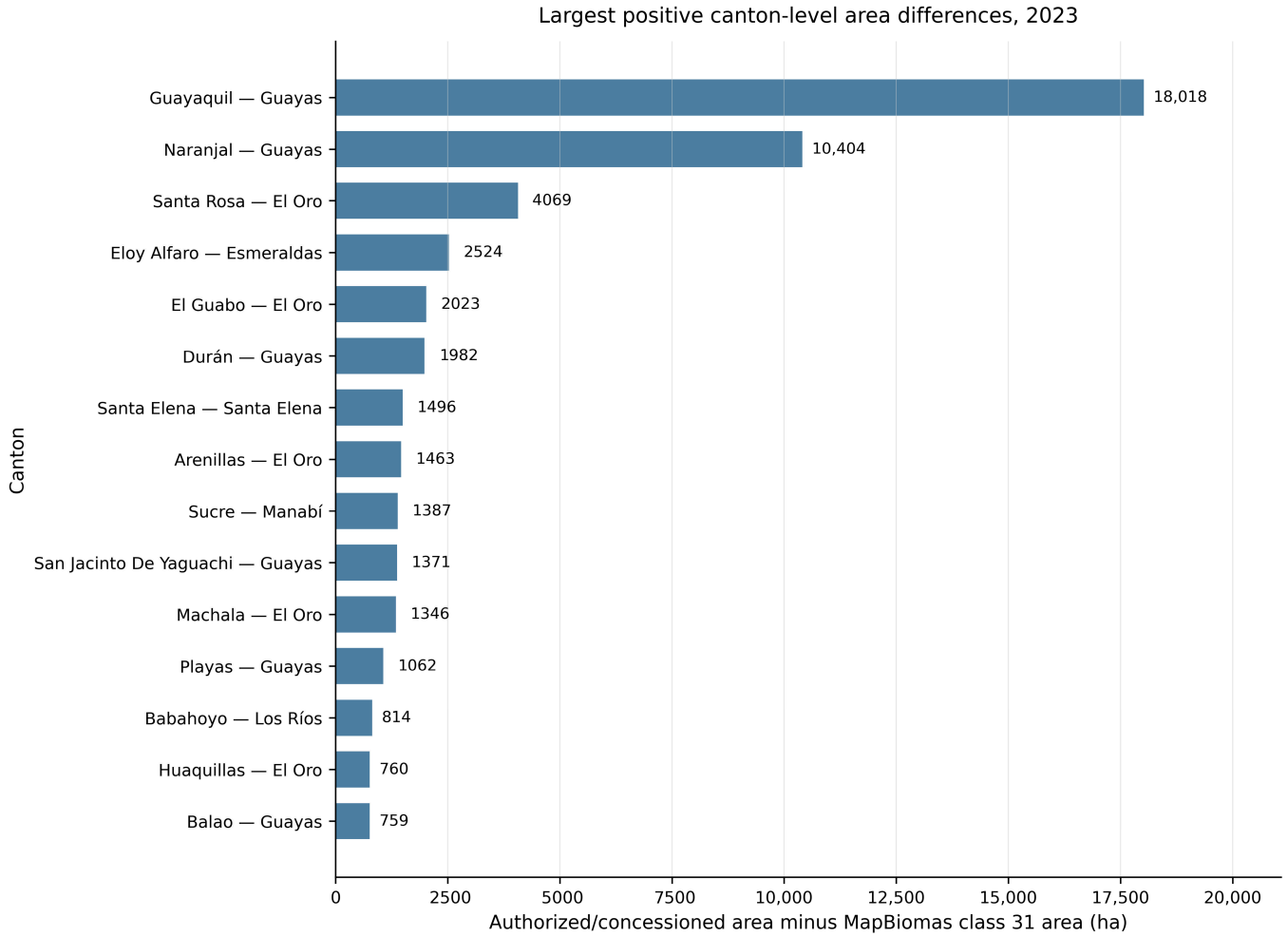

Figure 4. Fifteen largest positive canton-level differences between MPCEIP authorized or concessioned area and MapBiomas class 31 area in 2023. Positive values indicate that authorized area exceeds mapped class 31 area. These source-to-source differences do not demonstrate illegality, omission, abandonment, operational inactivity, or physical closure.

The largest positive differences were spatially concentrated. The two cantons with the largest positive values accounted for 53.902% of the total positive difference across cantons. The five largest accounted for 70.243%, and the ten largest represented 84.843%. The regional divergence was therefore not distributed evenly across the administrative framework but was dominated by a relatively small number of cantons.

Figure 4 presents the 15 largest positive canton-level differences, calculated as authorized or concessioned area minus MapBiomas class 31 area. Guayaquil showed the largest positive difference, followed by Naranjal and Santa Rosa. Other prominent cases included cantons in Guayas, El Oro, Esmeraldas, Manabí, Santa Elena, and Los Ríos.

The presence of Babahoyo among the largest positive differences reflects authorized area recorded in the MPCEIP registry despite the absence of a mapped class 31 footprint in Los Ríos in 2023. This result should be interpreted as an administrative-versus-mapped divergence at canton level and not as evidence that either source is necessarily incorrect.

Conversely, the three MAPBIOMAS_ONLY cantons contained mapped class 31 area without a positive authorized-area value in the harmonized registry. These cases likewise cannot be interpreted as proof of unauthorized aquaculture because the registry is administrative, contains no geometries, and may differ from MapBiomas in temporal coverage, classification scope, location attribution, and measurement definition.

The 2023 comparison revealed strong rank correspondence but substantial magnitude divergence between the two sources. The results support their use as complementary evidence while confirming that they should not be treated as interchangeable estimates of aquaculture extent.

3.4. Parish-Level Distribution of Recent Change, 2023–2024

The parish-level comparison provided a finer spatial view of the recent reduction in mapped class 31 area. Among the 301 parishes included in the harmonized administrative framework, 239 showed no net change between 2023 and 2024, 59 showed a negative change, and only 3 showed a positive change.

The predominance of parishes without net change reflects the fact that class 31 was absent or remained unchanged across most of the parish framework. Nevertheless, the regional decline was spatially distributed across multiple parishes rather than being confined to a single administrative unit. Negative change was observed in 59 parishes, while positive change was limited to a very small number of cases. Table 4 summarizes the parish-level direction of change in mapped aquaculture land cover between 2023 and 2024.

Table 4. Parish-level direction of change in mapped aquaculture land cover, 2023–2024.

Change Category	Number of Parishes	Share of All Parishes (%)
No net change	239	79.402
Negative net change	59	19.601
Positive net change	3	0.997
Total	301	100.000

Note: Change categories were defined according to the sign of the 2024-minus-2023 difference in MapBiomas class 31 area. A parish classified as having no net change may have had no class 31 area in either year or may have retained the same aggregate mapped area. Net stability does not necessarily exclude offsetting pixel-level gains and losses within the parish.

The parish-derived 2023 class 31 total was 150,591.195 ha. This value differed from the independently extracted provincial total of 150,591.587 ha by only 0.392 ha, corresponding to a relative residual of 0.000260%. The negligible difference confirmed the internal consistency of the parish-based administrative hierarchy used for the subprovincial analyses.

The parish-level direction of change alone does not describe the processes underlying the observed net values. A parish with a negative net change may simultaneously contain persistent pixels, gross losses, and gross gains, provided that losses exceed gains. Likewise, a parish with no net change may still contain offsetting transitions between class 31 and other land-cover classes.

For this reason, the parish-level change classification was complemented by the pixel-level transition accounting presented in Section 3.5. That analysis separates persistence, gross loss, gross gain, and the origin or destination classes associated with the 2023–2024 transition.

3.5. Recent Land-Cover Change and Classification-State Persistence

Recent mapped aquaculture change was examined at two complementary temporal scales. The 2023–2024 transition analysis describes the composition of the most recent annual change in terms of persistence, gross loss, gross gain, and origin or destination classes. The 2020–2024 classification-state diagnostic extends this interpretation by evaluating whether recent exits from or entries into class 31 persisted across consecutive annual classifications or were subsequently reversed.

3.5.1. Annual Transition Balance, 2023–2024

The pixel-level transition analysis confirmed that the recent decline in mapped class 31 area resulted from gross losses that substantially exceeded gross gains. Across the six-province study region, 135,774.430 ha remained classified as aquaculture in both 2023 and 2024. Gross loss from class 31 to other land-cover classes totalled 14,816.766 ha, whereas gross gain from other classes into class 31 totalled 2426.130 ha.

The resulting net change was:

$$N_{regional} = 2426.130 - 14816.766 = -12390.636 \text{ ha} \quad (4)$$

The negative net balance reproduced the decline identified from the independently extracted 2023 and 2024 class 31 totals, with only negligible numerical differences attributable to raster aggregation and boundary treatment.

The regional persistence rate was 90.161%, indicating that approximately nine-tenths of the area mapped as class 31 in 2023 retained the same classification in 2024. However, the gross loss area was more than six times the gross gain area, producing the marked negative net balance. Table 5 summarizes the regional transition balance and the corresponding provincial net changes between 2023 and 2024.

Table 5. Regional and provincial balance of MapBiomas class 31 transitions, 2023–2024.

Panel A. Regional Transition Balance		
Transition Component	Area (ha)	Share of 2023 Class 31 Area (%)
Persistence: class 31 → class 31	135,774.430	90.161
Gross loss: class 31 → other classes	14,816.766	9.839
Gross gain: other classes → class 31	2426.130	—
Net change: gross gain—gross loss	−12,390.636	−8.228
Panel B. Provincial Net Change		
Province		Net change, 2023–2024 (ha)
El Oro		−3371.896
Esmeraldas		−486.195
Guayas		−8035.156
Los Ríos		0.000
Manabí		−382.961
Santa Elena		−114.428
Six-province total		−12,390.636

Note: Persistence and gross loss together represent the mapped class 31 area in 2023. Gross gain is expressed relative to the 2024 classification and is therefore not included in the percentage partition of the 2023 area. Net change was calculated as gross gain minus gross loss.

The reduction occurred in all five provinces containing a mapped class 31 footprint. Guayas accounted for the largest absolute decline, with a net reduction of 8035.156 ha, corresponding to approximately 64.849% of the regional net loss. El Oro recorded the second-largest decline, with 3371.896 ha, or approximately 27.213% of the regional total. The remaining net reductions were substantially smaller: 486.195 ha in Esmeraldas, 382.961 ha in Manabí, and 114.428 ha in Santa Elena. Los Ríos recorded no transition because no class 31 footprint was mapped in either year.

The long-format transition dataset contained non-zero class 31 transition records for 78 parishes across five provinces. These records included 77 persistence combinations, 231 gross-loss combinations, and 185 gross-gain combinations after aggregation by parish and transition class. The number of records reflects distinct parish–transition combinations rather than individual pixels or aquaculture facilities.

The destination composition of gross loss was strongly concentrated in a small number of classes. The largest destination was MapBiomas class 25, Other anthropic non-vegetated area, which received 11,787.512 ha, representing 79.555% of total gross loss. MapBiomas class 3, Forest, accounted for 1802.259 ha, or 12.164% of gross loss. Open forest (class 4) accounted for a further 42.347 ha (0.286%), and Mangrove (class 5) accounted for 26.066 ha (0.176%). Mosaic agriculture and pasture accounted for 890.844 ha, or 6.012%.

The class 31-to-Forest transitions were not uniformly distributed across the study region. Guayas accounted for 804.613 ha, followed by Esmeraldas (389.213 ha), El Oro (347.213 ha), and Manabí (261.221 ha). At canton level, the largest areas occurred in Naranjal (381.810 ha), Muisne (335.317 ha), Guayaquil (280.660 ha), Pedernales (204.994 ha), and El Guabo (202.410 ha). The parish-level spatial distribution of these transitions is shown in Figure A1.

All remaining destination classes together represented approximately 2.269% of gross loss.

Gross gains into class 31 also originated predominantly from the same broad land-cover groups. Class 25 contributed 1076.250 ha, corresponding to 44.361% of total gross gain. Mosaic agriculture and pasture contributed 749.203 ha, or 30.881%, while forest-related classes contributed 566.111 ha, or 23.334%. Other origin classes jointly accounted for approximately 1.425% of gross gain. Figure 5 summarizes the regional transition balance, provincial net change, and the principal destination and origin classes associated with gross loss and gross gain.

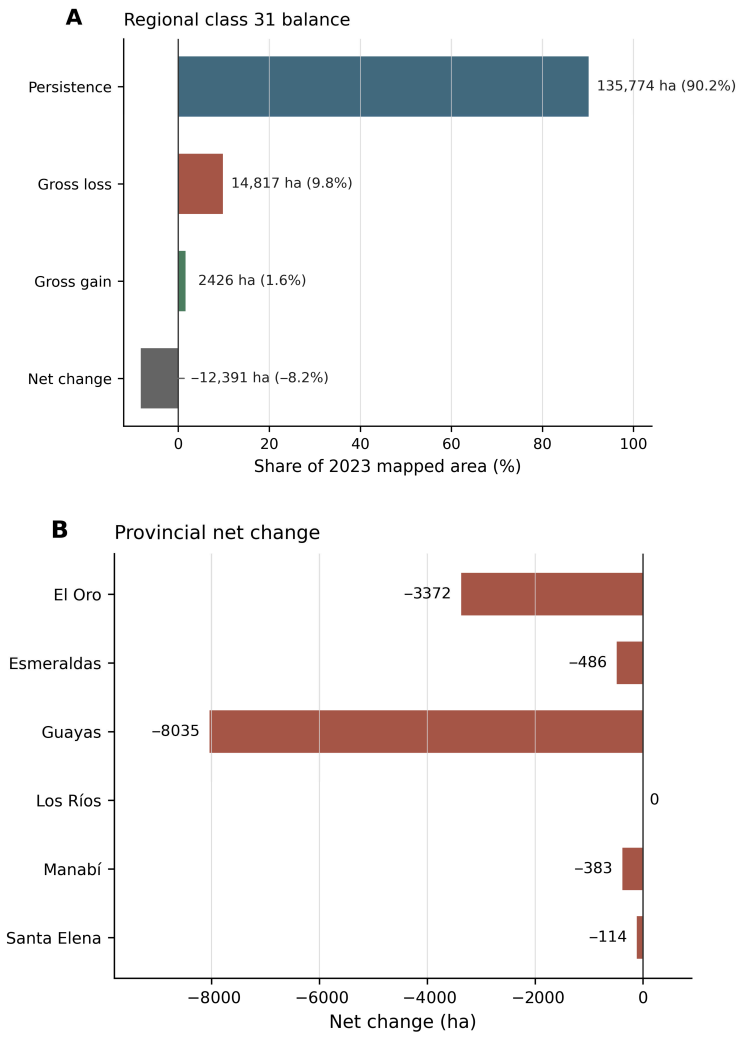

Figure 5. *Cont.*

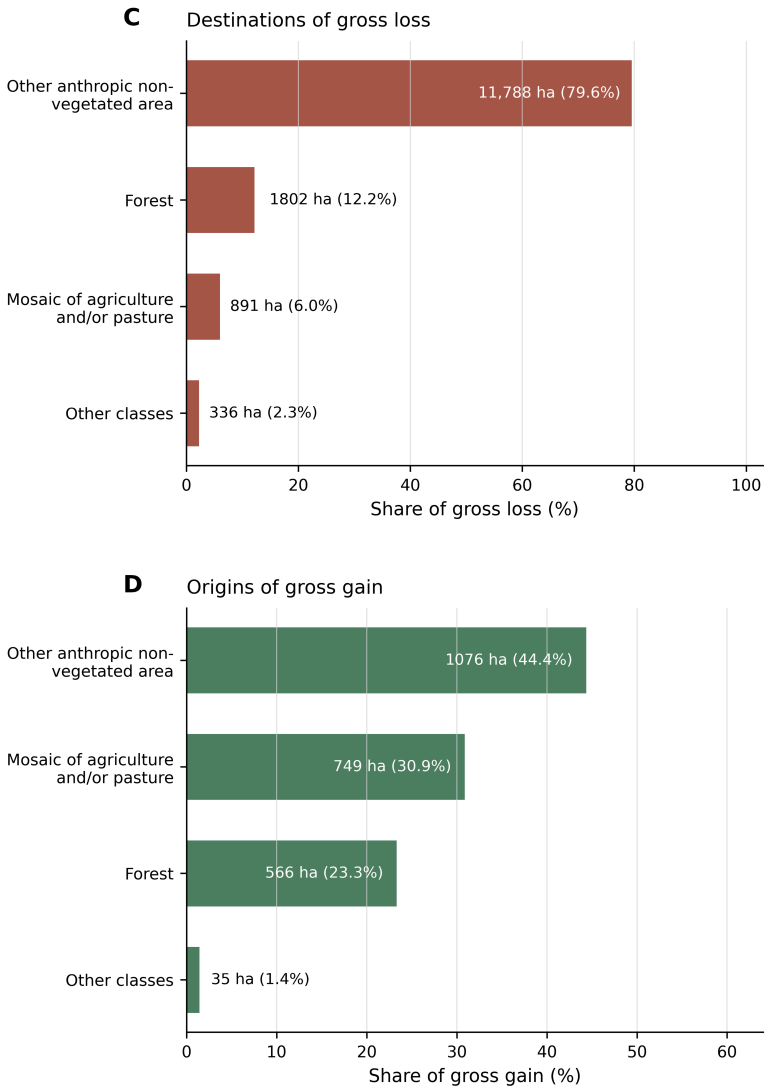

Figure 5. Regional balance and principal origin and destination classes of MapBiomas class 31 transitions between 2023 and 2024. (**A**) regional class 31 balance; (**B**) provincial net change; (**C**) destinations of gross loss; (**D**) origins of gross gain; Persistence represents pixels classified as class 31 in both years; gross loss represents transitions from class 31 to another class; gross gain represents transitions from another class into class 31; and net change is calculated as gross gain minus gross loss. Origin and destination classes are reported according to the MapBiomas Ecuador Collection 3.0 legend. These transitions represent changes between annual classification states and do not, by themselves, establish physical pond removal, new pond construction, operational status, legal status, or ecological recovery.

The predominance of transitions between class 31 and class 25 is consistent with changes in the spectral and surface condition of aquaculture infrastructure. Aquaculture ponds that are drained, temporarily inactive, exposed, sediment-covered, or otherwise lacking a water signature may be assigned to a non-vegetated anthropic class in one annual classification and return to class 31 in another. However, the transition data alone do not permit the individual cause of each class change to be determined.

Transitions from class 31 to forest-related classes represented a smaller but non-negligible share of gross loss. These transitions should not automatically be interpreted as forest restoration, because annual class changes may also reflect mixed pixels, boundary effects, classification uncertainty, vegetation regrowth of uncertain permanence, or differences in pond condition. Only 0.176% of gross loss transitioned to the mangrove-related

class, which does not support a generalized interpretation of mangrove recovery across the study region.

Similarly, gains from forest, agricultural mosaics, or non-vegetated anthropic classes into class 31 indicate a change in mapped classification state but do not independently demonstrate the construction, authorization, or commencement of operation of new aquaculture facilities. Confirmation of those processes would require temporally resolved imagery, infrastructure records, farm-level geometries, or field-based evidence.

The transition analysis showed that the 2023–2024 regional decline was driven primarily by class 31 pixels being reassigned to other anthropic non-vegetated areas, while a smaller reverse flow occurred from that same class into aquaculture. The high persistence rate nevertheless indicates that most of the 2023 mapped aquaculture footprint remained stable over the one-year interval.

3.5.2. Multi-Year Classification-State Persistence, 2020–2024

The multi-year classification-state diagnostic provided additional temporal context for the recent decline in mapped aquaculture. Among the 164,625.252 ha classified as class 31 at least once during 2020–2024, 127,543.234 ha (77.475%) remained classified as class 31 in all five annual classifications, whereas 37,082.018 ha (22.525%) changed classification state at least once. Of the latter, 33,801.218 ha (20.532% of the five-year class 31 union) underwent exactly one state change, while 3280.800 ha (1.993%) underwent two or more state changes.

Among pixels classified as class 31 in 2022, 133,279.481 ha (86.817%) remained classified as class 31 in both 2023 and 2024, 14,194.574 ha (9.246%) remained in class 31 in 2023 but exited in 2024, 5862.456 ha (3.819%) exited in 2023 and remained outside class 31 in 2024, and 180.666 ha (0.118%) exited in 2023 but returned to class 31 in 2024.

The occurrence of both sustained and reversible classification-state changes demonstrates that the post-2022 decline was not composed of a single temporal pattern. Persistent departures from class 31 and temporary exits followed by re-entry were therefore distinguished analytically, while neither was interpreted as direct evidence of the underlying physical or operational mechanism.

3.6. Long-Term Climate Exposure over the Fixed Aquaculture Footprint, 1985–2024

The fixed aquaculture footprint covered 185,382.977 ha across the five provinces in which MapBiomas class 31 was identified at least once during 1985–2024. Guayas contained the largest share of this footprint, with 115,477.122 ha, followed by El Oro with 36,959.920 ha, Manabí with 16,801.874 ha, Esmeraldas with 10,201.715 ha, and Santa Elena with 5942.346 ha. Los Ríos did not contribute to the climate summaries because no mapped class 31 footprint was identified there during the study period.

The fixed footprint was larger than the mapped class 31 area observed in any individual year because it represented the spatial union of all pixels classified as aquaculture at least once during the 40-year series. Consequently, the climate results describe precipitation and temperature exposure over a constant historical aquaculture domain rather than over the changing annual mapped extent.

Regional precipitation exposure showed pronounced interannual variability. The wettest year was 1998, when annual precipitation over the fixed footprint reached 2796.126 mm. This value was 211.768% above the 1985–2024 mean. In contrast, 1985 was the driest year, with 338.594 mm, corresponding to an anomaly of −62.247%.

The exceptional precipitation exposure recorded in 1998 coincided with the strong El Niño conditions affecting coastal Ecuador during that period. Within the present analysis, however, this temporal coincidence is treated only as climatic context. The study did not

estimate the effect of precipitation anomalies on aquaculture production, infrastructure, or subsequent land-cover change.

Regional mean temperature exposure also varied across the study period. The warmest year was 2023, when the area-weighted mean 2 m air temperature reached 25.171 °C. This corresponded to a positive anomaly of 1.521 °C relative to the 1985–2024 mean. The temperature series therefore places the 2023 administrative and land-cover comparison within an unusually warm regional exposure year. Figure 6 summarizes the long-term mapped aquaculture trajectory together with the precipitation and temperature anomalies over the fixed aquaculture footprint.

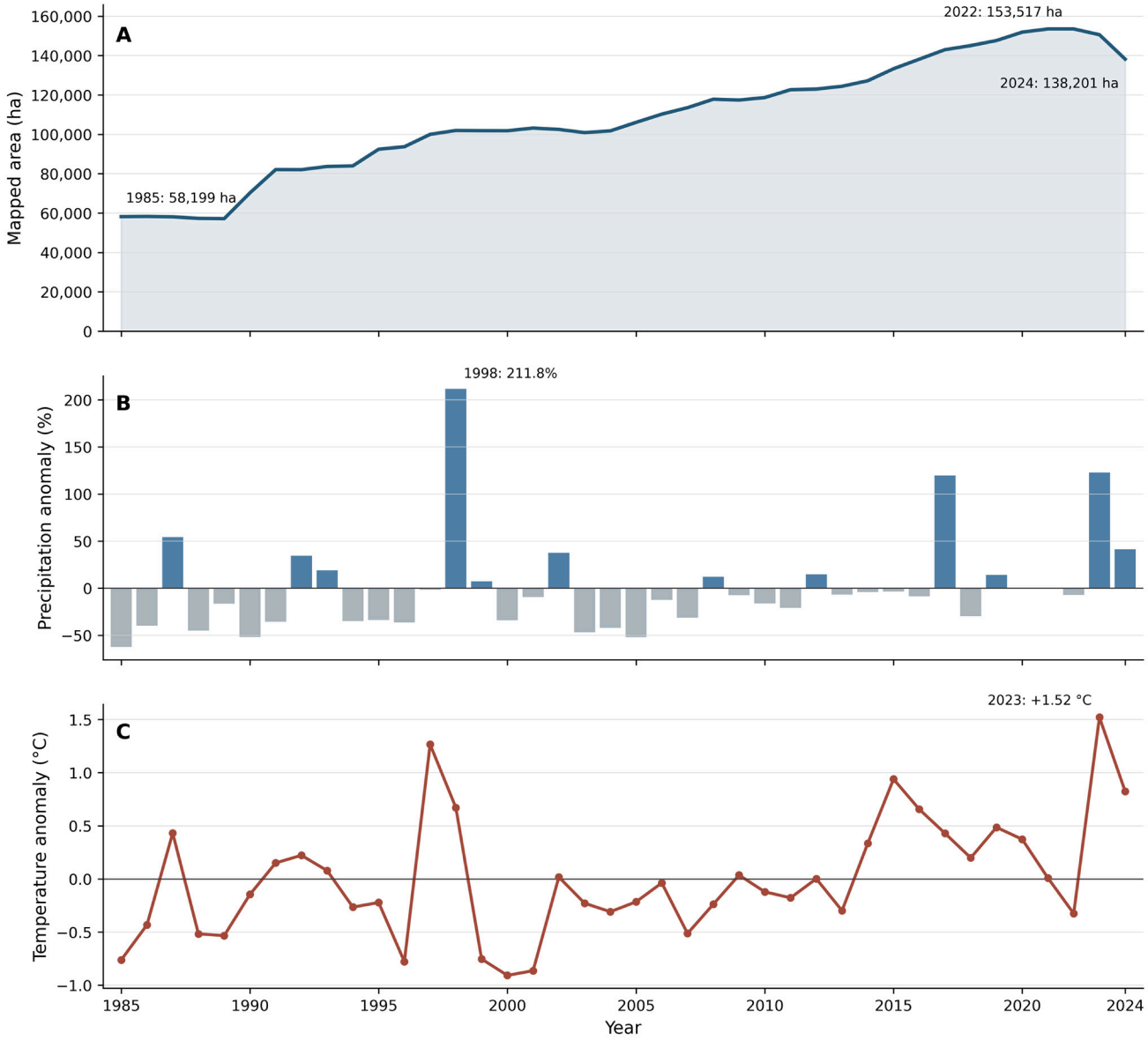

Figure 6. Long-term mapped aquaculture land cover and climate exposure across the coastal study region, 1985–2024. Panel (**A**) presents the annual MapBiomas Ecuador Collection 3.0 class 31 area across the six provinces. Panel (**B**) presents the annual precipitation anomaly, expressed as a percentage relative to the 1985–2024 mean and derived from CHIRPS v3 over the fixed aquaculture footprint. Panel (**C**) presents the annual mean 2 m air-temperature anomaly, expressed in degrees Celsius relative to the 1985–2024 mean and derived from ERA5-Land over the same fixed footprint. Climate anomalies describe environmental exposure and do not establish causal effects on mapped aquaculture change.

The principal land-cover and climate peaks did not occur in the same year. Regional mapped class 31 area reached its maximum in 2022, regional temperature exposure reached its maximum in 2023, and the highest precipitation exposure occurred much earlier, in 1998. This temporal separation reinforces the descriptive nature of the integrated figure and cautions against interpreting visual alignment between the series as causal evidence.

Climate-data coverage remained high across the validated provincial series. CHIRPS footprint coverage ranged from 98.687% in Santa Elena to 99.914% in El Oro, with corresponding values of 99.864% in Esmeraldas, 99.659% in Guayas, and 99.859% in Manabí. After application of the one-cell coastal completion procedure, ERA5-Land coverage ranged from 99.973% to 100% across the provinces with a fixed footprint.

The effect of the ERA5-Land coastal completion procedure on annual provincial temperature estimates was small. The largest absolute adjustment identified in the provincial series was 0.106 °C in Guayas. The maximum adjustment in the regional area-weighted series was 0.095 °C. These values indicate that the procedure improved coastal footprint coverage without materially changing the principal temporal pattern of the temperature series.

The climate results provide a consistent environmental frame for interpreting the four-decade land-cover trajectory. They should not be read as estimates of farm-level conditions or as evidence that a particular precipitation or temperature anomaly caused expansion, persistence, or decline in MapBiomas class 31.

4. Discussion

The findings are discussed by maintaining the conceptual separation established in the study design. MapBiomas class 31 represents annually mapped aquaculture land cover, the MPCEIP registry represents authorized or concessioned shrimp-farm area, and the climate series represents environmental exposure over a fixed historical footprint. These measures provide complementary perspectives, but none should be treated as a direct substitute for the others. The discussion therefore focuses on the long-term land-cover trajectory, the spatial concentration of aquaculture, the correspondence between mapped and administrative areas, the meaning of the recent transitions, and the role of climate information as contextual rather than causal evidence.

4.1. Long-Term Expansion and Spatial Concentration of Mapped Aquaculture

The four-decade trajectory shows that mapped aquaculture became a major and persistent component of Ecuador's coastal land-cover configuration. Importantly, the recent reduction in class 31 does not negate the much larger historical expansion observed over the complete study period. This distinction between long-term development and recent annual change is essential when interpreting the temporal trajectory.

The formal trend diagnostic supports this interpretation at the level of the complete series. The modified Mann–Kendall test identified a significant positive monotonic trend, with a Sen's slope of approximately 2461 ha year^{-1}. This result does not imply uniform annual expansion: the regional trajectory contains periods of slower growth, temporary decline, and the marked reduction observed after 2022. It therefore supports the long-term direction of change without converting individual annual fluctuations into evidence of structural turning points.

This long-term pattern is consistent with earlier remote-sensing research documenting the rapid development of shrimp ponds in Ecuadorian estuaries. One of the earliest multitemporal assessments reported simultaneous mangrove decline and shrimp-pond expansion in the southern Gulf of Guayaquil between 1966 and 1982 [4]. Later spatial analyses identified extensive conversion of mangrove and other estuarine land covers to

shrimp aquaculture across several Ecuadorian estuaries [5]. The present study extends this historical perspective by providing an annual, methodologically consistent land-cover series from 1985 to 2024 across six provinces.

The expansion was also strongly concentrated geographically, particularly in Guayas and El Oro. This spatial pattern is compatible with the historical importance of the Gulf of Guayaquil and the estuarine systems of southern Ecuador in the development of commercial shrimp aquaculture. Earlier work documented substantial mangrove-to-aquaculture conversion in these coastal environments and identified the initial periods of pond development as important phases of land-cover transformation [5]. The persistence of this concentration in the present annual series indicates that the historical geography of shrimp-farming development continues to structure the contemporary distribution of mapped aquaculture.

The provincial trajectories nevertheless demonstrate that expansion did not occur uniformly. Guayas showed the largest absolute and relative increase, whereas Santa Elena experienced a much smaller long-term change. El Oro, Esmeraldas, Manabí, and Santa Elena also reached their maximum mapped extents in different years. These differences show that a single regional curve can conceal distinct provincial trajectories. The present analysis does not test the factors responsible for those differences. Variables such as estuarine suitability, the timing of infrastructure development, administrative conditions, and the evolution of established production areas should therefore be regarded as hypotheses for future investigation rather than as explanations supported by the present dataset. The results identify the territories and periods in which such hypotheses could be examined more directly.

The decline following the near-maximum 2021–2022 plateau requires cautious interpretation. A reduction in class 31 indicates that fewer pixels were assigned to the aquaculture category in the subsequent annual classifications; it does not necessarily demonstrate an equivalent contraction in farm infrastructure or shrimp production. Ponds may remain physically present while being drained, temporarily inactive, exposed, undergoing maintenance, or presenting a spectral state that is assigned to another land-cover class. Recent research on the segmentation of Ecuadorian shrimp ponds has likewise emphasized that pond monitoring is affected by spatial complexity, image resolution, cloud cover, temporal availability, and the characteristics of the classification procedure [14].

The distinction between mapped land cover and production is also important when interpreting historical industry shocks. White spot syndrome virus was documented in cultured Penaeus vannamei in Ecuador during the severe disease crisis that began in 1999 [6]. Around 1999–2001, the MapBiomas trajectory shows a temporary interruption of the strong expansion observed during the preceding decade, including a flattening and modest decline in the dominant Guayas trajectory. This temporal correspondence is relevant as historical context, but it should not be interpreted as evidence that WSSV caused the observed land-cover pattern. A disease shock can substantially reduce production, stocking, or the number of production cycles while existing pond infrastructure remains visible in satellite-derived land-cover classifications.

The same interpretative constraint applies to the recent 2022–2024 decline. Market prices, export demand, production volumes, disease occurrence, feed costs, and other industry-level variables were not included in the analytical dataset, and the observed reduction in class 31 therefore cannot be attributed to a particular market or biological shock. Moreover, the 2023–2024 transition results show substantial bidirectional movement between aquaculture and other anthropic non-vegetated surfaces, reinforcing the possibility that changes in pond state or detectability contributed to the mapped decline. Disease and market conditions may influence production decisions and farm activity, but establishing

their relationship with mapped land-cover change would require temporally aligned production, price, trade, disease-surveillance, and farm-level data.

The four-decade series consequently reveals two simultaneous features: a durable historical expansion of mapped aquaculture and a recent reduction in the area assigned to class 31. Treating the 2022–2024 decline as a reversal of the entire development trajectory would ignore the magnitude of the accumulated expansion and the classification-state changes identified in the transition analysis.

4.2. Administrative Registry and Mapped Land Cover as Complementary Evidence

The comparison between the MPCEIP registry and MapBiomas revealed a strong territorial correspondence in the relative concentration of aquaculture but a substantial difference in absolute magnitude. This combination is more informative than either result considered separately: the two sources identify broadly similar centres of aquaculture concentration while measuring different aspects of those territories. Strong rank correspondence should therefore not be interpreted as equivalence between administrative authorization and remotely mapped land cover.

This distinction follows directly from the nature of the sources. The MPCEIP variable records the area attached to an administrative authorization or concession, whereas MapBiomas identifies pixels assigned to an aquaculture land-cover class in a particular annual classification. Authorized area may include ponds or associated surfaces that do not display the spectral characteristics required for assignment to class 31 during the reference year. Conversely, remotely mapped aquaculture may occur in locations for which no positive area was represented in the harmonized registry total. Neither situation can be resolved conclusively without farm polygons, acquisition dates for individual administrative records, and temporally matched high-resolution imagery.

Remote sensing is particularly valuable in this context because it provides spatially explicit and independently generated evidence that can complement administrative reporting. Studies using satellite time series have demonstrated that aquaculture ponds can be mapped consistently over extensive coastal territories, thereby supporting regional inventories and change analysis that would be difficult to obtain from administrative tabulations alone [2]. More recent work has also emphasized that spatially explicit remote-sensing estimates can supplement sparse, aggregated, or self-reported aquaculture information, while still requiring explicit treatment of classification and measurement uncertainty [3].

The present results illustrate the benefits and the limits of that complementarity. The high rank association indicates that both sources capture a similar broad spatial structure: Guayas and El Oro dominate the aquaculture geography, and the cantons occupying the upper part of the administrative ranking generally also appear among the largest remotely mapped areas. This agreement supports the use of the two datasets for identifying areas of major aquaculture concentration.

Magnitude differences remain important, however. The regional difference of 51,523.705 ha was highly concentrated, with the two largest positive canton-level differences accounting for 53.902% of the total positive divergence and the ten largest accounting for 84.843%. The mismatch was therefore driven predominantly by a limited group of cantons rather than by a uniform proportional difference across the study area. These cantons should be treated as priorities for source reconciliation, not as confirmed cases of error or non-compliance.

Several mechanisms could plausibly contribute to the positive differences, but the present dataset does not permit their relative contribution to be tested. An administrative authorization may cover a broader concession surface than the pond-water or pond-infrastructure signature detected by the classification. Some authorized units may

have been drained, under maintenance, temporarily inactive, partly occupied, or represented by exposed substrates during the imagery used in the annual product. Differences in administrative attribution can also arise when a record is assigned to a canton by textual location while the corresponding physical infrastructure lies close to an administrative boundary. At 30 m resolution, mixed pixels, narrow pond divisions, channels, embankments, and small facilities may further affect the area assigned to class 31. The segmentation of shrimp ponds in Ecuador has been shown to depend on image characteristics, spatial resolution, pond configuration, and classification architecture, reinforcing the need to treat mapped estimates as model-based observations rather than exact cadastral measurements [14]. These mechanisms are therefore presented as possible explanations to be evaluated in future source-reconciliation analyses, not as causes established by the present study.

The REGISTRY_ONLY and MAPBIOMAS_ONLY categories require particularly careful interpretation. A registry-only canton may contain authorized area without a detectable class 31 footprint in the 2023 classification, but that combination does not demonstrate that the authorization was inactive or incorrectly located. Similarly, a MapBiomas-only canton cannot be classified as containing unauthorized aquaculture solely from the absence of positive area in the processed registry. Possible explanations include temporal differences, incomplete administrative coverage, coding inconsistencies, differences in thematic scope, or classification error.

Babahoyo exemplifies this interpretative constraint. Its positive authorized area and absence of mapped class 31 contributed to one of the larger canton-level differences, while Los Ríos had no validated class 31 footprint during the complete MapBiomas series. The available evidence establishes an administrative-versus-mapped discrepancy but does not identify its origin. Resolving the case would require examination of the underlying administrative instrument, precise geographic coordinates or polygons, and independent imagery corresponding to the relevant period.

The comparison therefore serves primarily as a consistency and prioritization tool. It identifies where the two sources agree in relative territorial importance, where their magnitudes diverge most strongly, and where additional administrative or spatial verification would provide the greatest analytical value. It should not be used as a substitute for cadastral reconciliation or regulatory inspection.

The temporal scope of this comparison imposes an additional interpretative constraint. The correspondence observed in 2023 should be understood as a cross-sectional relationship between the administrative registry and the annual land-cover classification for that reference year. It does not establish whether the difference between authorized and mapped area was similar in previous years, whether it has widened or narrowed over time, or whether the ranking of cantons remained stable historically. The 74.508% regional correspondence and the canton-level rank correlations therefore characterize 2023 only and should not be extrapolated to the complete 1985–2024 land-cover trajectory.

A longitudinal assessment would require comparable administrative records for multiple years, preferably with stable farm identifiers, consistent definitions of authorized area, dated amendments, and georeferenced farm locations. Without such information, temporal changes in the MapBiomas series can be described independently, but they cannot be interpreted as changes in the degree of correspondence between mapped and administratively authorized aquaculture. This distinction is particularly important when considering whether source-to-source differences are persistent or temporary.

4.3. Recent Transition Balance and Post-2022 Mapped Decline

The 2023–2024 transition balance should be interpreted within the broader recent mapped-area trajectory. Regional class 31 area increased from 151,903.356 ha in 2020 to 153,516.337 ha in 2021, remained almost unchanged at 153,516.642 ha in 2022, declined modestly to 150,591.587 ha in 2023, and then decreased to 138,200.970 ha in 2024. The detailed 2023–2024 transition therefore captures the largest reduction within this recent sequence, but it is not interpreted as sufficient evidence of a persistent structural contraction. The transition matrix instead provides a detailed decomposition of the most recent annual change into persistence, gross loss, gross gain, and origin or destination classes.

The persistence rate of 90.161% indicates that most of the area classified as aquaculture in 2023 retained the same classification in 2024. The negative regional balance was generated by gross loss exceeding gross gain by a factor of approximately 6.1. This combination—a high persistence rate together with a substantial negative net change—shows that a relatively limited proportion of the 2023 footprint was sufficient to produce a marked regional reduction when the reverse flow into class 31 remained much smaller.

The provincial distribution of net change was highly concentrated. Guayas accounted for approximately 64.849% of the regional decline, while El Oro accounted for 27.213%. Together, these two provinces represented slightly more than 92% of the negative regional balance. This concentration is consistent with their dominant share of mapped aquaculture area, but it also indicates that the 2023–2024 reduction was driven principally by changes in the two largest aquaculture territories rather than by similar proportional losses across all provinces.

The most important interpretative result is the dominance of transitions between class 31 and class 25, Other anthropic non-vegetated area. Nearly four-fifths of gross loss moved from aquaculture to class 25, while class 25 was also the largest origin of gross gain. The substantial movement in both directions suggests that annual classification states may be influenced by temporary changes in water presence, exposed pond bottoms, maintenance conditions, sediment visibility, or other surface characteristics associated with aquaculture infrastructure.

This interpretation is supported by remote-sensing research showing that coastal aquaculture ponds may alternate between drainage and impoundment phases and that these phases can extend from several weeks to several months. Multitemporal imagery is therefore required to distinguish ponds with seasonal water regimes from permanently water-covered ponds or genuinely abandoned facilities [9].

The bidirectional exchange between classes 31 and 25 also explains why an annual transition should not automatically be interpreted as construction or removal of infrastructure. A pond that is drained or insufficiently inundated during the relevant observation period may lose the water-related spectral characteristics associated with aquaculture and be assigned to another anthropic class. When water returns, the same physical structure may again be classified as aquaculture. Confirmation of permanent conversion would require inspection of a longer image sequence, pond boundaries, or independent infrastructure records.

Transitions from class 31 to MapBiomas class 3, Forest, require particularly cautious interpretation. This class accounted for 12.164% of gross loss, while Open forest and Mangrove represented much smaller shares of 0.286% and 0.176%, respectively. These annual classification changes do not demonstrate forest restoration. Mixed pixels, vegetation along pond margins, temporary vegetation regrowth, changes in pond-water or substrate conditions, boundary effects, and classification uncertainty may all contribute to a transition from class 31 to a forest-related category. The spatial concentration of class 31-to-Forest transitions in a limited number of provinces and cantons

identifies locations for targeted verification, but it does not establish the ecological mechanism responsible for the change. A credible restoration assessment would require repeated observations showing persistent vegetation establishment, evidence of hydrological reconnection, and independent confirmation that aquaculture infrastructure was no longer functioning.

The very small share of gross loss assigned to the mangrove-related class—approximately 0.176%—does not support a generalized interpretation of mangrove recovery between 2023 and 2024. This result is particularly relevant given the historical relationship between shrimp-pond development and mangrove conversion in Ecuador [5]. A few localized transitions may deserve further investigation, but their combined area is insufficient to characterize the regional decline as an ecological restoration process.

Gross gains present the same attribution problem. Transitions from forest-related classes, agricultural mosaics, or class 25 into class 31 identify pixels newly assigned to aquaculture in the 2024 classification, but they do not establish when ponds were constructed, whether they were authorized, or whether production began during that year. Existing infrastructure may simply have become more clearly detectable after refilling or changes in surface conditions.

The transition analysis is therefore most informative when treated as a diagnostic of annual land-cover states. It identifies where the class 31 footprint remained stable, where reclassification was concentrated, and which origin and destination classes dominated the observed changes. Distinguishing temporary pond-state variation from permanent land conversion will require targeted examination of dense temporal imagery in Guayas, El Oro, and the parishes contributing most strongly to gross loss.

4.4. Climate Exposure as Environmental Context Rather than Causal Evidence

The fixed-footprint analysis revealed substantial climatic variability across the historical aquaculture domain, with the principal precipitation and temperature extremes occurring at different stages of the mapped land-cover trajectory. Their temporal separation from the principal land-cover changes reinforces the need to treat the climate series as contextual exposure information rather than evidence of a direct climatic effect on the expansion, persistence, or decline of class 31. Accordingly, the climate series is interpreted here only as environmental context and is not used to explain the timing or magnitude of mapped class 31 change.

The precipitation maximum observed in 1998 is consistent with the exceptional hydroclimatic conditions associated with the 1997–1998 eastern Pacific El Niño. Research covering Ecuador has shown that the 1998 phase produced precipitation substantially above the historical mean on the Pacific slope, with the strongest anomalies concentrated in low-elevation coastal areas where much of the country's agriculture and aquaculture is located [20].

The agreement between the CHIRPS-derived result and the documented 1998 event supports the climatic plausibility of the extracted precipitation series. It does not demonstrate that the event caused a particular change in aquaculture land cover. Heavy rainfall may affect flooding, freshwater inflow, salinity, pond infrastructure, water exchange, and farm management, but the present study did not include the hydrological, operational, or production variables needed to test those pathways.

The fixed-footprint approach was important for separating changes in climate exposure from changes in the mapped aquaculture domain. Had climate values been extracted only from the class 31 area mapped in each individual year, the spatial sampling area would have changed simultaneously with the land-cover series. Under that alternative design, differences between years could reflect both climatic variation and relocation or

expansion of the mapped footprint. Using the union of all historically mapped class 31 pixels maintained a constant spatial reference for the 1985–2024 climate comparison.

The temperature maximum in 2023 provides a relevant context for the registry comparison and the beginning of the recent transition interval. Nevertheless, ERA5-Land 2 m air temperature is not equivalent to pond-water temperature. Pond conditions may also depend on water depth, solar radiation, salinity, aeration, stocking density, water exchange, turbidity, and management practices. The climate series therefore represents regional atmospheric exposure over aquaculture-associated territory, not direct measurements of culture conditions.

This distinction is particularly important when discussing shrimp health. Experimental and epidemiological evidence indicates that the relationship between abiotic conditions and white spot disease susceptibility is complex and can involve interactions among temperature, salinity, dissolved oxygen, host condition, pathogen dynamics, and the rate at which environmental conditions change [21]. The annual precipitation and air-temperature variables used here are too aggregated to evaluate such mechanisms or to attribute disease outbreaks to a specific climatic anomaly.

The timing of the principal land-cover and climate events also argues against simple attribution. The wettest year occurred in 1998, the regional class 31 maximum occurred in 2022, the warmest exposure year occurred in 2023, and the largest recent mapped decline was observed between 2023 and 2024. These dates provide a chronological framework, but temporal succession alone does not establish a mechanistic relationship between the variables.

The climate component is therefore best understood as a reproducible exposure baseline that can support future analyses. Linking climate variability to aquaculture outcomes would require additional variables such as pond-water temperature, salinity, river discharge, flooding, production, mortality, disease occurrence, stocking and harvest dates, and farm-level locations. Such information would permit the formulation of temporal lags and causal pathways that cannot be evaluated from annual land-cover classifications and regional climate exposure alone.

4.5. Scientific and Monitoring Implications for Coastal Aquaculture

The combined use of annual land-cover maps, administrative records, transition matrices, and climate-exposure data provides a more informative monitoring framework than any of these sources could offer independently. MapBiomas supplies a spatially explicit and temporally consistent representation of mapped aquaculture land cover, whereas the MPCEIP registry records the administrative area associated with regularized shrimp-farming activities. The transition analysis clarifies how annual class 31 totals changed between consecutive classifications, and the climate series places the historical footprint within a consistent environmental context.

This integration is particularly useful because the sources answer different questions. MapBiomas indicates where land was classified as aquaculture in a given year. The registry indicates where authorized or concessioned area was administratively attributed. The transition matrix distinguishes persistence from gross gains and gross losses, while the fixed-footprint climate series describes the conditions to which historically mapped aquaculture territories were exposed. Combining these components reduces the risk of drawing conclusions from a single measure that was not designed to represent the complete aquaculture system.

Beyond its operational value for monitoring, this result has a broader implication for the study of coastal aquaculture development. Aquaculture expansion is often represented through a single observable dimension, such as mapped pond extent, production statistics,

or administrative records. The present results show that these dimensions should not be assumed to evolve synchronously or to measure the same underlying process. A territory may display strong correspondence in the spatial concentration identified by two sources while still showing substantial disagreement in measured area, and an annual decrease in the mapped aquaculture class may occur without demonstrating an equivalent loss of aquaculture infrastructure or production.

This distinction is particularly relevant for coastal land-use research because aquaculture ponds are both production infrastructure and dynamic land–water surfaces. Their remotely observed state can change with water management, maintenance, temporary inactivity, or classification conditions, while their administrative status follows a different institutional logic. Consequently, interpreting aquaculture development requires separating physical land-cover evidence from administrative recognition and from operational or productive status. The results therefore support a multi-evidence approach in which convergence among independent sources strengthens territorial interpretation, while divergence identifies locations or periods requiring additional verification rather than providing, by itself, evidence of regulatory failure or ecological change.

The canton-level results suggest that future monitoring should prioritize the territories contributing most strongly to the difference between authorized and mapped areas. The concentration of more than half of the positive divergence in only two cantons means that a targeted reconciliation strategy could be more efficient than applying the same verification effort across all 84 cantons. Such verification should examine the original administrative instruments, the dates and territorial descriptions attached to each authorization, and temporally matched high-resolution imagery.

Remote-sensing products can support this process by providing standardized spatial evidence over large regions, but they should complement rather than replace administrative and field-based information. Satellite-derived aquaculture maps are useful for regional inventories and temporal monitoring, while farm-level verification remains necessary when the analytical objective concerns legal status, operational condition, species, production, or compliance. This distinction is consistent with the broader use of Sentinel time series for mapping aquaculture ponds over extensive coastal territories [2].

The 2023–2024 transition results also indicate that monitoring based on one image or one annual classification may be insufficient for determining whether aquaculture infrastructure has been permanently converted. The strong bidirectional movement between class 31 and other anthropic non-vegetated areas supports the use of denser temporal sequences that can distinguish short drainage periods, maintenance states, seasonal inundation, and persistent land-cover change. In priority cantons and parishes, this could be implemented through Sentinel-1 and Sentinel-2 time series, complemented by higher-resolution imagery where available.

A practical monitoring system could therefore operate at three levels. Annual national or regional mapping would identify broad trajectories and unusual changes. Administrative comparison at province and canton levels would reveal territorial divergences between mapped and authorized areas. Targeted high-resolution or field verification would then be reserved for the locations presenting the largest, most persistent, or least readily explained differences. This tiered approach would use remote sensing as a screening and prioritization instrument rather than as an automatic regulatory decision mechanism.

From a governance perspective, the principal practical implication is the value of an inter-agency spatial information structure linking administrative authorization records with georeferenced farm boundaries, authorization dates and amendments, relevant environmental information, and periodically updated remote-sensing layers. Such a system would allow aquaculture-administration and environmental authorities to identify loca-

tions where independent evidence diverges and to direct those cases to documentary, high-resolution, or field verification. Importantly, the approximately 25.5% difference in magnitude between the 2023 mapped and authorized areas should not be interpreted as an estimate of unregistered aquaculture, regulatory non-compliance, or inactive infrastructure, because the two sources measure different constructs and the registry used here does not contain farm geometries. Its governance value lies instead in identifying where additional reconciliation is warranted. When combined with appropriate ecological, sanitary, and hazard information, the same spatial framework could also support mangrove-conservation screening, coastal spatial planning, biosecurity prioritization, and climate-adaptation planning. These applications would require additional datasets and are not evaluated directly in the present study.

The reproducibility package developed for this study provides a foundation for updating the analysis when new annual MapBiomas classifications, revised administrative records, or additional climate observations become available. Retaining stable administrative crosswalks, validation checks, source identifiers, and processing rules will allow future updates to be compared with the present results without rebuilding the entire analytical structure. The principal value of the framework lies in making differences among sources explicit, measurable, and traceable before they are interpreted for scientific or administrative purposes.

5. Limitations

The study integrates several complementary data sources, but each source represents a different analytical construct and carries its own uncertainty. The principal limitations concern thematic classification, spatial resolution, administrative completeness, absence of farm geometries, temporal comparability, and the descriptive treatment of climate exposure. These constraints do not invalidate the reported patterns, but they delimit the conclusions that can be drawn from the analysis and identify the evidence required for more detailed farm-level or causal assessment.

5.1. Land-Cover Classification and Temporal Comparability

MapBiomas class 31 provides a consistent annual representation of mapped aquaculture land cover, but it does not identify species, production systems, legal status, operational condition, or annual output. The class was therefore interpreted as aquaculture in general and not automatically as shrimp farming, even though commercial shrimp aquaculture is dominant in many of the coastal territories examined.

Annual class assignments may be influenced by pond-water presence, drainage, exposed sediment, vegetation, turbidity, mixed pixels, image availability, atmospheric conditions, and classification uncertainty. A pond may remain physically present while being assigned to another land-cover class in a particular year. Conversely, a pixel newly assigned to class 31 may represent improved detectability or refilling of existing infrastructure rather than newly constructed aquaculture.

The 30 m spatial resolution also limits the representation of narrow ponds, channels, embankments, small production units, and complex pond boundaries. Pixels located at interfaces between aquaculture infrastructure and neighbouring land covers may contain several surface types, affecting both mapped area and transition estimates. Differences of less than one pixel or involving narrow linear elements should therefore not be interpreted with cadastral precision.

The transition analysis compared only the 2023 and 2024 annual classification states. It distinguished persistence, gross loss, and gross gain, but it could not determine whether a change was temporary or permanent. Reliable identification of pond abandonment,

infrastructure removal, new construction, or ecological restoration would require denser temporal imagery, repeated observations after 2024, or independent field and administrative evidence. The broader 2020–2024 annual area trajectory provides temporal context for the recent decline but does not substitute for a multi-year pixel-level transition analysis.

The historical series is internally consistent because it was derived from a single MapBiomas collection and processing workflow. Nevertheless, consistency of processing does not eliminate the possibility that classification performance varies among years, provinces, landscape types, or image conditions. The present study did not conduct an independent pixel-level accuracy assessment using reference imagery or field observations for every year of the 1985–2024 series.

Cross-level validation confirmed that parish-derived and directly extracted provincial totals were numerically consistent, but this procedure assesses arithmetic and spatial aggregation rather than thematic accuracy. A land-cover estimate may reproduce correctly across administrative levels while still containing classification errors inherited from the source product.

For these reasons, the mapped trajectories are most reliable for identifying broad spatial and temporal patterns. They should not be used as exact inventories of active farms, production surfaces, or legally authorized infrastructure without additional verification.

5.2. Administrative Registry and Spatial Correspondence

The MPCEIP registry provided the official administrative record used to quantify authorized or concessioned shrimp-farm area in 2023. Its principal limitation is that the records did not include farm polygons or geographic coordinates. The analysis could therefore standardize and aggregate the registry by province and canton, but it could not spatially match individual administrative records to specific MapBiomas pixels or aquaculture patches.

Administrative harmonization depended on textual location fields. Province- and canton-level reconciliation achieved complete administrative coding coverage within the six-province framework, but successful coding does not prove that the recorded administrative location coincides exactly with the physical location of the authorized infrastructure. This issue is particularly relevant for records located near administrative boundaries or containing historical, abbreviated, or locally used place names.

The variable authorized_area_ha represents the area associated with an administrative authorization or concession. It does not necessarily correspond to the pond-water surface visible in satellite imagery, the area physically occupied by infrastructure, the area cultivated during 2023, or the area producing shrimp at the time represented by the annual classification. Comparisons with MapBiomas therefore assess correspondence between two different measurements rather than agreement between equivalent observations.

The registry also did not provide a complete set of dates required to reconstruct the operational history of each farm. The field associated with the ministerial agreement year identifies the year of the administrative instrument and was not interpreted as the year in which aquaculture began, the year in which ponds were constructed, or confirmation that the farm operated continuously until 2023. Administrative authorization may precede or follow changes in physical infrastructure and production status.

The absence of a unique farm identifier further restricts longitudinal interpretation. The ministerial agreement code was not unique across all records and could not be treated as a stable entity identifier without additional information. Consequently, the study did not attempt to reconstruct farm-level entries, exits, expansions, contractions, transfers, or renewals from the administrative file.

Parish-level registry fields were not used for formal correspondence analysis because their standardization was less reliable than province- and canton-level coding. Assigning records to parishes solely through text reconciliation would have introduced a level of geographic precision that could not be independently verified without coordinates or polygons. Parish was therefore reserved for aggregation of the spatially explicit MapBiomas results.

The 2023 comparison also represents a single-year administrative snapshot. Differences between the registry and MapBiomas may partly reflect non-synchronous update cycles, accumulated authorizations, administrative amendments, delayed changes in registry status, or imagery dates embedded in the annual land-cover product. The available information did not permit each canton-level difference to be decomposed into these possible components.

Complete canton-level linkage should therefore be understood as a validation of administrative standardization, not as validation of the registry's spatial or operational accuracy. The comparison identifies territorial patterns and priority cases for reconciliation, but definitive conclusions regarding compliance, unauthorized activity, inactive concessions, or incorrect administrative location require access to farm geometries, original authorization documents, and independent verification.

5.3. Climate Data, Fixed-Footprint Design, and Causal Interpretation

The climate component was designed to characterize environmental exposure over a constant spatial domain rather than to estimate farm-level meteorological or hydrological conditions. CHIRPS v3 precipitation and ERA5-Land 2 m air temperature are gridded products whose spatial resolutions are substantially coarser than the 30 m MapBiomas classification. Their values therefore represent regionalized estimates over climate-grid cells and should not be interpreted as direct observations within individual ponds.

The fixed aquaculture footprint was defined as the union of all pixels classified as class 31 at least once between 1985 and 2024. This design improves temporal comparability because the spatial sampling domain remains constant across years. However, it also means that the climate series includes locations that were not necessarily occupied by mapped aquaculture during every year of the study period. The resulting estimates describe exposure across the historical aquaculture domain, not the conditions experienced by the annual active or mapped footprint alone.

The fixed footprint also reflects the accumulated classifications of MapBiomas Collection 3.0. Any false-positive class 31 pixels occurring in an individual year may therefore be incorporated into the union footprint. Conversely, aquaculture areas never identified as class 31 during the 40-year series cannot contribute to the climate domain. The climate analysis inherits this dependence on the source land-cover classification.

Climate variables were aggregated annually. This temporal resolution is suitable for describing long-term climatic patterns but cannot represent short-duration events that may be important for aquaculture management, such as heat waves, intense rainfall episodes, floods, abrupt salinity changes, or disease-relevant temperature fluctuations. Annual means and totals may conceal the timing, duration, and sequencing of such events.

The precipitation analysis used annual CHIRPS v3 estimates over the valid portion of the footprint. Although coverage was high, it did not reach 100% in every province. Santa Elena had the lowest validated CHIRPS coverage, at approximately 98.687%. The uncovered fraction was retained in the coverage diagnostics rather than filled through extensive extrapolation. This approach limits artificial completion but means that annual precipitation estimates do not represent every footprint pixel uniformly.

Small ERA5-Land coverage gaps were concentrated near coastal land–water boundaries. The BILINEAR_FILL_1CELL procedure increased coverage while restricting interpolation to the immediate neighbourhood. The largest provincial adjustment to annual temperature was 0.106 °C, and the largest regional adjustment was 0.095 °C. These differences were small relative to the temporal variation in the final series, but the completed values remain interpolated estimates rather than independent climate observations.

The use of 2 m air temperature imposes an additional interpretative constraint. Air temperature is not equivalent to pond-water temperature and cannot capture management-related thermal conditions. Water depth, aeration, turbidity, salinity, solar radiation, water exchange, stocking density, and pond geometry may modify the temperature experienced by cultured organisms. The ERA5-Land series should therefore be described as atmospheric temperature exposure over aquaculture-associated territory.

Regional climate estimates were calculated as area-weighted combinations of the provincial values. Provinces with larger fixed footprints consequently contributed more strongly to the regional series, especially Guayas. The regional climate trajectory is therefore representative of the spatial distribution of the historical aquaculture footprint rather than an equal-weighted average of provincial conditions.

The study did not fit statistical or mechanistic models linking climate variables to mapped land-cover change. It did not incorporate temporal lags, hydrological connectivity, production records, disease events, pond management, or socioeconomic drivers. Associations suggested by chronological proximity or visual comparison of the climate and land-cover series cannot be interpreted as causal effects.

The climate analysis should consequently be regarded as a documented exposure baseline. Testing whether precipitation or temperature contributed to aquaculture expansion, contraction, production variability, infrastructure damage, or disease would require temporally finer climate indicators and spatially explicit farm-level outcome data.

5.4. Scope, Temporal Alignment, and Generalizability

The study was restricted to six provinces included in the coastal analytical framework: El Oro, Esmeraldas, Guayas, Los Ríos, Manabí, and Santa Elena. The results therefore characterize aquaculture land-cover dynamics and administrative correspondence within this defined territory and should not be extrapolated automatically to other Ecuadorian provinces, inland aquaculture systems, or the Galápagos Islands. Accordingly, references to the coastal study region in this manuscript denote this predefined six-province analytical framework rather than exhaustive geographic coverage of all provinces associated with Ecuador's Coast region.

The 1985–2024 MapBiomas series provides a long-term annual record, whereas the formal administrative comparison was limited to the 2023 MPCEIP registry. Consequently, the study cannot determine whether the relationship between mapped and authorized area observed in 2023 also applied in earlier years. A historical registry series with consistent variables, identifiers, and administrative units would be required to examine how administrative authorization evolved alongside mapped land-cover change.

The administrative and remotely sensed sources were aligned by reference year but were not temporally synchronized observations. The MPCEIP source identifies the administrative file as the 2023 registry, and the public dataset portal reports 16 June 2023 as the dataset update date; however, record-level observation or update dates are not available. In contrast, the 2023 MapBiomas classification is an annual product derived from multiple Landsat observations selected within year-specific temporal windows rather than from imagery acquired on a single date. The comparison should therefore be interpreted as same-year correspondence between an administrative registry and an annual

land-cover classification, not as a comparison of simultaneous observations. Residual temporal misalignment may contribute to differences between the two sources.

The analysis did not incorporate production volume, farm productivity, stocking density, harvest cycles, export performance, employment, input use, profitability, or farm ownership. The mapped-area trajectory therefore cannot be used to infer whether production increased or decreased proportionally. A smaller mapped footprint may coexist with stable or increasing output if production intensity rises, whereas a larger footprint does not necessarily imply greater productivity.

Socioeconomic, institutional, and infrastructural drivers were also outside the empirical design. The study did not test the effects of market prices, export demand, credit availability, feed costs, regulatory changes, disease-control measures, technological adoption, road access, port proximity, or land-tenure arrangements. These factors may help explain provincial differences and historical phases of expansion, but they were not represented by variables in the analytical dataset.

The use of administrative boundaries introduces the modifiable areal unit problem. Relationships and differences calculated at province or canton level may change if the same data are aggregated using other territorial units. Canton-level correspondence is useful for administrative comparison, but it may conceal substantial internal spatial variation and does not establish that authorized and mapped areas occupy the same locations within a canton.

The results are also dependent on the versions of the source products used in the study. Future MapBiomas collections may revise historical classifications, administrative registries may be updated, and climate products may receive new releases or retrospective corrections. Reproduction of the exact numerical results therefore requires preservation of the source versions, asset identifiers, processed tables, administrative crosswalks, and methodological parameters documented in the reproducibility package.

Despite these constraints, the study provides a consistent baseline for subsequent updates. The annual land-cover series, harmonized administrative framework, transition accounting, and fixed-footprint climate design can be rerun when new data become available. Comparisons with future versions should distinguish genuine temporal change from differences introduced by source revisions or methodological updates.

6. Conclusions

This study combined four complementary analytical perspectives to examine aquaculture dynamics in Ecuador's coastal region: annual mapped land cover, authorized or concessioned administrative area, recent pixel-level transitions, and long-term climate exposure. The conclusions are therefore framed according to the specific construct represented by each source. They describe changes in MapBiomas class 31, correspondence with the MPCEIP registry, transition balances between annual classifications, and environmental exposure over a fixed historical footprint, without treating these measures as interchangeable or inferring causal relationships that were not tested.

6.1. Principal Conclusions

Mapped aquaculture land cover expanded substantially across the six-province study region between 1985 and 2024. The MapBiomas class 31 area increased from 58,198.792 ha to 138,200.970 ha, corresponding to a net gain of 80,002.178 ha, or 137.464%. The complete 1985–2024 series showed a significant positive monotonic trend (modified Mann–Kendall $\tau = 0.910$, $p < 0.001$), with a Sen's slope of 2460.810 ha year^{-1}. The highest numerical annual value occurred in 2022, with 153,516.642 ha, but this differed from the 2021 value by only 0.305 ha; 2021–2022 is therefore interpreted as a near-identical high plateau rather than as

evidence of a distinct breakpoint. Mapped area declined in 2023 and decreased further in 2024. The recent contraction did not erase the magnitude of the four-decade expansion.

The long-term trajectory was geographically concentrated. Guayas accounted for the largest mapped area and the greatest contribution to regional growth, while El Oro represented the second principal aquaculture territory. Together, these two provinces contained approximately 82.1% of the mapped class 31 area in 2024. Esmeraldas, Manabí, and Santa Elena followed distinct trajectories and reached their provincial maxima in different years, demonstrating that the regional series combines heterogeneous territorial histories.

The 2023 comparison between the MPCEIP registry and MapBiomas revealed strong territorial correspondence in rank but incomplete agreement in magnitude. The mapped class 31 area represented 74.508% of the authorized or concessioned area recorded in the administrative registry. Spearman's rank correlation was 0.890 across all active cantons and 0.929 among cantons with positive values in both sources. These results indicate that, in 2023, the two datasets captured a similar broad geography of aquaculture concentration while measuring different administrative and land-cover constructs. This conclusion is explicitly restricted to the 2023 cross-sectional comparison. The available administrative data do not establish whether the observed magnitude difference or territorial correspondence persisted, increased, or decreased during the broader 1985–2024 period.

Differences between the registry and MapBiomas were highly concentrated. More than half of the total positive canton-level divergence was associated with only two cantons, and the ten largest positive differences represented 84.843% of the total. This concentration provides a rational basis for prioritizing future administrative and spatial reconciliation. It does not establish that the differences resulted from error, illegality, inactivity, abandonment, or omission by either source.

The 2023–2024 transition analysis showed that 135,774.430 ha persisted as class 31, while gross loss reached 14,816.766 ha and gross gain totalled 2426.130 ha. The resulting net reduction of 12,390.636 ha was driven mainly by changes in Guayas and El Oro. The persistence rate remained high at 90.161%, but gross loss exceeded gross gain by approximately 6.1 times.

Most gross loss involved transitions from class 31 to Other anthropic non-vegetated area, while the same class was also the principal origin of gross gains. This bidirectional movement indicates that changes in annual classification state may reflect pond drainage, exposed substrates, maintenance, temporary inactivity, spectral variation, or classification uncertainty, in addition to physical land-cover change. The transition matrix therefore supports a cautious interpretation of the 2023–2024 decline and does not justify treating all class losses as permanent pond removal.

The fixed-footprint climate analysis provided a consistent environmental reference for the 1985–2024 period. The wettest year was 1998, the warmest year was 2023, and the maximum mapped aquaculture extent occurred in 2022. These events occurred at different points in the historical series. Climate exposure was consequently used to contextualize the aquaculture trajectory, not to attribute expansion or contraction to precipitation or temperature.

The principal scientific contribution of the study is to show that the historical expansion, administrative extent, recent annual transitions, and climatic context of coastal aquaculture cannot be represented adequately by a single data source. The four evidence domains reveal complementary aspects of the same territorial system while also exposing important differences in what each measure represents. In particular, strong territorial correspondence between mapped and authorized areas does not imply equivalence in magnitude or farm-level coincidence, while short-term losses from the mapped aquaculture

class cannot automatically be interpreted as permanent pond removal. By making these distinctions explicit, the study provides both an empirical characterization of four decades of aquaculture land-cover change in coastal Ecuador and a reproducible basis for more cautious territorial monitoring and interpretation.

6.2. Monitoring Priorities and Future Research

The analytical framework developed in this study can support periodic updates of aquaculture monitoring in Ecuador. Annual MapBiomas releases can be incorporated into the existing workflow to extend the land-cover series, recalculate transition balances, and identify provinces, cantons, or parishes where recent changes depart from the established historical trajectory. Maintaining the same administrative crosswalks, source identifiers, processing parameters, and validation rules will be essential for distinguishing genuine temporal change from differences introduced by methodological revisions.

Future administrative comparisons should prioritize access to georeferenced farm polygons or, at minimum, reliable coordinates associated with each authorization. Spatially explicit administrative data would permit direct overlay with mapped aquaculture patches, assessment of within-canton correspondence, identification of boundary-related attribution problems, and separation of authorized concession area from the surface visibly occupied by ponds or associated infrastructure.

The cantons contributing most strongly to the positive difference between authorized and mapped area provide an immediate basis for targeted verification. Rather than examining all administrative units with equal intensity, future work could begin with Guayaquil, Naranjal, Santa Rosa, and the other cantons represented among the largest positive differences. Such analysis should combine original authorization documents, high-resolution imagery, annual pond-state sequences, and, where feasible, field verification.

A denser temporal analysis is also required to distinguish temporary pond-state changes from permanent land conversion. Sentinel-1 and Sentinel-2 observations could be used to examine drainage, refilling, maintenance, seasonal inundation, and persistent transitions within the class 31 footprint. Repeated observations would be particularly useful for pixels alternating between aquaculture and other anthropic non-vegetated areas, which constituted the dominant transition pathway between 2023 and 2024.

Future ecological assessments should separate land-cover reclassification from verified ecosystem recovery. Transitions from class 31 to forest- or mangrove-related classes should be examined across multiple subsequent years and supported by evidence of persistent vegetation establishment, hydrological reconnection, and loss of aquaculture functionality. A single annual transition is insufficient to demonstrate restoration.

The climate component could be extended by incorporating indicators that are more directly relevant to aquaculture operations. Potential variables include heat-wave duration, extreme rainfall, flood exposure, river discharge, sea-surface temperature, salinity anomalies, drought duration, and the timing of El Niño and La Niña conditions. These indicators should be combined with farm-level outcomes such as production, mortality, disease occurrence, stocking dates, harvest dates, and infrastructure damage before causal relationships are evaluated.

A historical administrative series would substantially strengthen the temporal analysis. Consistent annual or periodic records of authorized area, farm status, ownership, agreement amendments, and geographic location would allow the relationship between administrative expansion and mapped land-cover change to be examined beyond the single-year comparison conducted here. Stable identifiers would also permit longitudinal analysis of farm-level continuity, expansion, transfer, suspension, and closure.

The reproducibility package deposited in Zenodo provides a documented baseline for these extensions [16]. Future versions should preserve the original release while incorporating new annual data through versioned deposits. This approach will enable users to verify the published analytical outputs, identify subsequent revisions, and compare new results with the 1985–2024 baseline without overwriting the evidentiary record supporting the present manuscript.

The study establishes a defensible baseline for integrated aquaculture monitoring while also providing a broader interpretative result: mapped land cover, administrative authorization, annual classification state, and environmental exposure should be treated as complementary evidence rather than interchangeable representations of aquaculture development. This distinction is relevant both scientifically and operationally. It limits unsupported inference from any single source, identifies where independent evidence converges or diverges, and provides a structured basis for directing more detailed spatial, administrative, or field verification. Future progress will depend on improving the temporal alignment, spatial specificity, and independent validation of these evidence domains rather than assuming that one can substitute for another.

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Informed Consent Statement: Not applicable.

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Abbreviations

The following abbreviations are used in this manuscript:

ATBD	Algorithm Theoretical Basis Document
CHIRPS v3	Climate Hazards Center Infrared Precipitation with Stations, Version 3
DOI	Digital Object Identifier
ERA5-Land	European Centre for Medium-Range Weather Forecasts Reanalysis v5—Land
INEC	Instituto Nacional de Estadística y Censos
MAGP	Ministerio de Agricultura, Ganadería y Pesca
MD5	Message-Digest Algorithm 5
MPCEIP	Ministerio de Producción, Comercio Exterior, Inversiones y Pesca
SHA-256	Secure Hash Algorithm 256
WSSV	White Spot Syndrome Virus

Appendix A. Spatial Distribution of Class 31-to-Forest Transitions

Parish-Level Distribution of 2023–2024 Transitions

Figure A1 provides the parish-level spatial distribution of pixels classified as MapBiomas class 31 (Aquaculture) in 2023 and as class 3 (Forest) in 2024. The figure is intended to identify the spatial concentration of this classification-state transition and should not be interpreted as evidence of verified forest restoration.

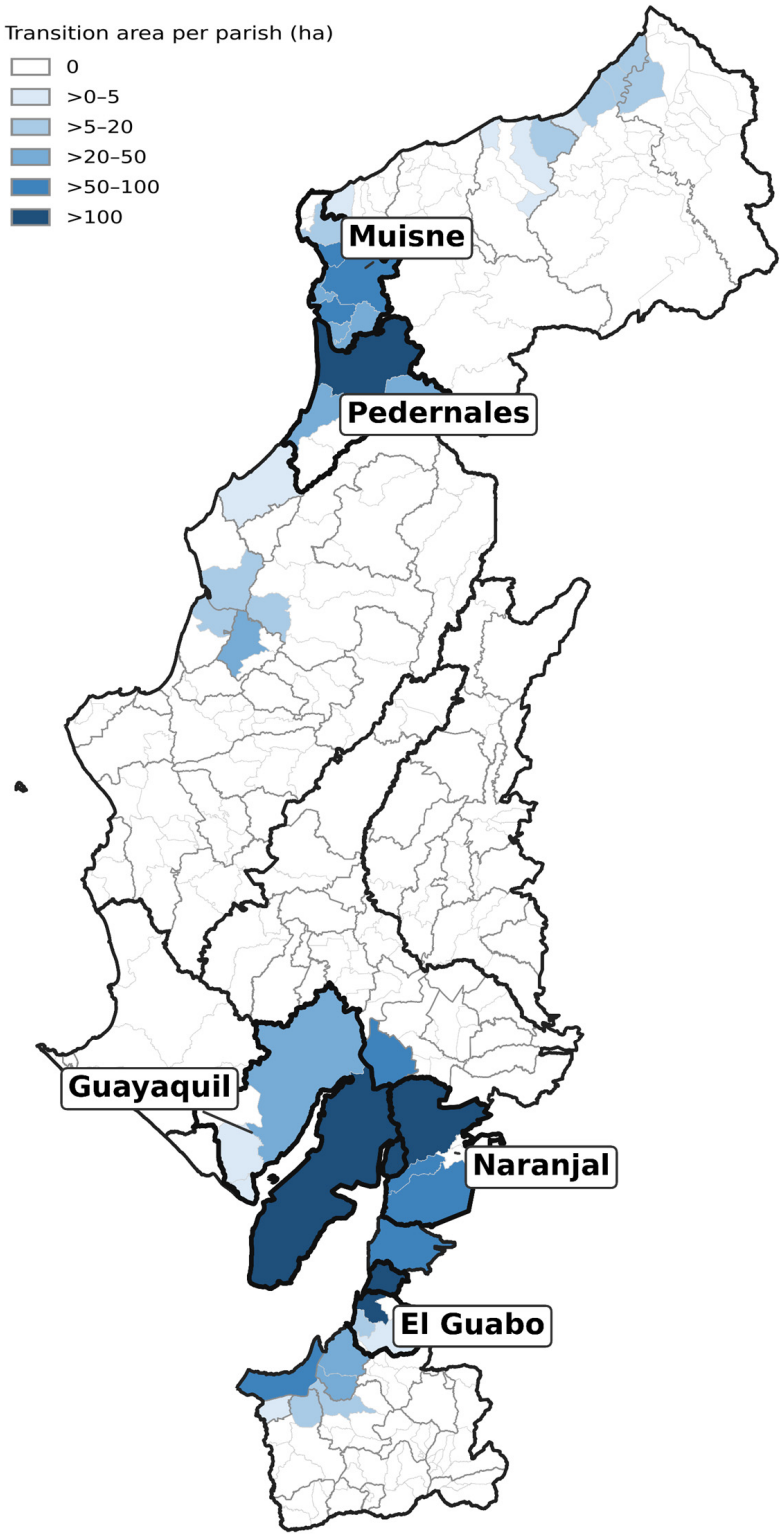

Figure A1. Spatial distribution of MapBiomas class 31-to-class 3 (Forest) transitions between 2023 and 2024 across the study region. Values represent the area in hectares within each parish that was classified as Aquaculture (class 31) in 2023 and as Forest (class 3) in 2024. The mapped transition represents a change between annual classification states and does not constitute evidence of verified forest restoration. Note: The mapped transition represents a change between annual classification states and should not be interpreted as evidence of verified forest restoration. Such transitions may also reflect mixed pixels, vegetation along pond margins, temporary vegetation regrowth, pond-state changes, boundary effects, or classification uncertainty.

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