

Hydrodynamic Model Sensitivity under Climate Change for Sustainable Aquaculture

Epistemic Uncertainty Analysis of Open Boundary
Conditions in Bantry Bay under SSP5-8.5

Master Thesis
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Hydrodynamic Model Sensitivity under Climate Change for Sustainable Aquaculture

Epistemic Uncertainty Analysis of Open Boundary Conditions in Bantry Bay under SSP5-8.5

by

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Preface

This Master's thesis marks the culmination of a two-year academic journey, a period defined by numerous challenges, yet rich in knowledge and invaluable experiences. As I reflect on this path, I am deeply grateful for the growth I have achieved, both personally and professionally.

My research was conducted in collaboration with Deltares, and I would like to express my sincere gratitude to them for providing me with the opportunity to further evolve in the field of hydrodynamic modeling. Working there meant being surrounded, side by side, by niche experts in exactly the field I was trying to grow in, with access to tools and resources I could not have found anywhere else, and I do not take that opportunity for granted. I am particularly thankful to my manager at Deltares, Alex, who kept me engaged through our weekly meetings, always challenging me to think critically about the "what" and the "why" of my research. My sincere thanks also go to Natalia, for her generous hydrodynamic support throughout this project; she was always available whenever I had a question or needed a second opinion, and I genuinely enjoyed working together. I also extend my heartfelt thanks to the entire Pharos team, especially Darshika and Willemijn; their presence was a constant source of comfort, whether I needed specific technical expertise or general support.

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*Nafsika Litzerinou
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Abstract

Coastal aquaculture in data-scarce regions is increasingly exposed to climate change, yet careful calibration of hydrodynamic models in these areas is often limited by a lack of in-situ observations. This thesis examines how the Bantry Bay estuary in Ireland, a stratified coastal system supporting significant kelp and mussel cultivation, responds to 2075 climate projections under the high emission SSP5-8.5 scenario. Given the scarcity of historical tide gauge data, the model calibration was shifted from a conventional deterministic to a probabilistic modelling approach, using a three-dimensional (3D) hydrodynamic model (Delft3D-FM) to test how the bay's interior environment reacts to plausible variations in open-boundary conditions (temperature, salinity, and sea level).

Physically bounded distributions for temperature and salinity change were built from the pooled projections of four CMIP6 models, and for sea-level rise from the NASA IPCC AR6 percentile bands. A candidate pool of 5,000 parameter combinations was generated by inverse-transform sampling from these distributions, from which the Maximum Dissimilarity Algorithm selected a final, space-filling ensemble of 50 members. Each member was applied to the 2022 baseline simulation through the delta-change method, superimposing the sampled temperature, salinity, and sea-level offsets onto the observed boundary forcing to represent plausible 2075 conditions.

The findings show that the bay is boundary-controlled: mean salinity, mean temperature, and mean water level are each governed almost exclusively by their own boundary offset, with no response meaningfully shaped by more than one driver. Salinity uncertainty is small and stable throughout the year, while temperature uncertainty is seasonal, concentrated in the summer tail, where the ensemble median already exceeds the kelp thermal threshold. This extreme regime tells a more complex story than the mean: thermal stress at cultivation sites is not driven by warming alone, but by the interaction of local freshening and sea-level rise, with the highest-risk scenarios arising from moderate to low warming compounded by strong freshening rather than warming in isolation. Spatially, the boundary-driven fields are close to uniform across the bay, yet thermal stress itself concentrates in the inner bay. Sea-level rise itself functions primarily as a mean-state shift, with no measurable change to the bay's tidal range.

This work demonstrates that in data-limited coastal systems, boundary uncertainty, rather than internal model complexity, is what dominates the predictive picture, and that resolving it requires more than a simple temperature projection. Climate-risk assessments for surface aquaculture must account for the complex interplay of multiple physical drivers, as the conditions most likely to cause biological stress arise from their interaction rather than from any single driver in isolation. This probabilistic workflow is designed to be directly transferable to other demonstration sites within the PHAROS project network and beyond.

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Nomenclature

Abbreviations

Abbreviation	Definition
ADCP	Acoustic Doppler Current Profiler
AMOC	Atlantic Meridional Overturning Circulation
AR6	Sixth Assessment Report (IPCC)
CDF	Cumulative Distribution Function
CMEMS	Copernicus Marine Environment Monitoring Service
CMIP6	Coupled Model Intercomparison Project Phase 6
CTD	Conductivity, Temperature, Depth
EMODnet	European Marine Observation and Data Network
ERA5	Fifth Generation ECMWF Atmospheric Reanalysis
EuroGOOS	European Global Ocean Observing System
GCM	Global Climate Model
GLORYS	Global Ocean Reanalysis and Simulation
HPC	High-Performance Computing
IMTA	Integrated Multi-Trophic Aquaculture
IPCC	Intergovernmental Panel on Climate Change
KDE	Kernel Density Estimate
MDA	Maximum Dissimilarity Algorithm
OAT	One At a Time
PERT	Program Evaluation and Review Technique
PRCC	Partial Rank Correlation Coefficient
PSU	Practical Salinity Unit
RANS	Reynolds-Averaged Navier-Stokes
RMSE	Root-Mean-Square Error
SSP	Shared Socioeconomic Pathway
TPXO	TOPEX/Poseidon global tide model

Symbols

Symbol	Definition	Unit
α	Significance threshold	[-]
ε	Turbulent kinetic energy dissipation rate	$[m^2/s^3]$
f	Coriolis parameter	$[s^{-1}]$
g	Gravitational acceleration	$[m/s^2]$
k	Turbulent kinetic energy	$[m^2/s^2]$
n	Manning's roughness coefficient	$[s\ m^{-1/3}]$
p	Statistical significance (p-value)	[-]
P	Pressure	[Pa]
r	Pearson correlation coefficient	[-]
R^2	Coefficient of determination	[-]
ρ	Spearman's rank correlation coefficient	[-]
S	Salinity	[PSU]
T	Temperature	[°C]
u, v, w	Velocity components	$[m/s]$

Symbol	Definition	Unit
$\Delta\eta$	Water level offset	[m]
ΔS	Salinity offset	[PSU]
ΔT	Sea surface temperature offset	[°C]
η	Water level	[m]
ν_H	Horizontal eddy viscosity	[m^2/s]
ν_V	Vertical eddy viscosity	[m^2/s]
ρ_0	Reference density	[kg/m^3]

Introduction

1.1. Research Context

Coastal hydrodynamic models are increasingly relied upon to inform decisions about aquaculture (Kastrasov et al., 2021), conservation, and climate adaptation (M. Marino et al., 2025). The stakes attached to these decisions are rising rapidly. Under a high-emission trajectory, more than a quarter of aquaculture-producing nations are projected to lose between 40% and 90% of their current production potential by mid-century, with semi-enclosed and coastal systems among the most exposed (Froehlich et al., 2018). Europe's marine aquaculture sits squarely within this crisis; coastal space is heavily contested, regulations remain uncertain, and environmental conditions are shifting dramatically under climate change. Operators and planners urgently need reliable modelling tools to understand how physical conditions behave now and how they will evolve in the future.

Robust three-dimensional hydrodynamic modelling depends fundamentally on the availability of in-situ measurements, both to constrain a model's internal parameterisation and to verify its predictive skill against independent observations; this dependence is particularly acute for 3D models, where reproducing vertical structure and stratification requires depth-resolved data that simpler depth-averaged approaches do not. Yet many of the coastal and estuarine systems where these models are most needed are themselves data-scarce. Despite substantial European investment in ocean observation through Copernicus, EMODnet, and EuroGOOS in-situ networks, the density of measurements thins markedly towards the coast (Le Traon et al., 2019). While open-ocean temperature and salinity are now well sampled, significant gaps remain in coastal and shelf seas, particularly at the fine spatial scales that small bays demand (Le Traon et al., 2019).

Global ocean reanalysis products go some way toward filling this gap. Products such as the Copernicus Marine Service's GLORYS12 (Lellouche et al., 2021) assimilate satellite and in-situ observations into a global ocean model at eddy-resolving resolution, providing a freely available, physically consistent estimate of ocean state anywhere in the world, including at locations with no local observational record at all, and it is exactly such a product that supplies the open-boundary forcing used in this thesis. These global systems are, however, designed and validated primarily for open-ocean and shelf-scale dynamics; near the coast, where bathymetric complexity, tidal dynamics, and freshwater influence operate at spatial scales finer than the reanalysis grid can resolve, their skill degrades, and the conditions they supply at a coastal boundary carry correspondingly larger and less well-characterised uncertainty than their open-ocean values. For an individual embayment such as Bantry Bay, local in-situ data would be needed to directly constrain and reduce this boundary uncertainty, and the long, spatially distributed records required frequently are not available.

In such situations, the useful scientific question changes, and it is worth distinguishing two genuinely separate sources of uncertainty that this reframing must address rather than treating as one. The first is uncertainty in model performance itself: how accurately the model's internal parameterisation reproduces the physical processes it represents, conventionally addressed through deterministic calibration against observations, and fundamentally a question about the model. The second is uncertainty in the

boundary forcing under future climate change: even a perfectly calibrated model is only as reliable as the open-ocean conditions imposed at its boundary, and how those conditions will evolve by 2075 is not a question of model skill at all, but of an inherently unknown future climate state. This second source is epistemic in a different sense than the first, it cannot be reduced by better calibration, more data, or a more sophisticated model, because the uncertainty lies in the future itself, not in how well the present is represented. In a small, transport-driven bay, these boundary conditions exert a disproportionate control on the interior, making this second source of uncertainty particularly consequential here.

Historically, coastal modelling has overwhelmingly prioritised the first of these, deterministic calibration of model performance, frequently neglecting explicit uncertainty propagation even when severe data gaps made such tuning fragile (Pianosi et al., 2016). This thesis instead addresses the second, comparatively neglected source directly. Bantry Bay's data scarcity means the first source of uncertainty, model performance, cannot be confidently resolved through calibration in the conventional sense; the focus therefore shifts to systematically characterising the second, quantifying how uncertainty in the projected 2075 boundary conditions propagates into the bay's interior. When these models are used to support real-world aquaculture decisions, stakeholders require more than a single definitive prediction; they must be empowered to navigate the risk margins inherent in an unknowable future. Consequently, the focus shifts from conventional model calibration toward transparently mapping how uncertainty in boundary states propagates through the system, an approach grounded in Decision Making under Deep Uncertainty (Marchau et al., 2019). This transition is essential for defining a robust risk envelope, transforming the model from a predictive tool into a platform for exploring system resilience.

This thesis examines exactly such a case. Bantry Bay, located on the southwest coast of Ireland, serves as one of the country's most productive marine farming zones. Blue mussel cultivation has operated here since the early 1980s. Today, the bay stands as Ireland's largest mussel-producing area; its rope-grown *Mytilus edulis* is widely recognized as a premium organic export across Europe (Roycroft et al., 2004). Mussels, however, are just one component of the local industry. The bay also supports a dense concentration of licensed operations, ranging from Atlantic salmon cages and oyster beds to abalone, sea urchins, and emerging seaweed and scallop farms. Local research efforts, spearheaded by the Bantry Marine Research Station, actively explore integrated multi-trophic aquaculture (IMTA). A prime example is the co-location of kelp with salmon farms to simultaneously curb nutrient loading and promote local biodiversity.

The presence of this rich aquaculture made Bantry Bay a key demonstration site for PHAROS (2024-2029). This EU Horizon Europe initiative connects international partners to test nature-based solutions for ecosystem restoration and sustainable farming across the Atlantic and Arctic basins (PHAROS Consortium, 2024). To succeed, the PHAROS project requires a reliable regional hydrodynamic model of Bantry Bay, which will serve as the physical foundation for future aquaculture modules representing seaweed, finfish, and shellfish production. While Bantry Bay sits outside the standard Dutch Continental Shelf Model routinely used by Deltares, a separate initiative developed an extended version covering the Irish coastline. An existing three-dimensional Delft3D-FM model of the bay has been set up but its performance has not yet been assessed (Boelsma, 2025). Before this model can confidently support aquaculture assessments and climate impact studies within such a data-scarce environment, its sensitivity to projected environmental changes must be explicitly understood, and this exactly is the challenge this thesis addresses.

1.2. Research Problem

The original scope of this project was the calibration and validation of the regional Delft3D-FM model for Bantry Bay. The aim was to establish a reliable physical baseline for the aquaculture modules to be developed in later stages of the PHAROS project. During the initial phase of the work, the model was evaluated against in-situ water level observations. However, apart from a single tide gauge, no other instruments were available to validate its performance. A three-dimensional model's calibration cannot rest on water level alone: confidence in its internal current structure, temperature field, and stratification each require their own independent validation data, current-profile measurements to constrain the vertical velocity structure, and depth-resolved temperature and salinity profiles to constrain stratification and density-driven circulation, none of which existed for Bantry Bay beyond the single tide gauge. Consequently, the model could not be tested further, since no additional observational data

existed to push the calibration and validation forward.

This data gap shifted the focus of the project. Rather than forcing an unverified calibration, the research question evolved to: given the existing model, how sensitive are the hydrodynamic conditions in Bantry Bay to the projected changes in ocean temperature, salinity, and mean sea level that climate change will bring by 2075? This horizon was chosen deliberately as a fifty-year outlook from the present: a timescale long enough to be climatically meaningful and clearly beyond natural variability, yet still within the planning horizon relevant to long-term aquaculture licensing, infrastructure investment, and coastal management policy, for which decisions made today must remain sound decades into the future.

This pivot from calibration to climate sensitivity analysis is both practically motivated and scientifically justified. From a practical standpoint, understanding which climate variables drive bay hydrodynamics most strongly is directly relevant to the next steps of the PHAROS project, as the ecological and aquaculture modules that will be built on top of this model need to be designed with the dominant physical forcings in mind. Beyond PHAROS, the results could support local planning and management of marine resources in Bantry Bay by providing a first quantitative picture of how projected climate changes may affect the conditions that mussel, salmon, and seaweed operations depend on.

From a scientific perspective, this thesis aims to contribute to an underexplored area of coastal modeling by applying a comprehensive multi-variable ensemble and sensitivity analysis to a stratified Atlantic bay. The methodology introduces a structured approach, utilizing inverse-transform (Monte Carlo) sampling and a Maximum Dissimilarity Algorithm (MDA) alongside delta perturbation boundary conditions and Partial Rank Correlation Coefficient (PRCC) sensitivity ranking. Together, these techniques form a robust and transferable workflow for climate sensitivity analysis that has the potential to be adapted for similar sites across the PHAROS network and beyond.

The workflow relies on a forward-modelling sensitivity analysis, and its core methodological principle is worth stating plainly before the individual steps are described: rather than simulating fifty independent future years, the analysis takes a single, fully-observed reanalysis year, 2022, as a fixed physical baseline, and constructs fifty plausible 2075 scenarios by systematically perturbing that one year's boundary conditions according to climate-model-derived deltas. Every ensemble member is therefore the same baseline year, reanalysis-driven and internally consistent, viewed through a different, physically justified climate offset – not a separate simulation of an actual future year. This is what allows the analysis to isolate the effect of the climate perturbation itself: the tides, weather, and seasonal cycle are held fixed and identical across all fifty members, so any difference between them can be attributed to the imposed boundary offset alone. To begin, marginal probability distributions for ΔT , ΔS , and $\Delta \eta$ are built using CMIP6 multi-model projections alongside NASA AR6 sea level data. From these distributions, inverse-transform sampling spins up a large 5,000-member candidate pool. The Maximum Dissimilarity Algorithm then steps in, filtering this field down to the 50 most optimal, space-filling members.

These 50 parameter sets are applied directly to the Delft3D-FM model, each as an offset superimposed on the same 2022 baseline described above. Using the delta perturbation method, they act as uniform offsets to the boundary conditions for temperature, salinity, and water level. To prevent numerical instability, an updated nudge file maintains consistency across the interior thermohaline fields. Simulation takes place on a High-Performance Computing Cluster (HPC), with each run covering a full 15-month period. Once complete, data is pulled from the model's history files at specific observation stations and post-processed to calculate the PRCC response metrics. Finally, map files generate the spatial outputs for a representative subset of the ensemble. These visuals track bay-wide temperature and salinity distributions, mean water level changes, and residual circulation, while explicitly mapping stress exceedance indicators around the inner bay seaweed farm.

1.3. Research Objectives

This research aims to quantify the sensitivity of the hydrodynamic conditions in Bantry Bay to projected changes in ocean temperature (ΔT), salinity (ΔS), and mean sea level ($\Delta \eta$), under the Shared Socioeconomic Pathway (SSP) 5-8.5 scenario for the 2075 horizon, using a 50-member ensemble of Delft3D-FM simulations, and to assess the spatial implications for aquaculture stress conditions in the bay.

Two supporting objectives frame this aim:

1. To design a space-filling 50-member climate ensemble using inverse-transform sampling and the Maximum Dissimilarity Algorithm, and to apply it to the Delft3D-FM model of Bantry Bay through the delta perturbation method.
2. To determine the hydrodynamic sensitivity to each climate variable, and translate the ensemble outputs into spatial stress indicators for the bay's aquaculture.

1.4. Research Scope

The study focuses on the hydrodynamic response of Bantry Bay to simultaneous perturbations of temperature, salinity, and water level applied as uniform offsets to the open boundary conditions of the existing Delft3D-FM model. Climate perturbations are derived from the Coupled Model Intercomparison Project Phase 6 (CMIP6) multi-model projections and NASA's Sixth Assessment Report (AR6) sea level estimates for the 2075 horizon under SSP5-8.5. The sensitivity analysis uses the PRCC applied to a 50-member ensemble of full model runs.

The study does not include ecological or biogeochemical modelling, sediment transport, wave forcing, or the aquaculture production modules that will be developed in the later stages of PHAROS. Aquaculture stress is assessed using physical thresholds applied to hydrodynamic model output, not through biological growth or mortality models. The model grid, bathymetry, and baseline parameterisation are adopted as provided by prior work (Boelsma, 2025), and the baseline is used as provided, with its performance checked against water level observations at the single available tide gauge in the bay.

1.5. Research Questions

The central research question is:

Which projected climate variables, ocean temperature change, salinity change, or sea level rise, most strongly drive the hydrodynamic response of Bantry Bay under SSP5-8.5 for the 2075 horizon, and what are the implications for aquaculture conditions in the bay?

Four sub-questions structure the analysis:

1. How do the individual oceanic boundary perturbations (ΔT , ΔS , and $\Delta \eta$) govern the hydrodynamic response of Bantry Bay, and what is their relative importance as evaluated through PRCC analysis?
2. How uncertain are future hydrodynamic conditions in the bay, and how wide are the P10/P50/P90 ensemble envelopes for the key response variables?
3. How do temperature, salinity, and mean water level distributions across the bay differ between extreme and median ensemble members, and where are the spatial gradients largest?
4. When and where do physical conditions exceed species-specific stress thresholds at the seaweed farm location in the inner bay, and how do compound stress days vary across the ensemble?
5. How sea level rise modifies the tidal range distribution across Bantry Bay under future climate scenarios?

1.6. Research Methods

The workflow relies on a forward-modelling sensitivity analysis. To begin, marginal probability distributions for ΔT , ΔS , and $\Delta \eta$ are built using CMIP6 multi-model projections alongside NASA AR6 sea level data. From these distributions, inverse-transform sampling spins up a large 5,000-member candidate pool. The Maximum Dissimilarity Algorithm then steps in, filtering this field down to the 50 most optimal, space-filling members.

These 50 parameter sets are applied as offsets to a single baseline simulation, the calendar year 2022, a recent, complete observed, and forced year available for the bay, with full-year ERA5 atmospheric forcing, CMEMS ocean boundary data, and the Castletownbere tide-gage record all overlapping. Rather than simulating 50 independent future years, every member perturbs this same 2022

baseline, so the resulting ensemble is best read as the sensitivity of a 2022-like Bantry Bay to a range of plausible 2075 boundary conditions, not as 50 independent forecasts. Using the delta perturbation method, the 50 sets act as uniform offsets to the boundary conditions for temperature, salinity, and water level. To prevent numerical instability, an updated nudge file maintains consistency across the interior thermohaline fields. Simulation takes place on a High-Performance computing Cluster (HPC), with each run covering a full 15-month period. Once complete, data is pulled from the model's history files at specific observation stations and post-processed to calculate the PRCC response metrics. Finally, map files generate the spatial outputs for a representative subset of the ensemble. These visuals track bay-wide temperature and salinity distributions, mean water level changes, and residual circulation, while explicitly mapping stress exceedance indicators around the inner bay seaweed farm.

1.7. Thesis Outline

The remainder of this thesis is structured as follows. Chapter 1 introduces the research context, defines the problem statement, and outlines the main objectives. Chapter 2 sets out the theoretical framework, detailing the sensitivity analysis and uncertainty concepts, the delta-change method, the relevant climate and coastal-hydrodynamic background, and the species stress thresholds. Chapter 3 describes the study area, Bantry Bay, and its physical system. Chapter 4 presents the baseline model and parameter screening, while also discussing the data gap that motivated the study's methodological reorientation. Building on this, Chapter 5 develops the sensitivity-analysis methodology, detailing the ensemble design and the application of the perturbed boundary conditions. Chapter 6 presents the results across the five core research questions. Chapter 7 interprets these findings and assesses their limitations. Finally, Chapter 8 draws the overall conclusions and provides recommendations for future work.

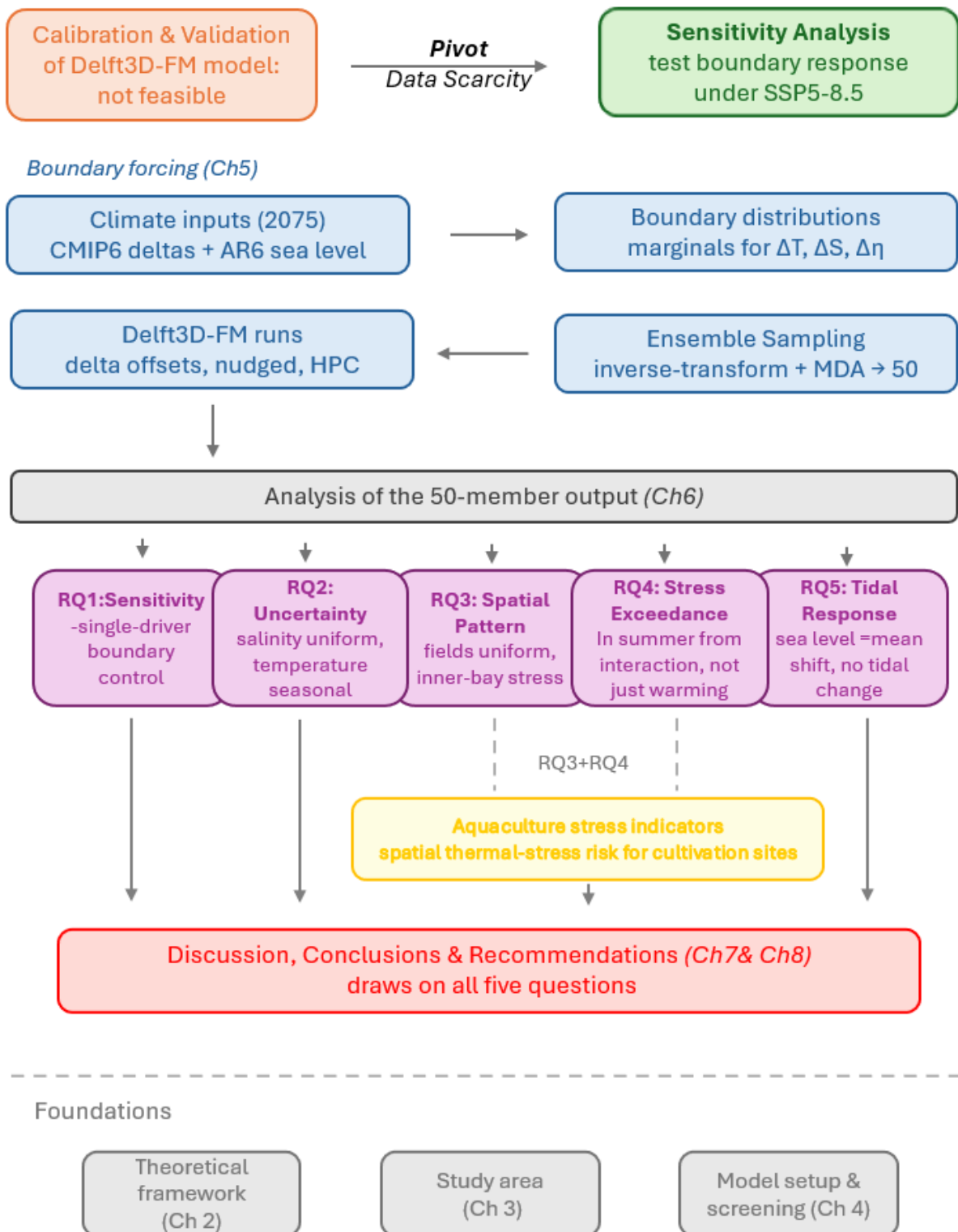


Figure 1.1: Overview of the thesis. The study pivots from an infeasible deterministic calibration to a probabilistic sensitivity analysis, then proceeds through climate-informed boundary forcing and a 50-member Delft3D-FM ensemble. The five research questions and their main findings feed the aquaculture stress indicators (from RQ3 and RQ4) and the overall discussion and conclusions (all five). The foundational chapters establish the system, data limits, and dominant internal control that motivate the design.

2

Theoretical Framework

This chapter establishes the theoretical background needed to follow the upcoming analysis, beginning with introducing sensitivity analysis and the role of uncertainty quantification in data-scarce modelling (§2.1). Then describes the translation of climate projections to regional scales through downscaling and the delta-change method (§2.2), the physics of boundary-forced coastal hydrodynamics (§2.3), the climate-scenario framework and the physical drivers of change in the Northeast Atlantic (§2.4–2.5). Finally the hydrodynamic controls and species thresholds that connect physical conditions to aquaculture are mentioned (§2.6–2.7 and the governing equations of the hydrodynamic model itself (§2.8).

2.1. Sensitivity Analysis and Uncertainty in Data-Scarce Modelling

Sensitivity analysis investigates how variation in the output of a numerical model can be attributed to variation in its input factors (Pianosi et al., 2016). Traditionally it is employed as a precursor to model calibration: by screening out non-influential parameters, modellers reduce the computational effort required to tune complex three-dimensional systems, allowing calibration to focus on the variables that genuinely dictate the hydrodynamic or ecological response (Ye, 2021).

A full three-dimensional calibration, however, requires extensive, high-resolution in-situ datasets: vertical current-profile measurements to constrain the circulation structure, and long-term thermohaline stratification records to constrain the vertical density field. Data of this kind are scarce in most coastal and estuarine systems more generally; even a small number of vertical profile measurements, where available, would already meaningfully inform a calibration exercise. Nevertheless, this reliance on deterministic calibration is increasingly challenged by the principle of equifinality, which posits that in complex environmental systems, multiple parameter combinations can often reproduce the observed data with equal plausibility (Beven et al., 2001). In data-scarce environments, forcing a single 'optimal' calibration risks obscuring the system's inherent uncertainty, leading to a baseline that is fragile rather than robust. Consequently, the productive research response is to pivot from deterministic calibration toward probabilistic uncertainty quantification (Pianosi et al., 2016), where the focus shifts from proving a model is 'correct' to transparently mapping how uncertainty propagates through the system.

A related but distinct gap concerns model input rather than calibration. Riverine freshwater discharge into the bay is highly variable and, unlike the calibration data discussed above, was not available as a forcing input to the model. This is a different category of data gap: absent calibration data limits how confidently an already-configured model's performance can be verified against observations, whereas absent discharge data limits what physical processes can be represented in the model configuration in the first place, since freshwater input could not be prescribed as a boundary forcing and is consequently not included in the present model setup.

When internal model parameters cannot be confidently constrained by observations, and when key forcing inputs, such as the freshwater discharge discussed above, are absent altogether, structural and epistemic uncertainties come to dominate the model output. This is the methodological position

adopted in this thesis: rather than forcing a poorly constrained deterministic baseline, an ensemble-based sensitivity analysis is used to map the bounds of prediction reliability.

The choice of sensitivity-analysis method is constrained by computational cost. Local methods, such as the One-At-a-Time (OAT) approach, are inexpensive and simple, varying a single parameter while holding the others constant. They are useful for basic screening but cannot capture non-linear effects or interactions across the parameter space (Pianosi et al., 2016). Variance-based global methods such as the Sobol approach capture these interactions and fully decompose the output variance, but require an unmanageable number of model evaluations, often tens to hundreds of thousands, which is prohibitive for high-resolution hydrodynamic models (Niederreiter, 1992).

A more efficient middle path is to combine probabilistic sampling with a space-filling selection step. In this study, a large candidate pool is first drawn from the marginal distributions by inverse-transform (Monte Carlo) sampling, which maps uniform random numbers through each variable's inverse cumulative distribution function to reproduce its full probability range at low computational cost. This pool is then reduced using a Maximum Dissimilarity Algorithm (MDA), which selects, from the many candidates, the subset that maximises the geometric distance between points (Camus et al., 2011). It is the MDA step that delivers the space-filling property: it actively spreads the final members across the parameter space, including its bounds, so that the design tests the full range of conditions without redundant simulations. The specific application of this two-step sampling-and-selection procedure in this study is described in Chapter 5.

To assess the relative influence of the sampled input parameters on model outputs, this thesis utilizes the PRCC. It is a global sensitivity analysis method that isolates the unique monotonic contribution of a specific input parameter to a model response while statistically discounting the effects of all other varying inputs (Pianosi et al., 2016). Formally, for an input factor X_i and output Y , each ranked against the remaining input factors X_j ($j \neq i$), PRCC is computed as the Pearson correlation between the residuals of two rank-transformed linear regressions:

$$\text{PRCC}(X_i, Y) = \text{corr}(e_{X_i}, e_Y), \quad e_{X_i} = \text{rank}(X_i) - \widehat{\text{rank}}(X_i), \quad e_Y = \text{rank}(Y) - \widehat{\text{rank}}(Y) \quad (2.1)$$

where $\widehat{\text{rank}}(X_i)$ and $\widehat{\text{rank}}(Y)$ are the values predicted by ordinary least-squares regression of $\text{rank}(X_i)$ and $\text{rank}(Y)$ on the ranks of the remaining input factors $\{X_j : j \neq i\}$ (Pianosi et al., 2016). The significance of each PRCC value is assessed via a two-tailed t test at $\alpha = 0.05$ (S. Marino et al., 2008). Operating on ranks rather than raw values, rather than a strictly linear correlation, is what allows PRCC to capture monotonic but nonlinear relationships between each input and the response.

The rank-based nature of PRCC is advantageous here, as it offers computational efficiency relative to variance-based alternatives such as Sobol, while effectively capturing monotonic, potentially non-linear, relationships that standard linear correlations often fail to identify (Niederreiter, 1992; Pianosi et al., 2016). However, the method carries inherent limitations. Because PRCC evaluates each input's contribution individually while statistically controlling for the others, it assumes each input's effect on the response is separable, and it cannot detect interaction effects, where two or more inputs jointly influence the response in a way that neither explains on its own. It also relies on the assumption that input parameters are independent (Pianosi et al., 2016). Consequently, any correlation between input factors can introduce bias into the sensitivity rankings. By treating the three boundary parameters as statistically independent during sampling, this study satisfies the input-independence assumption of the PRCC method, ensuring the validity of the subsequent sensitivity analysis (Pianosi et al., 2016; Camus et al., 2011). The practical application and interpretation of these PRCC rankings are detailed in Chapter 5.

Model fit and driver-response relationships in this thesis are also assessed using the coefficient of determination, R^2 , defined as

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2} \quad (2.2)$$

where y_i are the observed values of the response, $\hat{y}_i$ are the values predicted by a fitted model, and $\bar{y}$ is the mean of the observed values. R^2 gives the proportion of variance in the response accounted for by the fitted model, and is bounded above by 1 for a perfect fit. Unlike PRCC (Equation 2.1), R^2 as used

here is computed from a specific fitted functional form – most often a linear fit – and so it evaluates how well that particular functional form describes the relationship, rather than the strength of the underlying monotonic association independent of shape. A low R^2 from a linear fit therefore does not necessarily mean a driver has little influence on the response; it may instead mean the true relationship is not well described by a straight line, a distinction that becomes important in Section 6.5.

2.2. Climate Downscaling and the Cascade of Uncertainty

Global climate models provide large-scale climate trajectories, but their direct application to regional coastal systems is limited by coarse spatial resolution and systematic biases (Kristiansen et al., 2024). Coastal topography, intricate bathymetry, and local tidal resonance cannot be resolved on a global grid, so climate information must be translated to regional scales through a sequence of downscaling steps. This process generates an expanding envelope of uncertainty, the cascade of uncertainty (Toimil et al., 2021), which combines intrinsic uncertainty from the internal variability of the climate system with knowledge uncertainty arising from emission scenarios and global climate model structures.

Translating global projections into regional boundary conditions frequently relies on the delta-change approach. Applying a single annual-mean delta to a dynamic coastal boundary introduces severe seasonal aliasing. Because the seasonal amplitude of sea surface temperature is large, subtracting a single annual mean from all future monthly values produces a spuriously wide delta range driven entirely by winter-summer differences rather than actual climate change signal. A month-matched delta approach corrects this by subtracting historical monthly climatologies from their corresponding future months (Toimil et al., 2021). Deriving these climatologies typically requires averaging over a standard 30-year period to filter out natural interannual variability and isolate long-term climate signal (World Meteorological Organization, 2017). This non-parametric technique preserves the natural seasonal variability of the baseline while imposing the projected inter-decadal shift.

2.3. Boundary-Forced Coastal Hydrodynamics and Open-Boundary Uncertainty

Regional coastal models act as a bridge, propagating large-scale oceanic signals into local coastal geometries; downscaling global data into a high-resolution regional model provides a globally consistent simulation while resolving fine-scale shelf physics (Olbert et al., 2012).

The mechanics of boundary forcing are particularly important for limited-area domains. Open-boundary conditions are one of the most important sources of uncertainty in coastal modelling, because they control the interaction between a local domain and the larger ocean. In relatively small coastal models, the internal hydrodynamics are fundamentally governed by the water masses arriving at the open boundary. These domains frequently rely on regional ocean products, such as those from the Copernicus Marine Environment Monitoring Service (CMEMS), to prescribe offshore boundary conditions.

While CMEMS products provide consistent boundary information, the transfer from a regional product to a small coastal domain is not neutral: downscaling can amplify local sensitivity to small differences in the boundary conditions (Hendrickx et al., 2023). Although these products assimilate observations, they remain fundamentally model-based reanalyses and therefore carry epistemic uncertainty arising from the assumptions, resolution and simplifications of their parent models. For that reason it is physically inaccurate to treat a regional boundary product as a perfect, deterministic representation of the open ocean.

The consequences of this boundary uncertainty are well documented. Internal estuarine processes such as salt-intrusion length and residual circulation are highly sensitive to variations at the open boundary (Hendrickx et al., 2023). Sea-level rise affects the mean depth of a bay, modifies bottom friction, and can alter tidal propagation and exchange with the continental shelf (Idier et al., 2017); in shallow or semi-enclosed systems, where circulation is constrained by bathymetry and embayment geometry, even modest changes in mean water level can redirect circulation pathways (Dabrowski et al., 2016). Sea surface temperature and salinity are equally important, because together they set seawater density and therefore govern vertical stratification, turbulent mixing and density-driven circulation (Simpson et al., 1990). Warmer or fresher water arriving at the boundary can strengthen or weaken internal den-

sity gradients, directly affecting vertical exchange and the residence time of water inside a bay (Olbert et al., 2012). By treating the boundary forcing as uncertain rather than fixed, a coastal model can test how far its internal hydrodynamics depend on plausible variations around the boundary state.

2.4. Climate Scenarios and the SSP5-8.5 Stress Test

Any climate-impact ensemble must first define the future radiative forcing. Scenario-based projections are not predictions of a single definitive future; they are tools for exploring plausible conditions and identifying system vulnerability under severe forcing (Lee et al., 2021). The SSP5-8.5 scenario is frequently used as a stress test for coastal environments: it represents a fossil-fuel-intensive, high-emission future with strong warming and substantial climate forcing (Lee et al., 2021). For sensitivity analysis it is useful precisely because it provides an upper-range envelope, helping reveal non-linear hydrodynamic vulnerabilities and compound extreme events that may remain hidden under milder assumptions. Assessing the system response under this severe scenario helps ensure that subsequent adaptation strategies are robust to the worst-case trajectories.

Isolating the effect of specific open-boundary perturbations requires holding other forcing components, such as atmospheric conditions and astronomical tides, constant across all simulations. This experimental principle prevents secondary forcing from obscuring the response of the bay to the selected oceanic variables; its specific application is described in Chapter 5.

2.5. Physical Drivers of Change in the Northeast Atlantic

Defining the uncertainty space for a coastal sensitivity analysis requires a synthesis of the projected physical shifts in the Northeast Atlantic. Sea surface temperature and salinity in this region are strongly influenced by the Atlantic Meridional Overturning Circulation (AMOC). Proxy reconstructions and CMIP6 models indicate that a weakening AMOC produces regional cooling, or significantly reduced warming, alongside large-scale freshening (Nolan et al., 2023). This creates substantial structural uncertainty in future temperature and salinity signals: models with a severe AMOC slowdown project intense coastal freshening, while models with a stable AMOC project standard greenhouse-driven warming. This coupling of reduced warming with freshening is directly relevant to the interpretation of compound effects later in this thesis.

Future sea-level rise also carries deep uncertainty, particularly in the upper percentiles. The steric component can be extracted directly from CMIP6 dynamic sea-level variables, but this accounts for only a fraction of total projected rise (Lee et al., 2021). Ice-sheet dynamics, glacier mass loss and glacial isostatic adjustment introduce uncertainties that standard global ocean models do not resolve. Because CMIP6 ocean models are incomplete regarding total sea level, impact studies rely on integrated probabilistic frameworks, such as the NASA IPCC AR6 Sea Level Projection Tool, to capture the magnitude and uncertainty of future coastal sea-level change (Fox-Kemper et al., 2021).

2.6. Hydrodynamic Controls on Sustainable Coastal Aquaculture

Hydrodynamic modelling is closely connected to sustainable aquaculture, because circulation governs flushing, residence time, nutrient exchange and the dispersal of material from farming activities (Ferreira et al., 2007). In transport-driven systems, water level alone is usually insufficient to describe model performance or predict behaviour: it responds strongly to boundary forcing but can hide changes in the underlying circulation. Current magnitude and direction, residual circulation and transport timescales are more informative indicators of how a bay exchanges water with the shelf.

Flushing and residence time are widely used as proxies for water renewal, turbulent mixing and ecological vulnerability in bays and estuaries (Monsen et al., 2002). Where exchange with the open ocean is boundary-controlled, uncertainty in the circulation response feeds directly into decisions about site suitability and environmental risk. For suspension-feeding bivalves such as blue mussel (*Mytilus edulis*), ambient current speed and renewal rates regulate particle transport and filtration efficiency; sluggish flows and long residence times cause local food depletion, organic-waste accumulation and reduced meat content (Dabrowski et al., 2016). The productivity of suspended macroalgae such as sugar kelp (*Saccharina latissima*) is similarly correlated with moderate water velocities, which supply nutrients and carbon dioxide while limiting biofouling (Walton et al., 2022). Understanding how climate-driven shifts

in sea level, temperature and salinity perturb the baseline circulation of a bay is therefore central to assessing whether aquaculture operations remain viable.

2.7. Species-Specific Thermohaline Thresholds

The two primary aquaculture species considered in this study, *Saccharina latissima* (sugar kelp) and *Mytilus edulis* (blue mussel), exhibit distinct physiological responses to temperature and salinity. These physiological limits define the environmental stress thresholds applied to the hydrodynamic output in the analysis.

For sugar kelp, comprehensive reviews of environmental responses identify an upper thermal limit of approximately 18–20 °C for Atlantic populations (Sæther et al., 2024); above this, photosynthetic efficiency and growth decline markedly, with optimal growth between 10 and 15 °C, consistent with the historically cool, well-mixed conditions of southwest Irish waters. The salinity tolerance of sugar kelp is relatively broad, but growth is reduced when salinity falls below about 30 psu, particularly under combined thermal stress.

For blue mussel, experimental studies show that while survival is maintained across a broad thermal range (3–25 °C), growth rate and condition index decline progressively once temperatures exceed about 20 °C (Kamermans et al., 2022). The salinity tolerance of adult blue mussel is wide, but growth becomes impaired below approximately 25 psu (Riisgård et al., 2012), and molecular analyses reveal distinct stress responses to thermal and osmotic fluctuations across populations (Barrett et al., 2022). The two species also differ in their cultivation cycles, which matters for how the exceedance statistics presented later should be read. Sugar kelp in Bantry Bay is typically deployed in autumn or winter and harvested the following spring, so standing biomass is generally not in the water during the peak summer stress window. Mussel cultivation operates on a longer, multi-year cycle without a comparable seasonal removal.

These thresholds are function-specific, and the compound effect of several simultaneously changing variables typically exceeds the isolated impact of any single factor. The thresholds adopted in this study should therefore be read as first-order, physically-based indicators of conditions likely to impair farm productivity, rather than as absolute biological survival limits. Their detailed application, and the qualifications that attach to interpreting them, are taken up in the results and discussion.

2.8. Delft3D Governing Equations

To simulate the complex hydrodynamics of Bantry Bay, the Delft3D Flexible Mesh (Delft3D-FM) modelling suite was selected. The D-Flow FM module solves the unsteady shallow water equations, which are derived from the three-dimensional Reynolds-Averaged Navier-Stokes (RANS) equations for an incompressible fluid (Deltares, 2025; Kernkamp et al., 2011).

The core hydrodynamics are dictated by the continuity equation (conservation of mass) and the momentum equations. The continuity equation is expressed as:

$$\frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} + \frac{\partial w}{\partial z} = 0 \quad (2.3)$$

where u , v , and w are the velocity components in the x , y , and z directions, respectively.

The horizontal momentum equation in the x -direction (with an analogous equation for the y -direction) is given by:

$$\frac{\partial u}{\partial t} + u \frac{\partial u}{\partial x} + v \frac{\partial u}{\partial y} + w \frac{\partial u}{\partial z} - f v = -\frac{1}{\rho_0} \frac{\partial P}{\partial x} + F_x + \frac{\partial}{\partial z} \left(\nu_V \frac{\partial u}{\partial z} \right) + M_x \quad (2.4)$$

where t is time, f is the Coriolis parameter, ρ_0 is the reference density, P is the pressure, ν_V is the vertical eddy viscosity, F_x represents the unbalance of horizontal Reynolds stresses, and M_x denotes external momentum sources or sinks (Deltares, 2025).

Theoretical Limitations

To keep the model computationally viable over the large Bantry Bay domain, Delft3D-FM applies several standard theoretical approximations. The vertical momentum equation is reduced using the hydrostatic assumption, which treats vertical accelerations as negligible compared to gravitational acceleration, resulting in the hydrostatic pressure relation:

$$\frac{\partial P}{\partial z} = -\rho g \quad (2.5)$$

Alongside this, the Boussinesq approximation is applied so that density (ρ) variations are treated as constant within the conservation of mass and are only factored into the baroclinic pressure gradient term of the momentum equations. Finally, to account for sub-grid scale processes that the spatial resolution cannot explicitly simulate, the model utilizes a standard $k - \epsilon$ turbulence closure scheme. This solves transport equations for turbulent kinetic energy (k) and its dissipation rate (ϵ) to dynamically determine vertical eddy viscosity (ν_V) and diffusivity (Deltares, 2025). Taken together, this framework establishes the central premise of the thesis: in a boundary-sensitive, data-scarce coastal system, the productive question is not whether a model can be perfectly calibrated, but how its predictions respond to the uncertain conditions imposed at its open boundary, and how that uncertainty should be interpreted. The system to which this framework is applied, Bantry Bay, is described next.

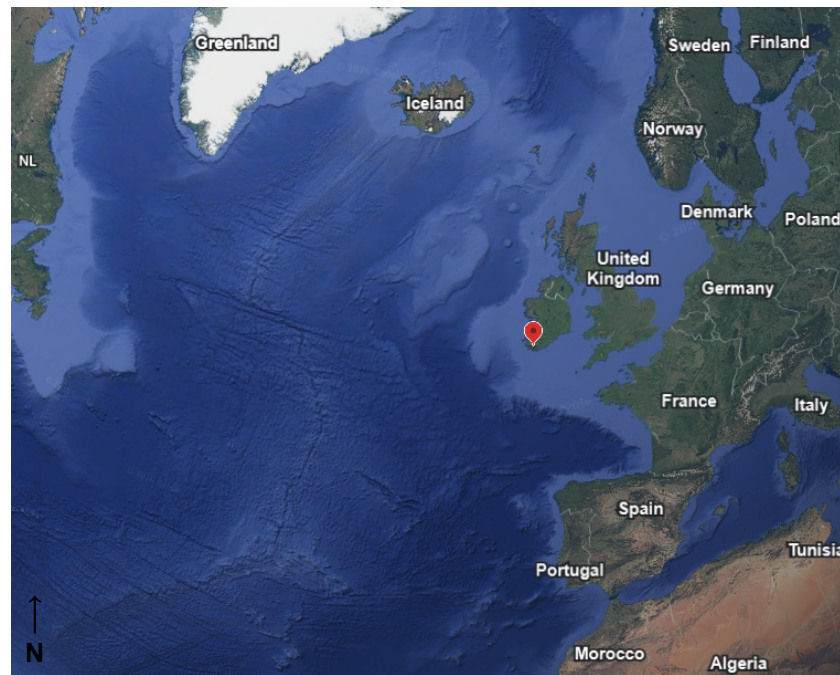
Study Area and Physical System

The physical characteristics of Bantry Bay directly dictate how climate signals from the open Atlantic are modified, amplified, or dissipated before reaching the aquaculture sites in the inner bay. Without understanding this physical context, it is difficult to explain the spatial sensitivity patterns observed later in Chapter 6. For example, local geography explains why the inner bay responds differently than the mouth, why the Whiddy Island constriction concentrates tidal currents, and how summer stratification influences the salinity distribution. To support the interpretation of the sensitivity ensemble, this chapter details the bay's physical environment. It first examines the geometric and bathymetric controls on boundary signal propagation (Section 3.1) alongside the baseline tidal regime against which climate perturbations must be measured (Section 3.2). Section 3.3 details the thermohaline structure, as its future evolution is the primary physical focus of this study. The local meteorological forcing is discussed in Section 3.4, including the rationale for keeping it constant across the ensemble to isolate the oceanic boundary signal. Finally, Section 3.5 introduces the local aquaculture operations, linking the bay's physical hydrodynamics to the applied motivation of this research.

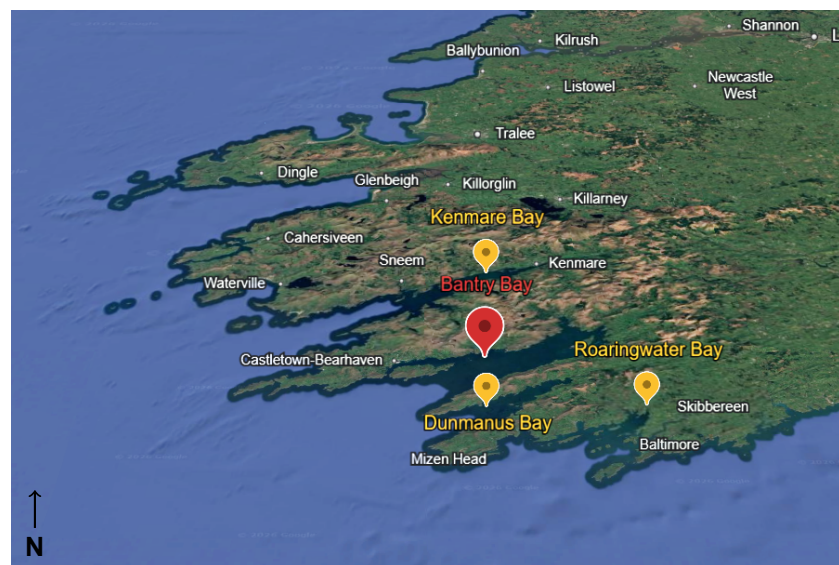
3.1. Geographic and Morphological Setting

Bantry Bay is a large, drowned river valley, or ria, located on the southwestern coast of Ireland in County Cork. The bay is framed by the rugged Beara Peninsula to the north and the Sheep's Head Peninsula to the south, which physically constrain the incoming Atlantic tidal energy. To the immediate north lies the smaller Kenmare Bay, while the coastline to the south and east is characterized by the complex, fragmented inlets of Dunmanus Bay and Roaringwater Bay, as illustrated in the regional and detailed maps provided in Figure 3.1. This deeply indented coastline, typical of the region, significantly influences the propagation and transformation of the oceanic tidal signal as it moves from the open Atlantic into the sheltered inner bay.

The bay spans approximately 40 to 50 km in length with an average width of about 4.5 to 5 km, featuring a deep, fjord-like morphology (Walton et al., 2022). A defining characteristic of the bay is its distinct southwest-northeast (SW-NE) orientation, aligned approximately along the 240°–060° axis. This orientation means the bay's mouth opens directly to the Atlantic Ocean at the southwest, leaving it fully exposed to incoming oceanic swells and prevailing weather systems that track along this same axis (Dabrowski et al., 2016).



(a)



(b)

Figure 3.1: Maps of the study area retrieved from Google Earth. (a) Regional context; (b) Detailed site location.

The bathymetry is characterized by a deep central channel where water depths increase evenly from about 25 m at the bay's inner head in the northeast to approximately 50 to 70 m at the open Atlantic mouth in the southwest (Nagy et al., 2021) (Figure 3.2). This deep axis is flanked by shallower coastal margins and intertidal zones. A major topographical control on the bay's internal dynamics is the Whiddy Island constriction, located about 12 km from the bay's head, which creates a narrow topological bottleneck.

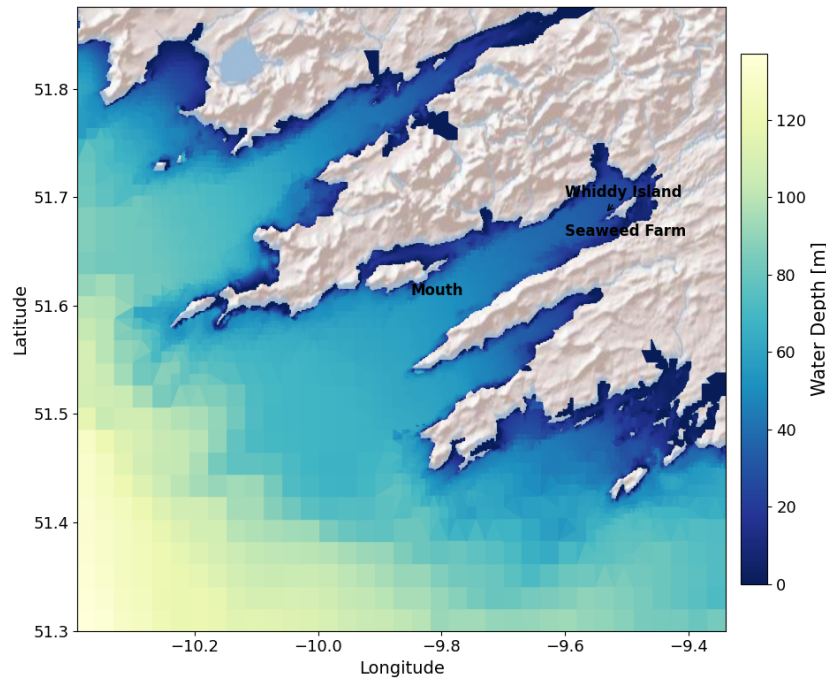


Figure 3.2: Bathymetry of Bantry Bay showing the deep central channel and the SW–NE oriented ria morphology.

Additionally, Bantry Bay features a highly heterogeneous seabed. The outer coast and mid-bay margins are predominantly composed of bedrock, coarse gravel, and rocky substrates, whereas the deeper central seabed and the sheltered inner bay regions, where aquaculture is concentrated, are characterized by finer sediments and complex biogenic habitats (Walton et al., 2022). Flow resistance is fundamentally governed by these bed materials (Arcement et al., 1989); therefore, the Manning’s n parameter must be carefully zoned to capture this spatial variability. While standard hydrographic tables assign lower base coefficients to smooth sand channels (0.012–0.026) and higher values to rocky substrates (0.025–0.070), the macro-scale calibration of this model requires a balanced approach.

The deep, wide channels of the rocky outer bay present lower flow resistance to the massive tidal volumes, justifying a lower calibrated Manning’s n range of 0.018 to 0.022. Conversely, the sheltered inner bay experiences significantly higher frictional drag. This is driven less by the underlying fine sediments and more by the intense form drag introduced by biologically active structures, such as aquaculture infrastructure, kelp beds, and biogenic reefs (Walton et al., 2022). These act as physical obstacles, increasing form drag and justifying a higher Manning’s n parameterization (0.025–0.030). Following the advice of Deltares experts and recent modeling applications in Bantry Bay (Boelsma, 2025), a uniform baseline Manning’s n of 0.023 was selected for this study. Consequently, the bay’s elongated geometry and the Whiddy Island constriction remain the primary spatial controls on tidal propagation, dictating the sensitivity patterns analyzed in Chapter 6.

3.2. Tidal Hydrodynamics

Bantry Bay is a high-energy, mesotidal environment whose circulation is tide-dominated. The regime is controlled by a semi-diurnal tide, steered almost entirely by the principal lunar (M_2) and principal solar (S_2) harmonic constituents (Dabrowski et al., 2016). Because the bay opens to the Atlantic at its southwest boundary, it receives the M_2 tidal wave from the southwest, which then propagates longitudinally towards the northeast head.

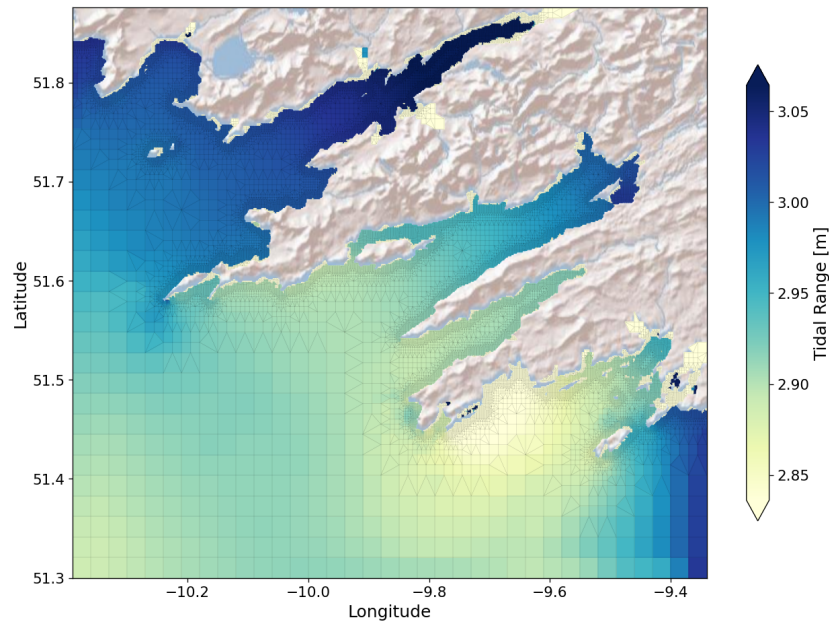


Figure 3.3: Spatial distribution of tidal range in Bantry Bay, computed as the difference between maximum and minimum water level over the simulation period. The range increases from the open mouth in the southwest towards the inner head in the northeast, reflecting the tidal amplification of the converging ria.

As the tidal wave travels up the bay it meets the convergent, funnel-like geometry of the ria. The structural confinement of the narrowing channel overcomes the damping effect of bottom friction, so the wave amplifies as it advances into the inner bay. This amplification is visible in the spatial distribution of tidal range (Figure 3.3): the range grows from the mouth towards the head, giving a spring tidal range of roughly 3.0–4.0 m and a neap range of about 1.4 m. The same propagation is apparent in the modelled current fields (Figure 3.4).

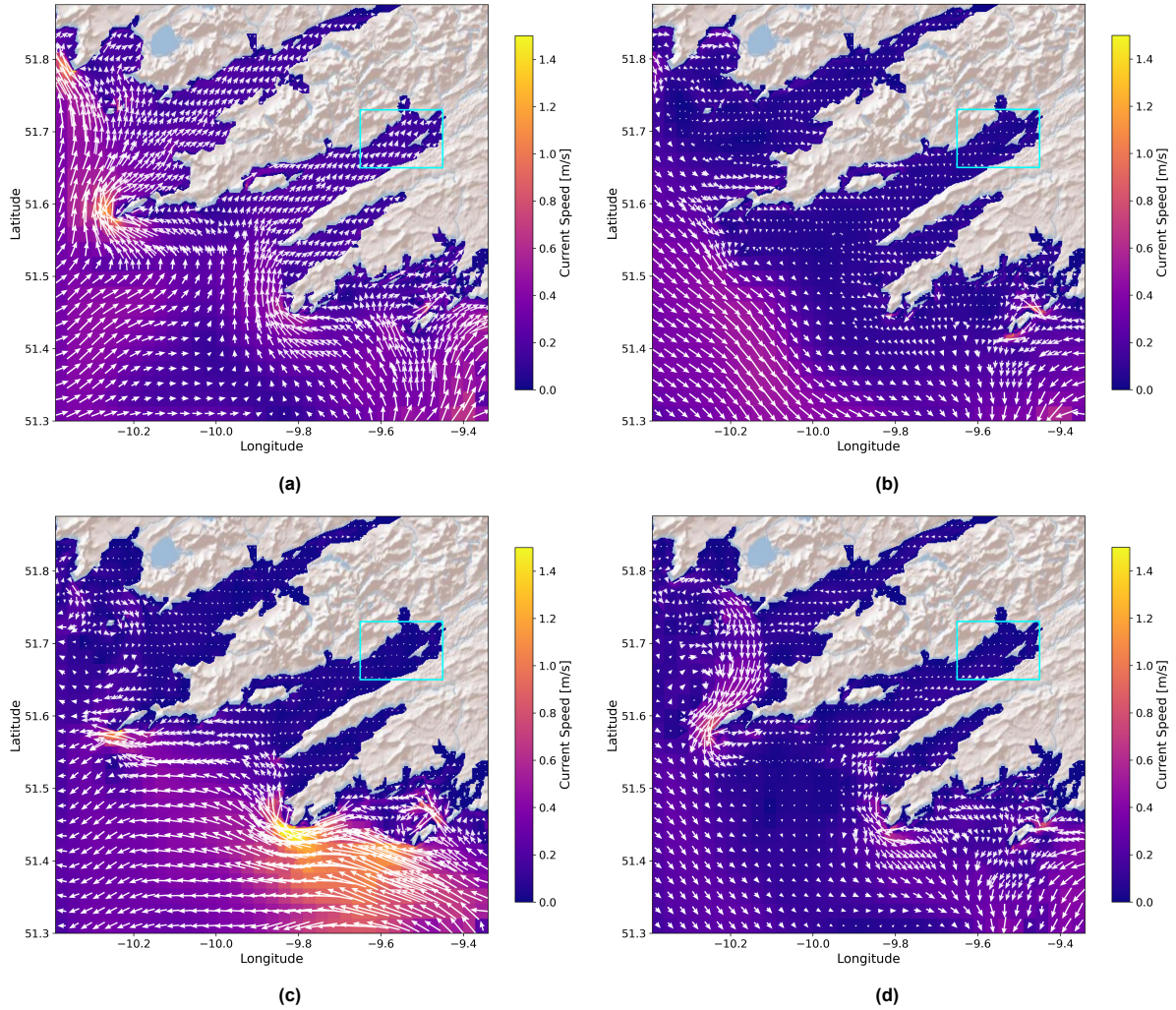


Figure 3.4: Surface tidal currents in Bantry Bay during peak flood (left) and peak ebb (right), for a winter storm period (top row, 18 February 2022) and a calm summer spring tide (bottom row); (a) Winter flood (18 Feb 2022); (b) Winter ebb (24 Feb 2022); (c) Summer flood (16 Jul 2022); (d) Summer ebb (22 Jul 2022). Colour shows current speed; black arrows show direction. The tidal jet through the Whiddy Island constriction is strongest on the flood and is shown in detail in Figure 3.5.

The instantaneous currents are strongly steered by the local topography. As the flooding tide pushes northeastward, the Whiddy Island constriction forces a pronounced flow acceleration: the funnelling of tidal volume through the narrow section generates a current jet exceeding 1.4 m/s during peak spring tides (Figure 3.5). This jet is most intense on the flood, when the constriction concentrates the inflowing volume into a narrow high-velocity core; the corresponding ebb is comparatively diffuse (Figure 3.4). The interaction between the jet and the surrounding topography produces flow separation and the formation of tidal eddies in the lee of the constriction (Dabrowski et al., 2016).

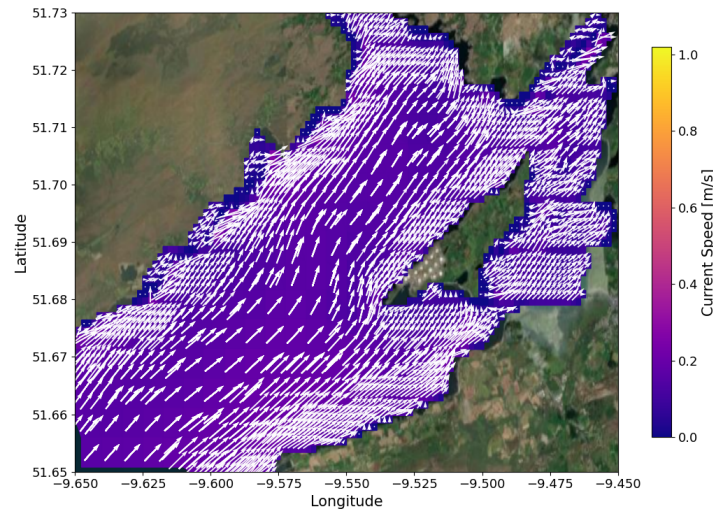


Figure 3.5: Zoomed view of current velocities near the Whiddy Island constriction during peak flood, showing the formation of a strong tidal jet and the associated localized accelerations.

The Whiddy Island constriction is therefore not merely a descriptive feature of the bay's geometry but a control on its dynamics: it is where bottom friction acts most strongly on the tidal flow. This is consistent with the parameter screening of Chapter 4, in which Manning's n emerged as the dominant internal control on current speed, with the largest spatial sensitivity concentrated precisely at this constriction.

A distinction must be drawn between these large instantaneous currents and the much slower net circulation that ultimately determines how the bay is flushed. Over a tidal cycle the strong semi-diurnal currents largely cancel, so the purely tidally-averaged residual in the broad bay is weak. The renewal of bay water, however, is not governed by this tidal residual alone. On timescales of a few days the residual transport in Bantry Bay is dominated by wind forcing: the passage of Atlantic depressions drives a two-layer oscillatory exchange in the stratified water column that can mobilise a substantial fraction of the bay's volume, with wind-driven flows an order of magnitude stronger than the tidal residual (Edwards et al., 1996). The instantaneous tidal currents and this slower, wind-driven residual transport must therefore be read together, rather than equated, when assessing water renewal at the inner-bay aquaculture sites: the fast tidal flow describes how vigorously the water moves at any instant, whereas the wind-modulated residual describes where that water is actually carried over days and weeks.

Finally, the water-level signal itself is the cleanest and most reliable basis for calibrating the model. Because the bay's dynamics are dictated by the regular, energetic M_2 tide, and because the tidal phase and amplitude are directly governed by how Manning's n regulates the loss of tidal energy along the bay, the tide-gauge record provides a clean physical target against which model skill can be assessed (Chapter 6).

3.3. Thermohaline Structure

The thermohaline structure of Bantry Bay follows a distinct seasonal cycle driven by solar insolation, Atlantic oceanic intrusions, and local freshwater runoff. During winter, strong wind-induced energy and surface cooling create a vertically well-mixed water column. As solar heating increases throughout the spring, the bay develops strong thermal stratification during the summer months (Dabrowski et al., 2016).

This vertical density structure is significantly influenced by freshwater inputs discharging into the bay head, most notably from the Owvane, Coomhola, Glengarriff, Adrigole, and Mealagh rivers (Nagy et al., 2021). These riverine discharges create a horizontal salinity gradient, forming a fresher lens in the inner bay compared to the highly saline Eastern North Atlantic Water entering at the mouth. Setting this baseline thermohaline state, capturing the transition from a well-mixed winter to a stratified summer, as well as the inner bay freshening, ensures the model correctly resolves the density-motivated circulation that governs the system. This baseline thermohaline structure justifies the selection of temperature and

salinity as two of the three open boundary parameters perturbed in the climate ensemble. As these properties evolve under future climate conditions, they will directly alter the density-driven circulation that controls water transport and mixing throughout the bay.

3.4. Meteorological Forcing and Wave Climate

Southwest Ireland is exposed to one of the most energetic wind and wave climates globally. The predominant wind direction over Bantry Bay is from the southwest quarter (240° – 060°), which aligns directly with the longitudinal axis of the bay. Because the bay experiences fetch-unlimited exposure to passing atmospheric depressions, meteorological forcing is a critical secondary forcing of circulation (Blauw et al., 2004).

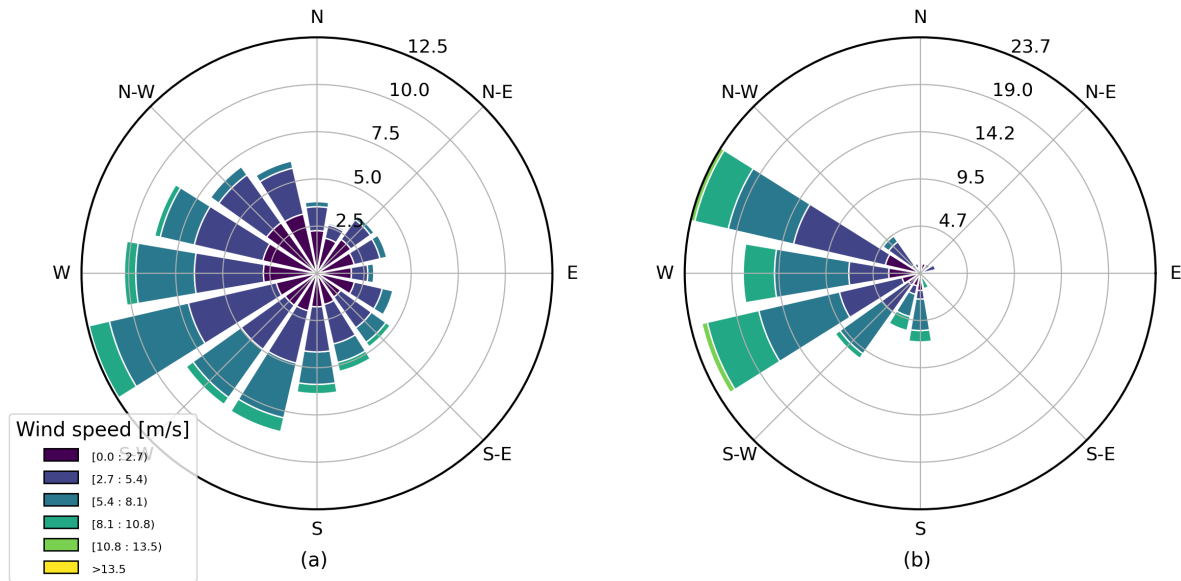


Figure 3.6: Wind roses for Bantry Bay centre based on ERA5 data, showing dominant southwesterly winds annually (left) and during February 2022 (right). (a) Full 2022; (b) February 2022.

Wind forcing plays a decisive role during energetic winter events. Variations in the axial component of the surface wind stress frequently result in a two-layer oscillatory flow, generating rapid and massive water exchanges (Blauw et al., 2004). For this study, February 2022 was selected as a primary calibration window because it recorded the highest storm intensity of the year, with peak winds reaching 13.5 m/s.

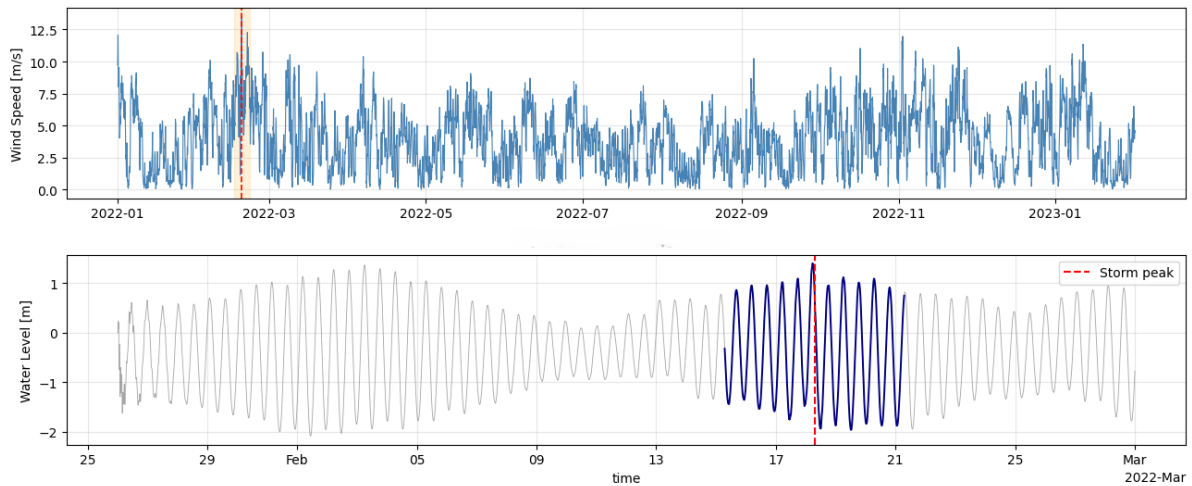


Figure 3.7: Time series of wind speed and water level showing the coupling between atmospheric forcing and storm surge during February 2022. The peak storm event is highlighted.

During such events, wind-surge coupling (as shown also in Figure 3.7) adds a crucial residual water level on top of the astronomical tide. Given how significantly these storm surges alter water depths and flow velocities, applying high-resolution atmospheric forcing, such as the ERA5 global reanalysis (Hersbach et al., 2020) is essential. Without ERA5 wind and pressure fields, a hydrodynamic model would only reproduce the regular tidal signal and entirely miss the important storm-induced surge residuals. For that reason the model incorporates ERA5 atmospheric forcing. This forcing is kept constant across all ensemble members to ensure that the sensitivity results in Chapter 6 strictly reflect oceanic boundary uncertainty, without interference from atmospheric variations.

3.5. Ecological and Socioeconomic Context

The accuracy of hydrodynamic predictions in Bantry Bay carries direct implications for the local economy, as the region supports one of Ireland's most valuable marine aquaculture sectors. Commercial activities in the area include suspended blue mussel (*Mytilus edulis*) lines, Atlantic salmon (*Salmo salar*) net-pens operated by Mowi Ireland, and an expanding sugar kelp (*Saccharina latissima*) industry that utilizes longline setups (Walton et al., 2022). Because these facilities are primarily clustered in the inner bay, they are highly exposed to climate-driven shifts in temperature, salinity, and sea level propagating inland from the open Atlantic boundary.

A primary focus of this study is the extensive seaweed farm located along the northern shoreline, which spans approximately 5 km by 1 km (Boelsma, 2025) Figure 3.8).

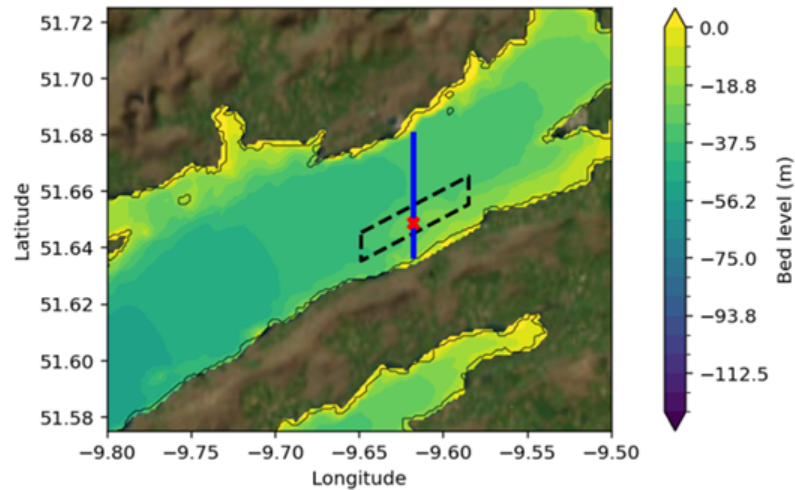


Figure 3.8: Detailed bed level map of the inner Bantry Bay. The dashed black polygon indicates the location and spatial extent of the commercial seaweed farm. Adapted from (Boelsma, 2025).

The viability and yield of this infrastructure rely heavily on local hydrodynamic and thermohaline patterns, which are projected to alter under the future climate scenarios tested in this thesis. The presence of active commercial aquaculture in the inner bay is a constant reminder that this sensitivity analysis carries consequences beyond the academic. Understanding how climate-driven changes in ocean temperature, salinity, and sea level propagate from the Atlantic boundary into the bay is not an abstract modelling exercise; it directly informs the long-term viability of operations that sustain the local economy and marine ecosystem of southwest Ireland.

4

Model Setup, Sensitivity Screening & The Adaptation

D-Flow FM solves the unsteady shallow water equations, derived from the three-dimensional Reynolds-Averaged Navier–Stokes (RANS) equations for an incompressible fluid (in Section 2.8 governing equations and theoretical approximations are described). This exact baseline of the Delft3D set-up and its governing equations is established in the theoretical framework following by the physical system description. This chapter returns to the model itself to focus now in the model domain, the baseline forcing (§4.1–4.2), and the parameter screening that was carried out to assess the model's behaviour (§4.3). It then presents the data limitation that made a full calibration infeasible and explains how this motivated the reorientation of the study towards boundary-sensitivity analysis (§4.5). The screening described here was a *preliminary* step that preceded the main analysis; to keep it clearly separate from the ensemble results of Chapter 6, its outputs are referred to throughout as preliminary screening results, and the full per-run detail is collected in Appendix A.

4.1. Model Domain and Grid

Delft3D-FM uses an unstructured, flexible mesh that maps the bay's complex curvilinear coastlines. Although CMEMS provides regional boundary data, its coarse horizontal resolution of approximately 9 km ($\sim 0.083^\circ$) cannot resolve the interior geometry of Bantry Bay (Nagy et al., 2021), so the grid was locally refined to better than 500 m in the interior. This refinement is necessary to resolve the abrupt constriction at Whiddy Island and the intense (> 1.4 m/s) tidal jets and eddies that the coarse CMEMS grid cannot capture. A key consequence of the relatively small domain (about 50 km long) is that the open oceanic boundary conditions exert a strong, and in this context expected, control on the simulated interior relative to internal model parameters. This follows directly from the nature of the modelling approach: Bantry Bay is effectively a downscaled regional domain nested within a much coarser global ocean model, so the interior state is, by construction, largely inherited from the boundary conditions supplied by that global driving model rather than generated independently through the regional model's own internal dynamics. The smaller the domain relative to the resolution of the driving global model, the more directly this inheritance governs the interior solution, making the open boundary, rather than the internal parameterisation, the dominant control in a system of this scale. This property, noted during model development, is the central motivation for the boundary-sensitivity analysis: it is why the ensemble of Chapter 5 perturbs the open boundary rather than internal parameters.

4.2. Forcing and Boundary Conditions (Baseline)

The baseline scenario for the Bantry Bay model is forced by astronomical, meteorological, and oceanic boundary conditions to fully reproduce the bay's complex hydrodynamics and thermohaline structure for the study year 2022.

Forcing and Boundary Conditions (Baseline)

The primary driver of water movement in the bay is the tide. Tidal water levels are prescribed at the open boundary using astronomical tidal constituents from the TPXO global tide model. TPXO provides tidal water level (elevation) constituents only; it does not supply current velocities, which are instead obtained from the GLORYS ocean reanalysis, described below.

Meteorological Forcing (ERA5)

To simulate the wind-surge coupling and surface heat exchange, high-resolution atmospheric forcing is supplied by the ECMWF ERA5 global reanalysis dataset (Hersbach et al., 2020). The atmospheric boundary conditions explicitly applied to the model surface include:

- **Wind Forcing:** 10 m u - and v -wind velocity components to generate surface shear stress.
- **Atmospheric Pressure:** Mean sea level pressure to resolve storm-induced inverse barometer effects.
- **Heat Flux Parameters:** 2 m air temperature, relative humidity, and net solar radiation (cloud coverage) to parameterize the ocean heat flux model and regulate seasonal thermal stratification.

Oceanic Open Boundary (CMEMS)

The open Atlantic boundaries are dynamically nested using data from CMEMS regional reanalysis products. This oceanic forcing continuously updates the open boundary with:

- **3D Thermohaline Fields:** Vertical profiles of temperature and salinity to regulate density-dependent intrusions.
- **Subtidal Water Levels:** Residual (non-tidal) water levels are prescribed at the open boundary using the GLORYS global ocean reanalysis (Lellouche et al., 2021), which accounts for broader shelf surges and density-driven (baroclinic) sea-level variability propagating into the bay. Because GLORYS does not include astronomical tides, this residual signal reflects genuinely sub-tidal, largely baroclinic ocean-model dynamics rather than any tidal contribution, with the tidal component supplied separately by TPXO as described above.

The choices made in specifying these boundary conditions, including the source datasets, the spatial interpolation approach, and the temporal resolution, are highly deliberate. Given the small domain size, minor errors or uncertainties in the open boundary specification propagate directly into the interior of the bay with limited attenuation. This high sensitivity to boundary condition specification explains exactly why the Inverse Transform Sampling ensemble in Chapter 5 focuses on perturbing the oceanic open boundary rather than internal model parameters.

Selection of Observation Points

To systematically evaluate the model's performance and extract spatially representative outputs during the sensitivity screening, a network of observation points was defined within the Delft3D-FM domain. The selection of these points was informed by two primary criteria:

1. **Spatial and Bathymetric Coverage:** Points were distributed along the longitudinal axis of the ria (from the open Atlantic boundary to the inner bay) and across different bathymetric depths, ensuring that both the deep central channel and the shallower coastal margins were adequately represented.
2. **Alignment with Marine Institute Measurements:** To facilitate direct empirical comparisons between the model outputs and historical *in-situ* data, the numerical observation points were explicitly chosen to match the precise geographic coordinates of known Irish Marine Institute measurement stations.

Applying these criteria, a total of 16 observation points were strategically placed across the domain. This network incorporates continuous monitoring sites such as the Castletownbere tide gauge and the Bantry Bay wave buoy, the exact spatial coordinates of eight sporadic CTD profiling casts (CTD_1 through CTD_8), several offshore boundary extraction points, and the location of the commercial seaweed farm.

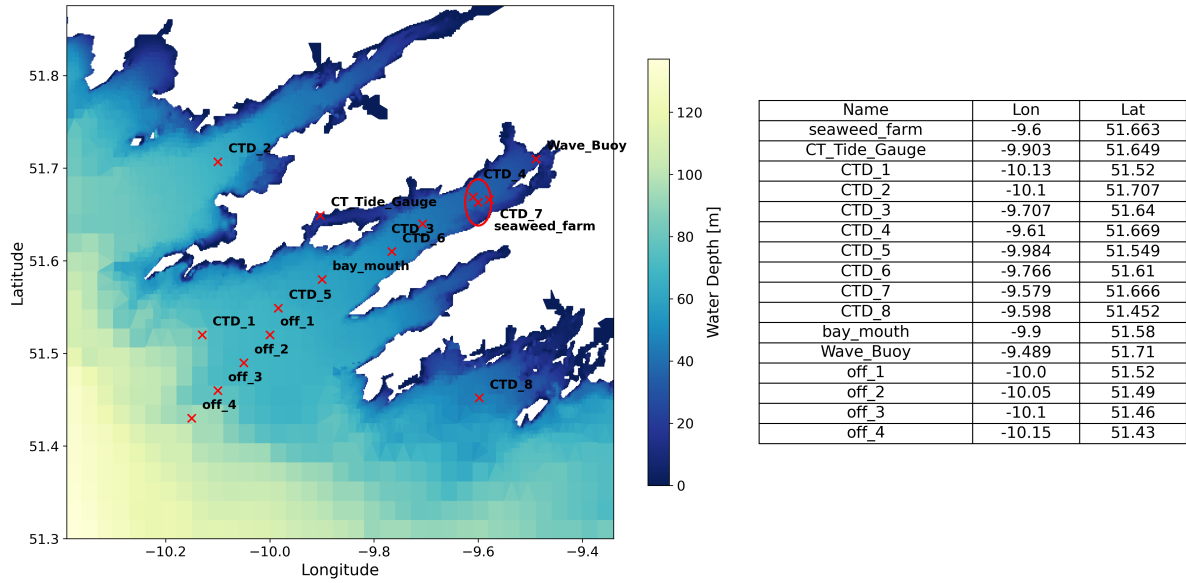


Figure 4.1: Overview of the selected numerical observation points within the Bantry Bay Delft3D-FM model. The points are distributed to provide bathymetric coverage and are strictly aligned with historical Marine Institute monitoring stations.

4.3. Parameter Sensitivity Screening OAT

The original modelling plan was to calibrate the model, and a full three-dimensional calibration of a transport-dominated system like Bantry Bay is computationally expensive. A preliminary screening was therefore carried out to identify which internal parameters most strongly control the measurable response (water levels and currents), so that a subsequent calibration could focus on those parameters (Pianosi et al., 2016). Three parameters were screened: bottom friction (Manning's n), horizontal eddy viscosity and vertical eddy viscosity.

A One-At-a-Time (OAT) screening was used, comprising seven runs: a baseline at the central parameter values, and six runs testing the upper and lower bound of each parameter in turn while holding the others fixed. This is a bounded screening designed only to rank the parameters by influence; it is not a probabilistic sampling of the parameter space, and no probability distribution is assigned to the runs.

Logic of the Parameter Perturbations

Rather than arbitrarily guessing the low and high values to test, each parameter's screening range was derived from an assumed statistical distribution representing informed, physically bounded uncertainty. The distribution's shape reflects what is physically known about the parameter; its bounds define the two values tested in the screening runs.

1. **Bottom Friction (Manning's n):** Assumed to follow a truncated normal distribution ranging from 0.018 to 0.035, centred on the baseline value of 0.023. This range reflects the bay's heterogeneous seabed discussed in Section 3.1 standard roughness tables (Arcement et al., 1989) and the rocky-outer-bay versus biogenically-drag-dominated inner-bay distinction established there justify the lower and upper bounds respectively, while values near the calibrated baseline are physically more plausible than either extreme. The screening tests the two bounds of this range against the baseline.
2. **Horizontal Viscosity:** Perturbed using a log-uniform distribution ranging from 0.01 to 1.0 m^2/s . Horizontal eddy diffusivity in the ocean is well established to scale strongly with the spatial scale of the phenomenon it is diffusing, spanning several orders of magnitude with no single representative value (Okubo, 1971); a log-uniform distribution, which assigns equal weight in log-space, was therefore selected over a range reflecting this order-of-magnitude, scale-dependent uncertainty.
3. **Vertical Viscosity:** Perturbed using a log-uniform distribution ranging from 1×10^{-5} to 1×10^{-3} m^2/s . This range reflects the same order-of-magnitude uncertainty documented for vertical eddy

diffusivity generally, from background values of order $10^{-5} \text{ m}^2/\text{s}$ away from strong mixing sources to values an order of magnitude or more higher in regions of enhanced turbulence, such as those driven by rough topography or strong tidal currents (Munk, 1966) — both plausible in a constricted, tidally energetic embayment such as Bantry Bay. No site-specific vertical turbulence measurements exist to constrain this further (Section 3.1).

The baseline configuration (Run 0) utilized the central values. The subsequent six runs tested the upper and lower bounds of these three variables independently.

Table 4.1: Overview of the 7 sensitivity runs and their corresponding parameter values.

Run ID	Manning's n [s m ^{-1/3}]	Horizontal Viscosity [m ² /s]	Vertical Viscosity [m ² /s]	Description
R0	0.023	0.20	1×10^{-4}	Baseline model configuration
R1	0.018	0.20	1×10^{-4}	Manning roughness – low value
R2	0.035	0.20	1×10^{-4}	Manning roughness – high value
R3	0.023	0.01	1×10^{-4}	Horizontal viscosity – low value
R4	0.023	1.00	1×10^{-4}	Horizontal viscosity – high value
R5	0.023	0.20	1×10^{-5}	Vertical viscosity – low value
R6	0.023	0.20	1×10^{-3}	Vertical viscosity – high value

4.3.1. Preliminary Screening Results

Skill metrics. Model performance at the tide gauge is quantified with three standard skill metrics, computed on the demeaned modelled (m_i) and observed (o_i) water level over the N common time steps. The root-mean-square error (RMSE) measures the typical magnitude of the model–observation discrepancy,

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (m_i - o_i)^2}, \quad (4.1)$$

the bias measures the mean signed offset, indicating whether the model systematically over- or under-predicts,

$$\text{Bias} = \frac{1}{N} \sum_{i=1}^N (m_i - o_i), \quad (4.2)$$

and r is the Pearson linear correlation coefficient, which measures how well the modelled and observed signals co-vary in phase,

$$r = \frac{\sum_{i=1}^N (m_i - \bar{m})(o_i - \bar{o})}{\sqrt{\sum_{i=1}^N (m_i - \bar{m})^2} \sqrt{\sum_{i=1}^N (o_i - \bar{o})^2}}, \quad (4.3)$$

where $\bar{m}$ and $\bar{o}$ are the time-mean modelled and observed values. RMSE and bias are reported in metres; r is dimensionless and bounded by $[-1, 1]$, with $r = 1$ denoting a perfect in-phase match. For a tide-dominated signal such as Bantry Bay, r primarily reflects how accurately the model reproduces the phase and shape of the M_2 tide, while RMSE and bias capture amplitude and mean-level errors.

Water Level Sensitivity

The simulated water levels from the 7 runs were first compared against observational data from the Castletownbere tide gauge (Figure 4.2). A short data gap is visible in the gauge record around 17-18 February 2022; this is most likely a sensor disconnection, so the apparent discontinuity reflects missing data rather than a physical event, and the affected interval is excluded from the skill calculation.

The analysis of the metric skills for these runs, revealed a clear hierarchy of parameter importance. The baseline reference run (R0) yielded a Root Mean Square Error (RMSE) of 0.0850 m and a high correlation of 0.9949. The sensitivity results demonstrated that order-of-magnitude variations in both horizontal and vertical viscosity had a negligible impact on water level errors ($\Delta\text{RMSE} < 0.0001 \text{ m}$). In contrast, variations in Manning's n drove the largest discrepancies, with the low Manning configuration performing the worst and increasing the RMSE to 0.0883 m ($\Delta\text{RMSE} = +0.004 \text{ m}$). To place these

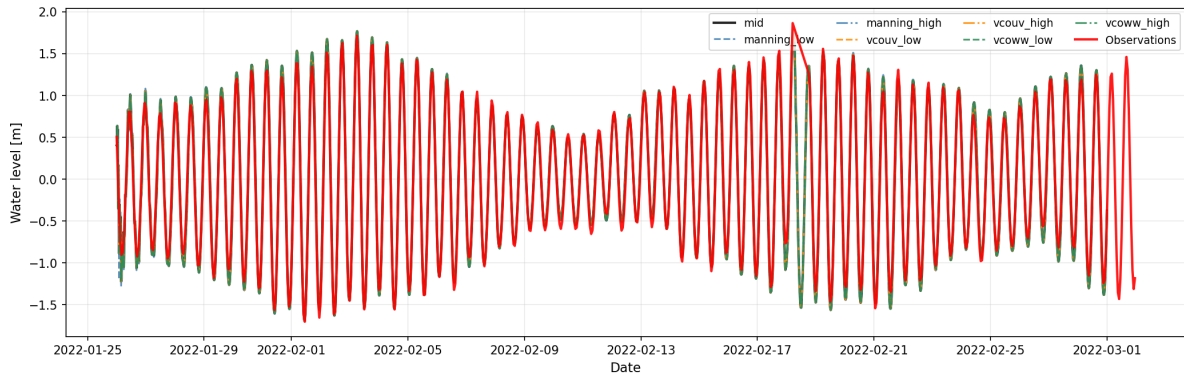


Figure 4.2: Water level (demeaned) per run at the Castletownbere Tide Gauge. The stacked subplot shows the 7 sensitivity runs plotted against the observational record.

errors in the context of the signal they describe, the baseline RMSE of 0.085 m is roughly 2% of the mean tidal range of about 2.3 m at Castletownbere (and below 3% of the 3–4 m spring range), so the model reproduces the tide to within a few percent of its amplitude. On the same basis, the Manning-driven change of ~ 0.003 m between the best and worst runs is well under 0.2% of the tidal range, confirming that even the most influential parameter shifts the water-level error by an amount that is small in absolute terms but nonetheless the largest of the three parameters tested.

Table 4.2: Skill metrics of the 7 sensitivity runs at the Castletownbere tide gauge, ranked by RMSE, bias, and correlation.

Run ID	Parameter	RMSE [m]	Bias [m]	Correlation
manning_high (R2)	Manning	0.0845	0.0003	0.9951
vicoww_high (R6)	V-viscosity	0.0849	0.0003	0.9950
vicoww_low (R5)	V-viscosity	0.0849	0.0003	0.9950
vicouv_high (R4)	H-viscosity	0.0849	0.0003	0.9950
mid (R0)	Reference	0.0850	0.0003	0.9949
vicouv_low (R3)	H-viscosity	0.0850	0.0003	0.9949
manning_low (R1)	Manning	0.0883	0.0003	0.9945

Velocity Profiles and Spatial Sensitivity

While water levels provided a clean 2D validation signal, Bantry Bay is a 3D environment where current velocities govern aquaculture-relevant processes. To assess this, spatial sensitivity maps were generated to evaluate the absolute influence of each parameter on depth-averaged current speeds (Appendix B.1).

Looking at current speeds across all model locations, the pattern observed in the water levels repeats: variations in Manning’s n produced the largest spatial differences in current speed. This sensitivity is intensely concentrated in shallow areas and at topological constrictions (such as the Whiddy Narrows), where current jets exceed 1 m/s and bottom friction becomes highly active. Viscosity variations showed almost zero effect on the depth-averaged currents.

However, evaluating the 3D vertical velocity profiles from onshore to offshore (Appendix B.2) revealed a more nuanced story. Even across the vertical dimension, Manning’s n continues to exert the most substantial overall influence on velocity magnitudes, particularly at shallow onshore locations where bed friction strongly retards a large proportion of the water column. Nevertheless, both horizontal and vertical viscosity affect the vertical structure significantly more than they affect the 2D depth-averaged currents. From a mechanistic perspective, this is a result of bottom roughness (Manning’s n) dictating the bed shear stress that anchors the velocity at the seabed, thereby shifting the magnitude of the entire flow. In contrast, vertical eddy viscosity explicitly mediates the internal turbulent momentum exchange between adjacent fluid layers; it determines the vertical shear and dictates the specific curvature and shape of the velocity profile from the bed to the surface (Bosboom et al., 2023; Deltares, 2025). While this 3D structural distinction is theoretically essential for predicting depth-specific drag forces on sus-

pendent aquaculture lines (Boelsma, 2025), consultation with Deltares experts confirmed that the bay's macro-scale hydrodynamics are fundamentally controlled by bottom friction. Since Manning's n directly dictates the tidal phase, amplitude, and total water transport, it was deliberately selected as the sole internal parameter to carry forward for hydrodynamic tuning. Independent of the observational data limitations (detailed in Section 4.4), the viscosity parameters were thus fixed at their baseline values to avoid over-parameterization.

As a final conclusion of the Sensitivity Screening, Manning's n was identified as the dominant parameter shaping tidal phase, amplitude, and depth-averaged currents in Bantry Bay. This finding effectively transforms a highly complex 3D calibration problem into a targeted focus on bottom friction mapping. Furthermore, the skill metrics evaluated at the water level station confirm that the baseline model already achieves high accuracy, demonstrating strong overall performance.

4.4. The Data Gap

Moving from the initial sensitivity screening to a full 3D calibration requires a comprehensive observational dataset. The initial modelling plan assumed access to multi-dimensional validation data, including ADCP current velocity profiles, continuous thermohaline records, and accurately gauged river discharges. However, an assessment of the available in situ data for Bantry Bay revealed a severe shortfall, showing a stark contrast between the theoretical calibration requirements and the data that was actually accessible.

Available Data

We possessed highly reliable and continuous water level records from the Castletownbere tide gauge, providing a robust basis for validating the tidal phase and amplitude.

Missing Data

However, critical 3D and forcing datasets were either entirely absent or insufficient for a rigorous calibration:

- The paucity of deployed Acoustic Doppler Current Profilers (ADCPs) in Bantry Bay precludes the validation of 3D velocity profiles.
- Conductivity, Temperature, and Depth (CTD) profiles are sparse and temporally limited, failing to track continuous seasonal stratification cycles.
- There is no reliable river discharge data for the freshwater inputs at the head of the bay. Local runoff is highly variable and poorly gauged, which prevents the accurate constraint of inner-bay estuarine dynamics (Dabrowski et al., 2016; Nagy et al., 2021).

4.5. The Methodological Adjustment

The lack of continuous and spatially representative data limited the scope of a traditional 3D calibration. While the initial plan aimed to calibrate both depth-averaged and vertical hydrodynamic structures, the lack of ADCP data made it impossible to constrain vertical velocity profiles or reliably calibrate vertical viscosity parameters. The available water level records were also confined to a single tide gauge at Castletownbere, providing no spatial coverage across the bay and leaving the model's ability to reproduce water level gradients between the mouth and the inner bay unconstrained. Similarly, the absence of continuous river discharge data prevents the accurate representation of estuarine density gradients and freshwater-linked circulation in the inner bay.

Since these internal parameters could not be reliably optimized with the available observations, the methodology was adapted. Rather than focusing solely on internal parameter calibration, the analysis shifted to **Boundary Condition Sensitivity and Epistemic Uncertainty Quantification under future Climate Change Scenarios**. This approach utilizes ensemble-based methods to systematically evaluate the model's sensitivity to uncertain, CMEMS-derived open boundary conditions, thereby formally quantifying the epistemic uncertainty propagated into the Bantry Bay model domain.

Sensitivity Analysis Methodology

5.1. Parameter Selection and Justification

The sensitivity analysis targets the 2075 horizon under the SSP5-8.5 scenario. This specific time-frame ensures the climate change signal in the Northeast Atlantic is robust enough to drive physically meaningful contrasts across the ensemble, while remaining highly relevant to the operational planning lifespans of local aquaculture infrastructure.

Before running the simulations, it is necessary to establish which forcing components actually introduce genuine uncertainty at this late-century horizon. The Bantry Bay Delft3D-FM model is driven by several external inputs: atmospheric forcing from the ERA5 reanalysis, tidal constituents from TPXO, and open ocean boundaries from CMEMS. However, these components do not contribute equally to the future uncertainty budget.

Atmospheric forcing is held constant across all ensemble members to strictly isolate the bay's hydrodynamic sensitivity to the Atlantic boundary. Extending ERA5 into a future climate scenario would require a separate downscaling chain, adding an entirely independent layer of atmospheric uncertainty. Isolating oceanic from atmospheric drivers is a standard methodological approach in coastal impact modeling to prevent the compounding of uncertainties (Toimil et al., 2020; Vousdoukas et al., 2017). Similarly, tidal forcing from TPXO is treated as deterministic. Tides are astronomically governed, and their amplitude and phase at the bay mouth are well-constrained over decadal timescales. While rising sea levels can alter tidal resonance in shelf seas, the magnitude of this effect by 2075 is estimated to be less than 2% of the tidal amplitude in the Celtic Sea (Pickering et al., 2017).

River discharge is also excluded as a variable parameter. While future precipitation regimes are inherently uncertain, the catchment area draining into Bantry Bay is small, giving the system limited estuarine characteristics. Because the volumetric seawater flux from the Atlantic vastly exceeds local terrestrial freshwater input, the dominant hydrodynamic forcing at the western mouth is driven almost entirely by oceanic water mass properties rather than riverine discharge (Dabrowski et al., 2016).

As a result, the experimental design strictly varies three open boundary parameters: sea surface temperature offset (ΔT), salinity offset (ΔS), and water level offset ($\Delta \eta$). These three variables represent the core epistemic uncertainty in the boundary condition specification because they are prescribed via CMEMS, a model-derived reanalysis product lacking direct observational constraints at the future domain boundary. The variance across the CMIP6 projections under SSP5-8.5 provides the physical basis for quantifying this uncertainty, as detailed in the following sections.

5.2. Methodological Overview

The internal hydrodynamics of this exposed, transport-driven system are governed to a large degree by the open Atlantic boundary conditions supplied by the CMEMS. Because these regional boundary conditions are model-derived, they carry epistemic uncertainty that propagates into the bay interior. The aim of the methodology developed in this chapter is to quantify how sensitive the interior dynamics are

to variation at the open boundary, and to express the resulting predictive uncertainty as robust bounds on the future projections. Before the individual steps are described in detail, a brief overview of the full workflow is given.

The experimental design isolates the oceanic boundary signal under a single high-end climate scenario. Atmospheric forcing (ERA5) and astronomical tides (TPXO) are held constant across all simulations, so that the three perturbed open-boundary parameters, sea surface temperature (ΔT), sea surface salinity (ΔS), and mean sea level ($\Delta \eta$), are the only sources of variation in the ensemble. The choice of the SSP5-8.5 scenario as a stress test, and the rationale for selecting these three parameters in particular, are set out in Section 5.1; the sampling design that turns their uncertainty ranges into a 50-member ensemble together with the Maximum Dissimilarity Algorithm (MDA), is developed in Section 5.4. The present section gives only the high-level structure that connects these pieces.

The workflow is organised around the objectives of the study: establishing which boundary parameter dominates the bay's response, and how far the predictions can be trusted under future conditions. Answering this first requires a defensible estimate of the plausible ranges of ΔT , ΔS , and $\Delta \eta$ at the model boundary for the 2075 horizon, which is why the workflow begins with the construction of those ranges and ends with the sensitivity and uncertainty outputs. The full sequence is summarised in Figure 5.11 and proceeds in five steps.

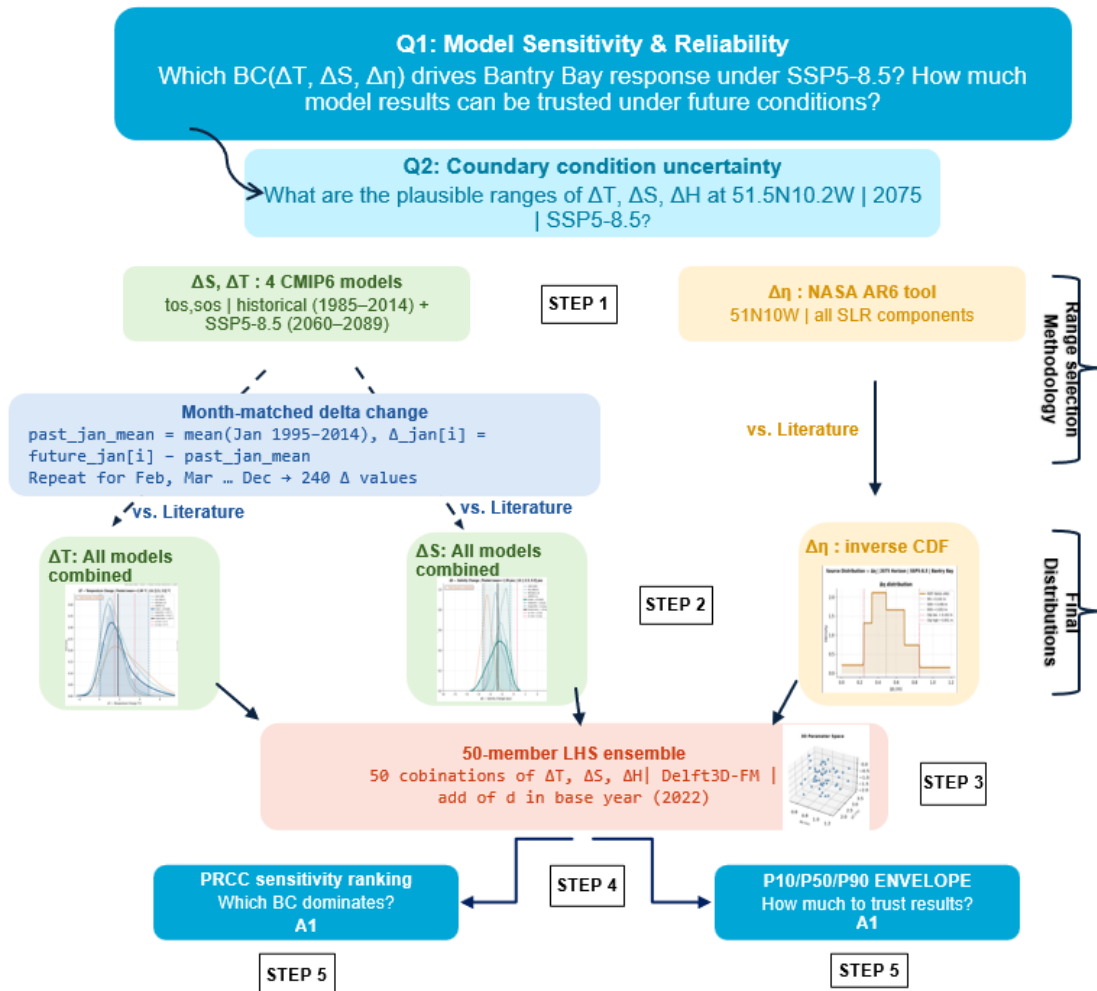


Figure 5.1: Workflow for the boundary-condition sensitivity and uncertainty analysis. Forcing data are extracted and fitted to probability distributions (Steps 1–2), sampled into a 50-member ensemble with ITS and MDA (Step 3), run through Delft3D-FM (Step 4), and post-processed into the PRCC sensitivity ranking and the P10/P50/P90 uncertainty envelope (Step 5).

Step 1: Data extraction and variable mapping. Credible 2075 ranges for the three boundary parameters are assembled. For temperature and salinity, τ_{os} (sea surface temperature) and s_{os} (sea surface salinity) are extracted from four CMIP6 models for the reference period (1985-2014) and the future period under SSP5-8.5 (2060-2089), and a month-matched delta-change is applied to yield 360 delta values per model and variable. Sea-level rise ($\Delta\eta$) is obtained separately from the NASA AR6 projection tool, which captures the ice-sheet and steric components that CMIP6 ocean output alone does not resolve.

Step 3: Ensemble generation (Inverse-Transform Sampling + MDA). The multidimensional parameter space is sampled with Inverse Transform Sampling and reduced to a space-filling subset with the Maximum Dissimilarity Algorithm, producing 50 physically consistent combinations of $(\Delta T, \Delta S, \Delta\eta)$.

Step 4: Delft3D-FM simulations. Each of the 50 combinations is applied as a uniform offset to the 2022 open-boundary conditions through the delta-change method, and the model is run once per member to resolve the corresponding hydrodynamic response.

Step 5: Output evaluation. The ensemble outputs are post-processed into the two deliverables that address the objectives: a Partial Rank Correlation Coefficient (PRCC) ranking, which identifies the dominant boundary driver, and a P10/P50/P90 envelope, which quantifies the uncertainty in the predicted response under SSP5-8.5.

The sections that follow develop each of these steps in turn.

5.3. Defining the Uncertainty Bounds for SSP5-8.5

5.3.1. CMIP6 Model Selection

Having identified temperature, salinity, and water level as the critical parameters to perturb, the next step is to quantify their plausible future ranges. This requires selecting a robust subset of global climate projections capable of accurately representing the Northeast Atlantic dynamics. For this study, four CMIP6 models were chosen: CMCC-ESM2, IPSL-CM6A-LR, MPI-ESM1-2-LR, and UKESM1-0-LL.

This specific subset was curated to satisfy two primary criteria: comprehensive scenario coverage and demonstrated regional performance. First, the four models span the projected SSP5-8.5 warming for the Northeast Atlantic, from CMCC-ESM2 (low warming) to UKESM1-0-LL (high), so the ensemble captures a wide spread of plausible trajectories rather than a single median outcome.

Second, each selected model has been rigorously evaluated against observational data for the Northeast Atlantic and European shelf. Both IPSL-CM6A-LR and UKESM1-0-LL belong to the ISIMIP3b international protocol for impact model forcing, a framework that requires models to pass strict regional performance thresholds. MPI-ESM1-2-LR has been specifically validated against Northeast Atlantic coastal observations by Varela et al. (2022), who ranked it among the top-performing CMIP6 models for capturing sea surface temperature and salinity along the Spanish Atlantic coast, a region hydrodynamically linked to the study area. Furthermore, Kristiansen et al. (2024) statistically downscaled a subset of CMIP6 models for European Atlantic waters, confirming that all four models chosen here realistically reproduce the historical temperature and salinity climatology (1993-2020) across the region, including the adjacent Bay of Biscay.

While utilizing four models sits at the lower end of standard regional coastal impact studies, which generally employ between three and seven (Kristiansen et al., 2024), expanding the ensemble indiscriminately would simply widen the apparent parameter spread without necessarily adding physically meaningful information. Prioritizing models with proven regional fidelity ensures the bounds of the parameter space remain physically credible. As an additional validation step, the literature ranges described later in Section 5.3 provide an independent check to confirm that this four-model spread successfully encompasses the broader uncertainty reported in published Northeast Atlantic assessments.

5.3.2. Data Extraction

With the subset of global climate models established, the next step is to define the spatial coordinates and temporal window for the data extraction.

Extraction Box

The climate change signal must represent the water mass arriving at the western mouth of Bantry Bay (approximately 10.39°W), where Atlantic forcing enters the model domain. Extracting data from coordinates within the inner bay would instead isolate water that has already been modified by local circulation, which is physically inappropriate for boundary condition derivation (Ådlandsvik, 2008).

To capture this offshore signal, an extraction box spanning 51.3°N to 52.0°N and 11.0°W to 10.0°W was defined (Figure 5.2). The underlying climate projections for this study were sourced from the Coupled Model Intercomparison Project Phase 6 (CMIP6), which provides the standardized framework for modern multi-model climate experiments (Eyring et al., 2016). Evaluating the varying horizontal grid structures of the four selected CMIP6 models confirmed that exactly one grid cell per model falls within this boundary, with cell centers consistently located near 51.6°N , 10.6°W . Because these global model grid cells span approximately 100 km, the spatial extraction naturally collapses to a single-cell value. This approach is consistent with the recommendation of Giorgi et al. (2015) for target domains smaller than a Global Climate Model (GCM) grid cell, meaning the extracted signal represents the large-scale Atlantic water mass rather than any resolved shelf or coastal feature.

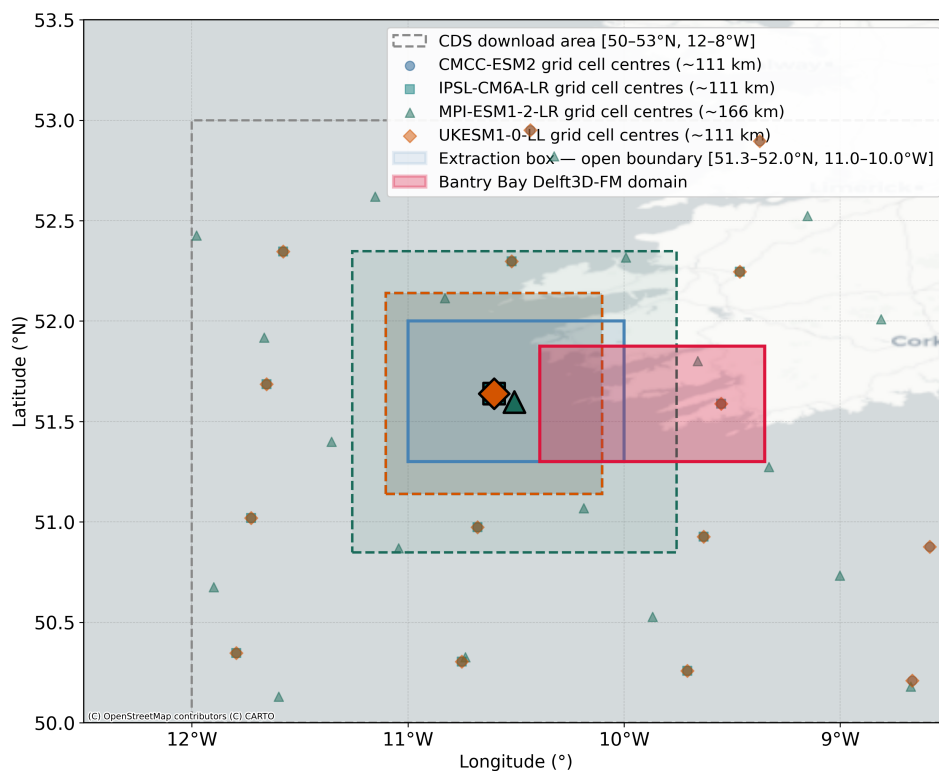


Figure 5.2: Location of the CMIP6 extraction box (red rectangle, $51.3^\circ\text{--}52.0^\circ\text{N}$, $10.0^\circ\text{--}11.0^\circ\text{W}$) relative to the Bantry Bay model domain and the western open boundary. The box targets the Atlantic grid cell at the open boundary rather than the inner bay, consistent with boundary-focused delta change approaches (Ådlandsvik, 2008).

Extraction Period

For the temporal extraction, boundary perturbations were calculated over a thirty year climate window from 2060 to 2089, establishing 2075 as the representative central horizon. Following consultation with modeling experts at Deltares, and corroborated by standard climatological practice (Section 2.2), averaging climate data over this thirty year block was adopted to fulfill the fundamental requirement necessary to filter out interannual background noise and isolate a statistically robust climate trend.

As introduced earlier, the 2075 target itself was specifically selected to balance signal clarity against predictive uncertainty. If the target year were set too close to the present (for example, 2050), the climate change signal in the Northeast Atlantic might not yet be sufficiently distinct from natural ocean variability. Conversely, targeting the end of the century (2100) introduces significant epistemic uncer-

tainty regarding long term global emission trajectories and ice sheet dynamics. The window from 2060 to 2089 avoids both extremes, providing a clear, physically meaningful contrast across the ensemble members while reflecting a practical planning timeframe for regional coastal infrastructure.

5.3.3. Variable Selection and Approach for Each Parameter

To establish the final uncertainty bounds, the three boundary condition parameters require distinct derivation approaches. While temperature and salinity offsets are calculated directly from CMIP6 global climate models, sea level rise necessitates a separate multi-component methodology to capture critical ice sheet dynamics.

For temperature and salinity, the variables *tos* and *sos* were downloaded from the Copernicus Climate Data Store for the reference period (1985–2014) and the future period (2060–2089) under SSP5-8.5. The Delft3D-FM boundary conditions utilize *thetao* (three-dimensional sea water potential temperature) and *so* (three dimensional sea water salinity), the three-dimensional ocean fields from CMEMS. However, using *tos* and *sos* as the source variables for the delta derivation is consistent with standard practice in regional climate downscaling, where sea surface temperature serves as the conventional boundary variable (Kim et al., 2023). Because *tos* and the first layer of *thetao* are numerically close at the surface in most CMIP6 models, the practical difference in the derived delta is negligible. Adopting *tos* and *sos* is physically preferable because they are formally defined at the air-sea interface, avoiding the depth-level ambiguity of three-dimensional fields. A comparable approach was recently validated in a Delft3D climate change study of the Ría de Arousa, a bay of similar scale on the Northwest Spanish coast, where CMIP6 boundary conditions were used under SSP5-8.5 to assess impacts on temperature and salinity stratification (Ribeiro et al., 2025).

Temperature Change (ΔT)

Sea surface temperature at the open boundary is expected to rise under greenhouse gas forcing, but the magnitude and seasonal structure of this change remain uncertain and model-dependent. The offset ΔT is defined as a spatially uniform shift applied to the CMEMS temperature boundary condition timeseries. This simplification is justified both by the coarse resolution of the CMIP6 models (approximately 100 km grid cells spanning the entire domain) and by the fact that the horizontal temperature gradient across the open boundary section is small relative to the projected inter-model spread.

Following the theoretical framework established in Section 2.2, the climate change signal was computed using the month-matched delta approach to prevent seasonal aliasing. For each calendar month separately, the climatological mean over the reference period (1985–2014) was subtracted from each corresponding future monthly value over 2060–2089:

$$\Delta x_{i,m} = x_{i,m}^{\text{fut}} - \bar{x}_m^{\text{hist}} \quad (5.1)$$

where $x_{i,m}^{\text{fut}}$ is the future value for year i and calendar month m , and $\bar{x}_m^{\text{hist}}$ is the historical climatological mean for that specific month. This produces 360 delta values per model per variable (30 future years $\times$ 12 calendar months).

Examining the seasonal structure of the delta reveals a physically meaningful pattern. Three of the four models show stronger warming in summer and weaker warming or slight cooling in winter (Figure 5.3). CMCC-ESM2 produces the most muted seasonal warming, with ΔT remaining positive year-round but dropping to roughly +0.5 °C in late winter and early spring, while the ± 1 inter-annual standard deviation band briefly extends below zero in those months. This aligns with a projected weakening of the Atlantic Meridional Overturning Circulation (AMOC), which reduces the northward transport of warm water and dampens winter warming, whereas summer surface warming from greenhouse forcing is less affected by ocean circulation changes. This mechanism is well-documented in Northeast Atlantic literature (Caesar et al., 2021; Boers, 2021), confirming that the CMCC-ESM2 result represents a coherent physical response rather than a numerical error.

Salinity Change (ΔS)

Salinity changes at the open boundary are represented as a spatially and vertically uniform shift applied to the CMEMS salinity condition. Similar to temperature, the CMIP6 models cannot resolve fine horizontal gradients at their native resolution, and reliable distributed freshwater discharge data for the local

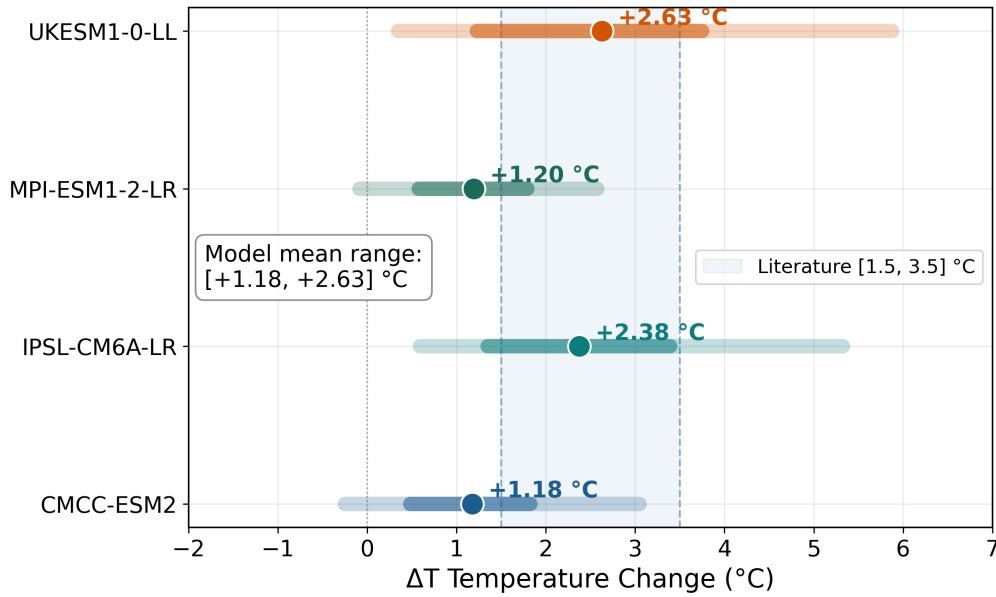


Figure 5.3: Month-matched ΔT distributions for each of the four CMIP6 models.

catchment is unavailable. Furthermore, on decadal timescales, salinity variability at the open boundary is controlled by basin-scale freshwater transport from the North Atlantic rather than local coastal processes (Holliday et al., 2020), making a uniform large-scale offset the most physically appropriate representation.

The same month-matched delta approach described in Equation 5.1 was applied to salinity. The seasonal pattern of the resulting delta is nearly uniform across months: all four models project a freshening signal of similar magnitude year-round, with only minor month-to-month variation (Figure 5.4). This uniformity strongly supports the choice of a constant offset rather than a seasonally varying perturbation, and it confirms that the spread in the distribution captures genuine inter-model disagreement regarding the magnitude of freshening, rather than seasonal noise.

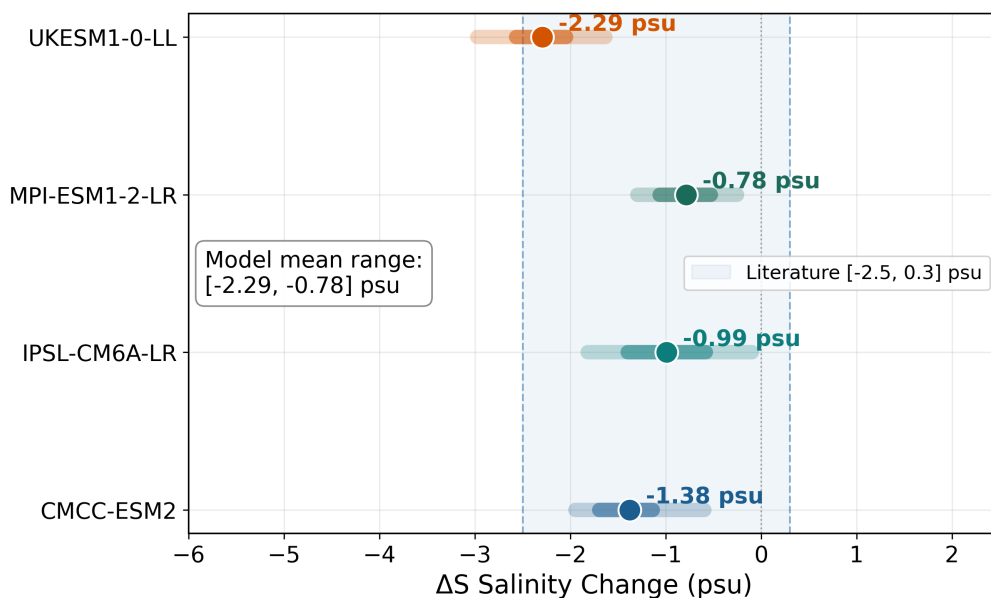


Figure 5.4: Month-matched salinity delta distributions for each of the four CMIP6 models.

Sea Level Rise ($\Delta\eta$)

In contrast to the methodology applied for temperature and salinity, defining the boundary perturbations for sea level rise ($\Delta\eta$) required a different approach. Specifically, as mentioned in Section 2.5 the future water level distributions could not be derived directly from the CMIP6 dynamic sea level output (zos). As illustrated in Figure 5.5, the zos variable captures only the steric component (thermal expansion). At the study location in 2075, this accounts for only 0.275 m of the total 0.469 m median projection, representing roughly 59% of the total change. The remaining 41% is driven by glaciers (0.075 m), the Antarctic ice sheet (0.069 m), glacial isostatic adjustment (0.034 m), land water storage (0.013 m), and the Greenland ice sheet (0.003 m).

To capture the full spectrum of these components, the comprehensive sea level projection was instead obtained from the NASA IPCC AR6 Sea Level Projection Tool (Fox-Kemper et al., 2021) for the coordinates 51°N, 10°W under the SSP5-8.5 medium confidence scenario. Because the downloaded dataset only provides decadal percentile outputs for 2070 and 2080, an equal-weight linear interpolation was applied between these two datasets to derive the 2075 values for each percentile separately. While simple linear interpolation may not perfectly capture the complex physical dynamics of sea level changes over a decade, this approach is highly justified for this framework. First, sea level rise trajectories under SSP5-8.5 are approximately linear at the decadal scale during the mid-century period, with no abrupt transitions anticipated between 2070 and 2080 (Slangen et al., 2017). Second, and more importantly, the interpolation error over a 10-year window is negligible relative to the massive width of the uncertainty range. The difference between a linear midpoint and the true 2075 value is estimated to be well below 5 mm, which is mathematically insignificant compared to the broad 0.6 m spread between the 5th and 95th percentiles.

This interpolation yielded a final 2075 distribution characterized by a median of 0.490 m, a 5th percentile of 0.242 m, and a 95th percentile of 0.853 m.

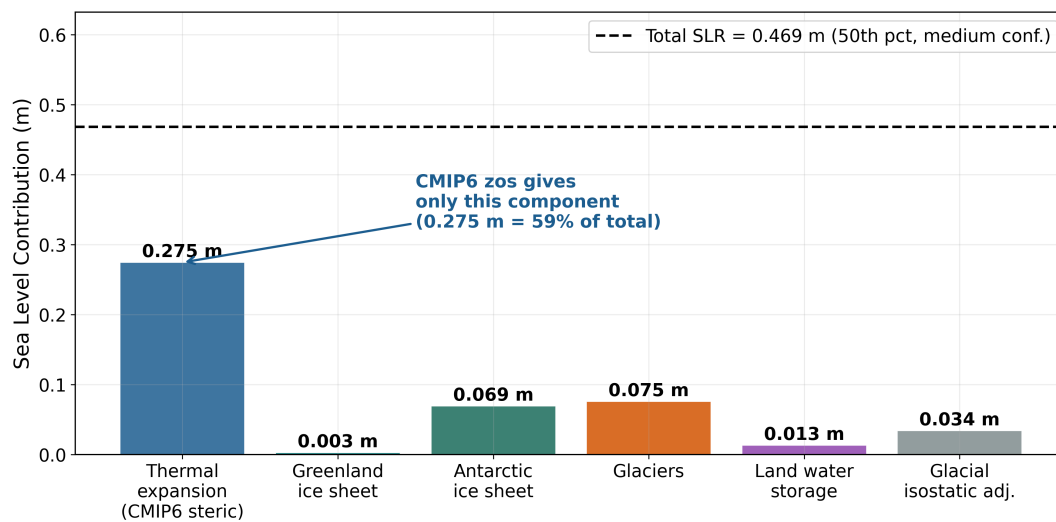


Figure 5.5: Sea level rise component breakdown at 2075 at 51°N, 10°W under SSP5-8.5 (50th percentile, medium confidence), derived from the NASA IPCC AR6 Sea Level Projection Tool. The CMIP6 zos variable incorporates only the thermal expansion component (0.275 m, blue bar), which represents 59% of the total. The remaining 41% comes from ice sheet dynamics, glaciers, and glacial isostatic adjustment and is not included in zos .

5.3.4. Consistency Check Against Literature

Before finalizing the sampling distributions, the derived four-model delta ranges were compared against published regional assessments to verify their physical plausibility. Table 5.1 summarizes the individual model results, the corresponding literature bounds, and the final probability distributions adopted for all three boundary parameters.

Regarding temperature, the individual model means range from +1.18°C (CMCC-ESM2) to +2.63°C (UKESM1-0-LL), resulting in a pooled mean of +1.84°C. This model spread aligns closely with the ICES Celtic Seas projection of +1.5 to +2.5°C (ICES, 2022) and the broader Kristiansen et al. (2024)

Table 5.1: Summary of CMIP6 month-matched delta values at the 2075 horizon (51.5°N, 10.2°W, SSP5-8.5, 2060–2089 vs 1985–2014) and adopted sampling distributions for the ensemble. Individual model 5th–95th percentile ranges reflect inter-annual and seasonal spread across the 360 monthly delta values. Literature ranges are from Kristiansen et al. (2024) and ICES (2022) for ΔT and ΔS , and from the NASA IPCC AR6 Sea Level Projection Tool (Fox-Kemper et al., 2021) for $\Delta\eta$.

Parameter	Model	Mean Δ	5th–95th pct	Literature range	Adopted distribution
ΔT (°C)	CMCC-ESM2	+1.18	[−0.25, +3.05]	[+1.5, +3.5]	Pooled model KDE median = +2.01°C 5th–95th = [+0.15, +4.01]
	IPSL-CM6A-LR	+2.38	[+0.59, +5.33]		
	MPI-ESM1-2-LR	+1.20	[−0.09, +2.58]		
	UKESM1-0-LL	+2.63	[+0.34, +5.87]		
	<i>Pooled mean</i>	+1.84			
ΔS (psu)	CMCC-ESM2	−1.38	[−1.94, −0.59]	[−2.5, +0.3]	Pooled model KDE median = −1.30 psu 5th–95th = [−2.43, −0.28]
	IPSL-CM6A-LR	−0.99	[−1.82, −0.09]		
	MPI-ESM1-2-LR	−0.78	[−1.30, −0.25]		
	UKESM1-0-LL	−2.29	[−2.98, −1.63]		
	<i>Pooled mean</i>	−1.36			
$\Delta\eta$ (m)	NASA AR6 5th percentile		0.242	NASA AR6	PERT (0.242, 0.490, 0.853) m
	NASA AR6 50th percentile		0.490		
	NASA AR6 95th percentile		0.853		

envelope of +1.5 to +3.5°C. While the means for CMCC-ESM2 and MPI-ESM1-2-LR fall marginally below the ICES lower bound, this discrepancy reflects an AMOC-driven suppression of the annual mean via winter cooling (as discussed in Section 5.3.3), rather than a fundamental model deficiency.

For salinity, all four models project a consistent freshening trend, with no ensemble member producing a positive delta. The model means range from −0.78 psu (MPI-ESM1-2-LR) to −2.29 psu (UKESM1-0-LL), yielding a pooled mean of −1.36 psu. This entire spread sits comfortably within the Kristiansen et al. (2024) range of −2.5 to +0.3 psu. Furthermore, this uniform freshening is physically consistent with the expected response of the North Atlantic freshwater budget to greenhouse gas forcing and AMOC weakening (Holliday et al., 2020).

Two methodological considerations help contextualize these comparisons. First, the published literature ranges do not align perfectly with the 2075 horizon: the ICES assessment spans 2050 to 2099, while the Kristiansen et al. (2024) projections target the end of the century. Because the 2075 model results align well with these broader literature timeframes, the derived distributions clearly represent a realistic mid century trajectory. Additionally, the chosen delta method prevents underlying model biases from skewing the final ranges. Any systematic error present in a model’s historical baseline will also exist in its future projection. When the historical data is subtracted from the future data using Equation 5.1, this constant error naturally cancels out. As a result, the calculated offset captures only the isolated climate change signal, effectively removing the model’s absolute baseline error (Cannon et al., 2015), assuming it does not change across simulations.

For sea level rise, the NASA IPCC AR6 projections inherently serve as their own literature check. Because the tool directly maps the global consensus projections from IPCC AR6 Chapter 9 (Fox-Kemper et al., 2021), the dataset represents a comprehensive, peer-reviewed synthesis of the most advanced ice sheet, glacier, and steric modeling available. It is therefore already the most authoritative baseline for this location and scenario. While the tool also reports a low-confidence 95th percentile of 1.136 m (reflecting extreme scenarios with accelerated Antarctic ice sheet instability), this upper extreme was intentionally excluded. Instead, the final distribution relies strictly on the medium-confidence framework to maintain methodological consistency across all three perturbed parameters.

5.4. Ensemble Design

5.4.1. Distribution Selection

Having confirmed that the CMIP6 model ranges are consistent with the broader literature, the first step in designing the ensemble is to construct the final sampling distributions.

For temperature (ΔT) and salinity (ΔS), a Kernel Density Estimate (KDE) was fitted to the 360 monthly

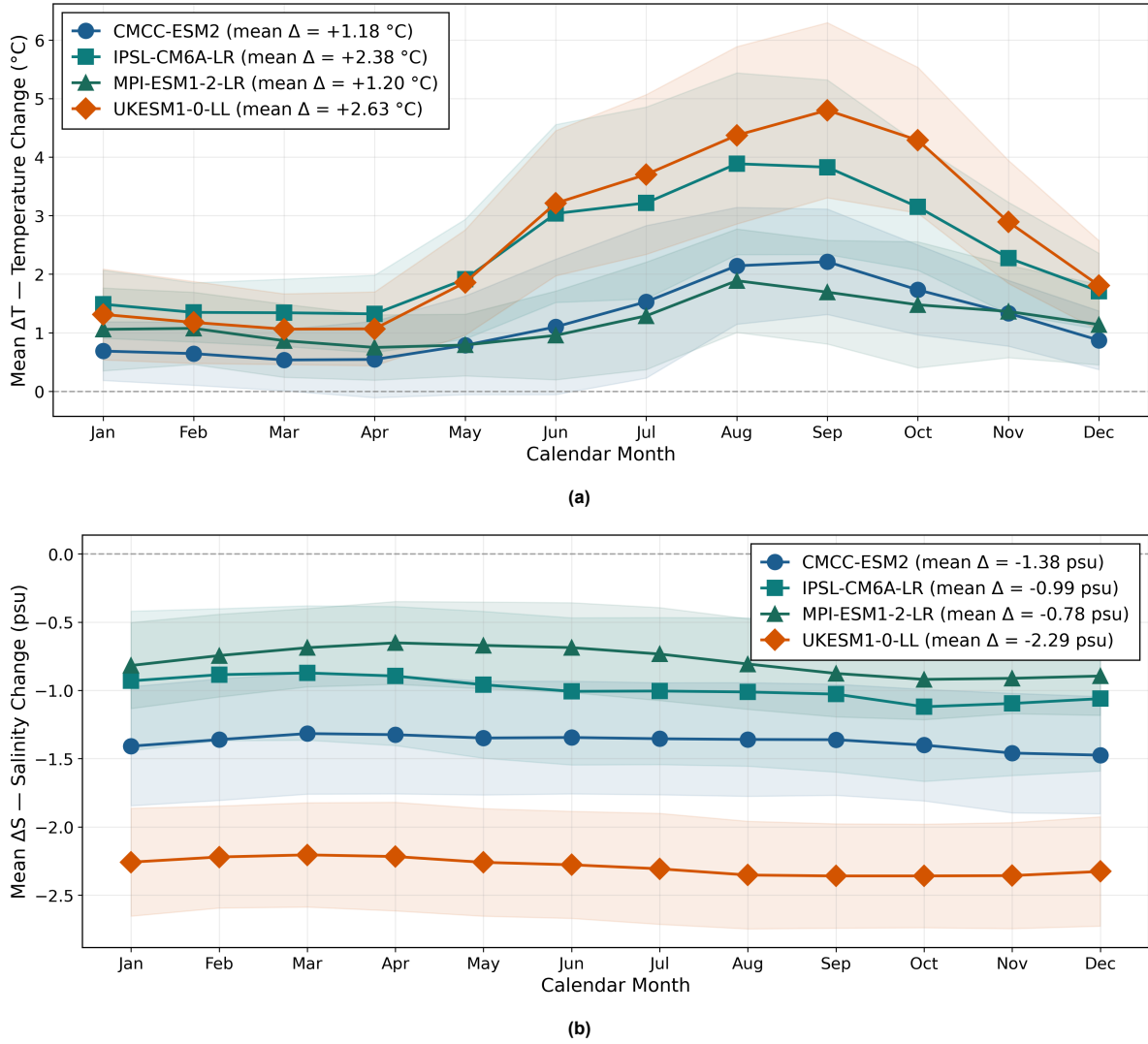


Figure 5.6: CMIP6 model spread for (a) ΔT and (b) ΔS at the 2075 horizon compared against published literature ranges. Each point represents the annual mean delta of one model; horizontal bars show the individual model 5th–95th percentile spread across the 360 month-matched delta values. The shaded band indicates the literature range from Kristiansen et al. (2024); the dashed lines indicate the ICES Celtic Seas bounds.

delta values from each model. The four individual KDEs were then pooled into a single distribution, giving equal weight to each model. This pooled KDE successfully captures the full inter-model spread, including the low warming tail of CMCC-ESM2 and the extreme high warming and freshening tail of UKESM1-0-LL.

Initially, a combined distribution blending this pooled model KDE with a Program Evaluation and Review Technique (PERT) distribution built from the literature bounds was evaluated. However, this approach was ultimately discarded for two methodological reasons. First, assigning an equal statistical weight between the four local models and the broader literature cannot be objectively justified. The literature synthesizes a much larger ensemble, which might argue for a higher weight, but selecting a specific ratio requires arbitrary assumptions. Second, published assessments typically provide only the minimum, mode, and maximum values rather than the underlying probability density. Consequently, the PERT shape itself is an assumption. Blending a distribution of uncertain shape with a KDE risks introducing artificial structures that lack a physical basis.

The pooled model KDE was therefore adopted as the final sampling distribution for both ΔT and ΔS . As demonstrated in Figures 5.7a and 5.7b, the model KDE already encompasses the literature bounds for both variables. For temperature, the pooled 5th to 95th percentile range of $[+0.15, +4.01]^{\circ}\text{C}$ extends beyond the literature limits on both extremes. For salinity, the model spread similarly covers and slightly exceeds the published range on the freshening side. Because the literature comparison confirms rather than constrains the model distribution, artificial blending is unnecessary to achieve adequate coverage of the uncertainty space.

For sea level rise ($\Delta\eta$), a different approach was required. Instead of fitting a standard parametric curve to the quantiles, which forces an assumed shape unconstrained by the actual data and introduces arbitrary behaviors at the distribution tails, a direct empirical inverse cumulative distribution function (CDF) was applied (Figure 5.7c). Connecting the five quantile value pairs with piecewise linear segments is a standard non parametric approach in hydrology and climate bias correction (Cannon et al., 2015). The resulting inverse CDF smoothly maps any uniform sample to a sea level value while honoring the projected decadal constraints exactly.

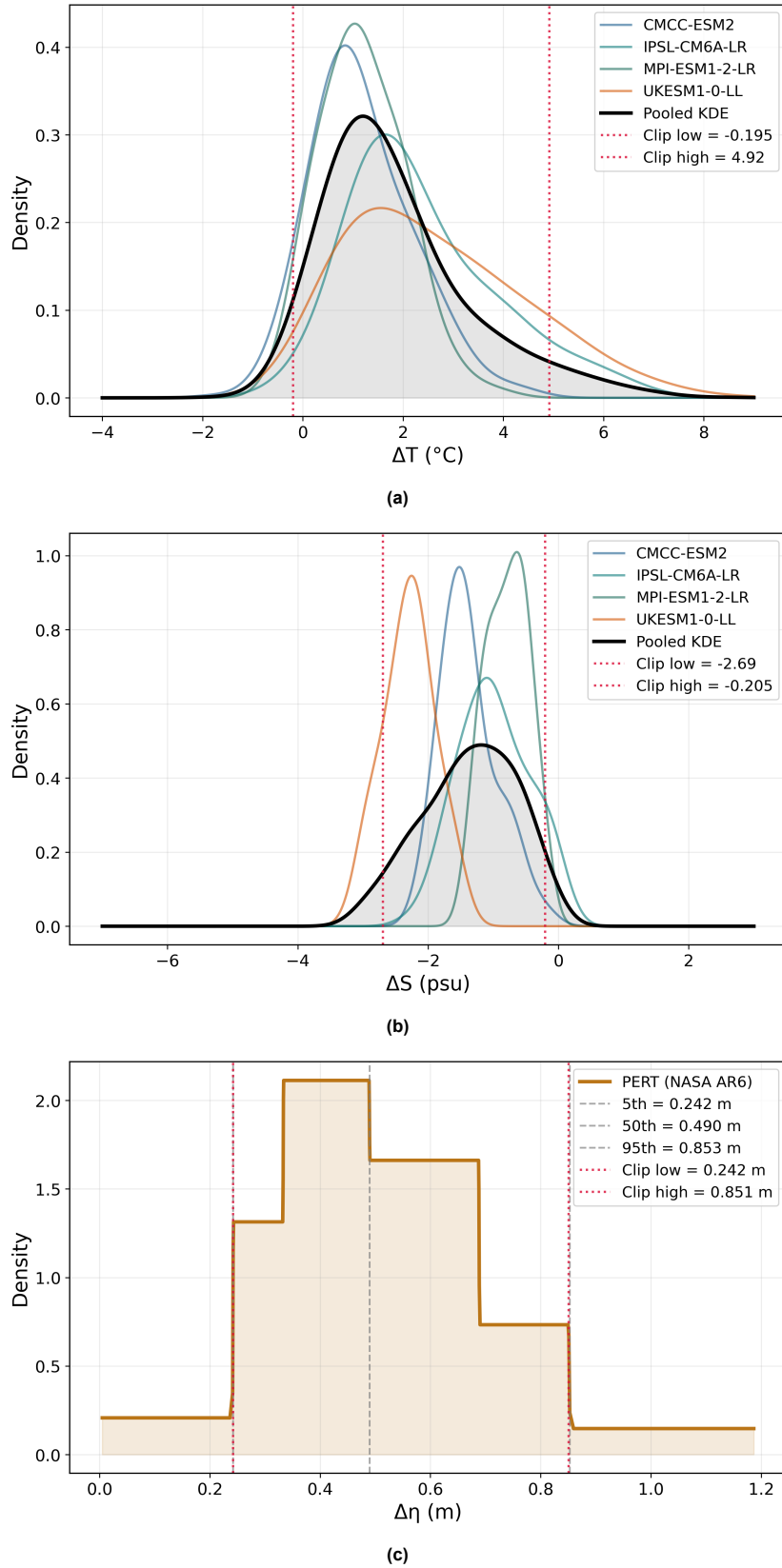


Figure 5.7: Source probability distributions for the three boundary perturbations (a) Temperature change (ΔT), (b) Salinity change (ΔS) and (c) Sea-level change ($\Delta \eta$), at the 2075 horizon under SSP5-8.5 at 51.5°N, 10.2°W. For (a) ΔT and (b) ΔS , individual model KDEs are shown in colour and the pooled all-model KDE in black; for (c) $\Delta \eta$, the PERT distribution derived from the NASA AR6 percentiles is shown. Crimson dotted lines mark the clip bounds applied before sampling; grey dashed lines in (c) mark the NASA AR6 5th/50th/95th percentiles.

5.4.2. Ensemble Sampling 3D Design

Independence Versus Correlation Structure

Before generating the multidimensional samples, a critical decision is whether to treat the three boundary parameters as strictly independent or to impose a statistical correlation structure.

A physical argument does exist for correlating temperature and salinity changes, as a weakening AMOC produces both reduced warming and stronger freshening simultaneously. However, the extracted climate data does not statistically support imposing a formal mathematical correlation. Pearson's correlation coefficient is used here because the claim being tested is specifically linear co-variation between two continuous physical quantities on their raw scale, the question is whether a stronger ΔT is accompanied by a proportionally stronger ΔS , not merely whether the two are monotonically related. The Pearson correlation coefficient between the temperature and salinity deltas across the pooled monthly CMIP6 samples is weak and negative ($r = -0.24$, $n = 1440$). The negative sign is physically consistent with a weakening AMOC, which produces reduced warming alongside stronger freshening. A two-sided t-test confirms that, given the large sample size, this correlation is statistically significant ($t = -9.2$, $p < 0.001$); however, significance here reflects the large sample size rather than practical relevance. The effect size remains negligible: the shared variance explains only about 6 percent of the total ($r^2 \approx 0.06$), making the joint distribution virtually indistinguishable from independent marginal distributions.

Sea level rise ($\Delta\eta$) is likewise treated as independent, since at this horizon it is dominated by global-scale thermal expansion and land-ice melt that operate largely independently of the local seasonal thermohaline variability, and the projections provide no statistical basis for a $\Delta\eta$ – ΔT or $\Delta\eta$ – ΔS correlation. Forcing a correlation structure would introduce modeling assumptions.

Furthermore, maintaining an independent sampling design provides a strict practical advantage. The Partial Rank Correlation Coefficient (PRCC) method, which is utilized later to map hydrodynamic sensitivity, fundamentally assumes independent input variables (Pianosi et al., 2016). Imposing a correlation during the generation phase would violate the core mathematical assumptions of the PRCC method. The independent design is therefore adopted as a deliberate first-approach simplification, grounded in the weakness of the empirical correlation (r) rather than a claim that the correlation is negligible or physically meaningless. Testing the ensemble's sensitivity to imposing this correlation explicitly is identified as recommended extension in Section 8.2. It should be noted that this design is not strictly conservative with respect to compound extremes: were the drivers genuinely correlated, the probability of their joint extreme occurrence would be higher than under the independence assumption. Rather, independence is justified because the data do not support a dependence structure and because it cleanly satisfies the assumptions of the sensitivity method applied downstream.

5.4.3. Samples Generation

The final ensemble requires 50 hydrodynamic model runs. This number represents a practical balance between the heavy computational expense of running the Delft3D-FM model and the statistical robustness required for sensitivity analysis. To select these 50 optimal members, a two-step generation process was employed, combining two distinct algorithms: first, a large candidate pool was generated by inverse transform sampling from the marginal distributions; second, the Maximum Dissimilarity Algorithm (MDA) was applied to filter this pool down to the most representative, evenly spread subset. Both stages are described below. Both stages were implemented directly in Python. The candidate pool was drawn by inverse-transform sampling: uniform random draws were generated with NumPy's `random.uniform`, and each variable's inverse CDF was evaluated via SciPy's `interpolate.interp1d` applied to the empirical CDF (for ΔT , ΔS) or the AR6 percentile fit (for $\Delta\eta$). The MDA was implemented from scratch, following the greedy maximin formulation of Kennard and Stone (1969), using NumPy's pairwise Euclidean distance computation rather than an external MDA package.

Candidate Pool via Inverse Transform Sampling

To prevent sampling physically impossible conditions that could destabilize the hydrodynamic model, the theoretical probability distributions were explicitly clipped to their defined minimum and maximum bounds. Each climate variable $X \in \{\Delta T, \Delta S, \Delta\eta\}$ is characterized by a marginal cumulative distribution function $F_X(x)$. For temperature and salinity, this CDF is derived by integrating the pooled model KDE; for sea level rise, it is the empirical CDF defined previously.

To draw random samples from these distributions, the probability integral transform is applied:

$$X = F_X^{-1}(u), \quad u \sim \mathcal{U}(0, 1) \quad (5.2)$$

where F_X^{-1} represents the inverse CDF (or quantile function) of the respective variable. To avoid boundary pileup near the absolute distribution tails, the sampling domain is restricted to the 5th to 95th percentile range before drawing. Restricting the sampling domain to the 5th–95th percentile range reflects a deliberate focus on the central, well-constrained portion of the projected uncertainty rather than on distribution tails. The extreme tails of the CMIP6-derived distributions are populated by very few model-months and are therefore poorly constrained statistically; sampling them would risk driving the hydrodynamic model with values that are numerical artefacts of the KDE rather than physically credible boundary conditions. The objective here is to characterise hydrodynamic sensitivity across the plausible central range, so the most extreme percentiles are intentionally excluded. The inverse CDF is remapped as:

$$\tilde{F}_X^{-1}(u) = \text{clip}(F_X^{-1}(u), F_X^{-1}(0.05), F_X^{-1}(0.95)), \quad u \in [0, 1] \quad (5.3)$$

so that all sampled values fall strictly within $[x_{0.05}, x_{0.95}]$ by construction.

A pool of $N_c = 5,000$ independent candidate triplets is then generated. Producing this large candidate pool is computationally inexpensive and ensures the probability space is densely populated, providing a rich foundation for the spatial filtering algorithm. The candidates are defined as:

$$\mathbf{c}_i = (\tilde{F}_{\Delta T}^{-1}(u_i^{(1)}), \tilde{F}_{\Delta S}^{-1}(u_i^{(2)}), \tilde{F}_{\Delta \eta}^{-1}(u_i^{(3)})), \quad i = 1, \dots, N_c \quad (5.4)$$

where $u_i^{(1)}, u_i^{(2)}, u_i^{(3)} \stackrel{\text{iid}}{\sim} \mathcal{U}(0, 1)$ are drawn independently, ensuring the three variables remain uncorrelated in the candidate pool.

Maximum Dissimilarity Algorithm

From the 5,000 available candidates, the final 50 members are selected using the Maximum Dissimilarity Algorithm (MDA) (**Kennard1969**). Random sampling alone can lead to unintended clustering, where multiple samples test nearly identical conditions while leaving other regions of the parameter space empty. The MDA prevents this by actively selecting points that are as far away from each other as possible.

Because the three variables have completely different units and magnitudes, all candidates are first normalized to a unit cube to ensure equal weighting during distance calculations:

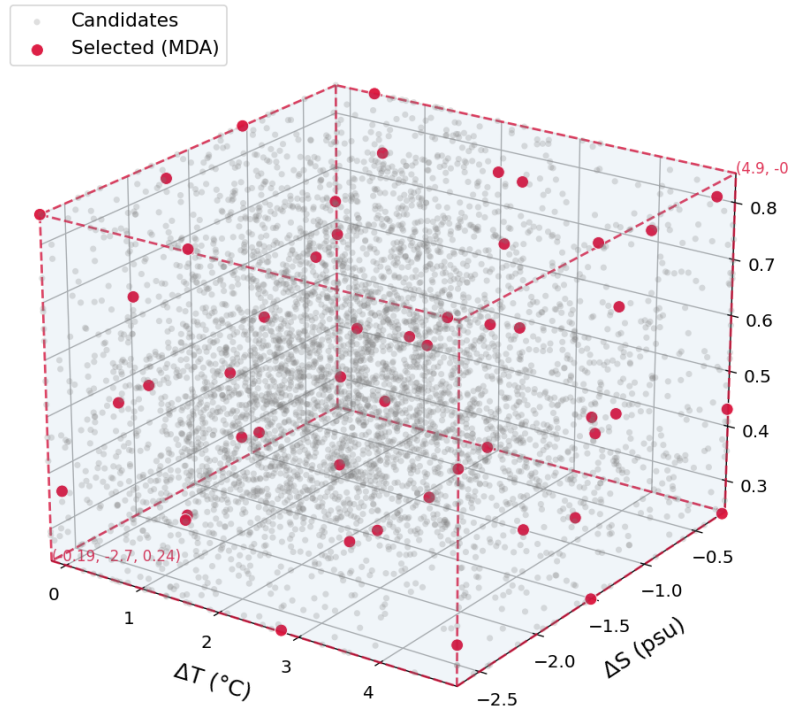
$$\hat{\mathbf{c}}_i = \frac{\mathbf{c}_i - \mathbf{x}_{\min}}{\mathbf{x}_{\max} - \mathbf{x}_{\min}} \in [0, 1]^3 \quad (5.5)$$

where $\mathbf{x}_{\min}$ and $\mathbf{x}_{\max}$ are the component wise minimum and maximum of the candidate pool.

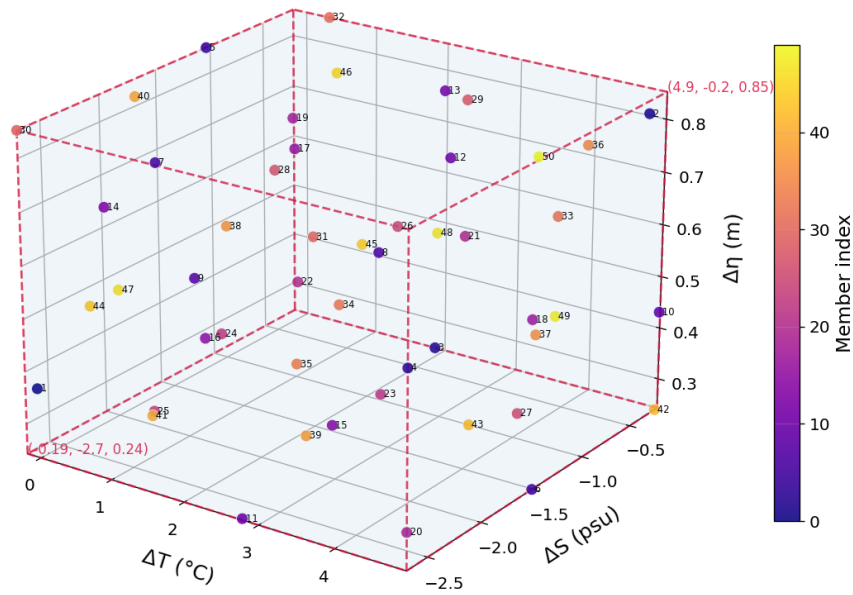
The algorithm then proceeds greedily. Let S_k denote the set of k already selected indices. The $(k+1)$ -th member is chosen as the candidate that maximizes the minimum Euclidean distance to all previously selected points:

$$i^* = \arg \max_{i \notin S_k} \min_{j \in S_k} \|\hat{\mathbf{c}}_i - \hat{\mathbf{c}}_j\|_2 \quad (5.6)$$

The first point is chosen at random, and Equation 5.6 is applied iteratively until 50 members are selected. The outcome is a set of points perfectly spread across the bounded parameter space. This is visually confirmed in Figure 5.8: the left panel shows the dense 5,000 candidate pool with the selected members highlighted, while the right panel displays the final, evenly distributed 50 member ensemble.



(a)



(b)

Figure 5.8: Maximum Dissimilarity Algorithm selection in the three-dimensional parameter space (ΔT , ΔS , $\Delta \eta$). (a) The 5,000 candidate pool, with the 50 MDA-selected members highlighted in red; (b) The final 50-member ensemble, coloured by member index. The dashed crimson box marks the 5th–95th percentile bounds used to clip the sampling domain.

Coverage Quality of the Final Ensemble

The space filling quality of the MDA can be quantified mathematically by the *coverage radius* (r). This metric represents the largest empty gap in the parameter space, defined as the maximum distance from any unselected candidate to its nearest selected member:

$$r = \max_{i=1,\dots,5000} \min_{j \in S} \|\hat{\mathbf{c}}_i - \hat{\mathbf{c}}_j\|_2 = 0.2596 \quad (5.7)$$

The mean minimum distance across all candidates is $\bar{d} = 0.1477$, which is substantially smaller than r , indicating that the maximum identified gap is localized rather than systematic. The most isolated candidate corresponds to the triplet $(\Delta T, \Delta S, \Delta \eta) = (-0.04^\circ\text{C}, -0.736 \text{ psu}, 0.371 \text{ m})$, a near central combination located between two selected members. This behavior is consistent with the known mechanics of the MDA, which prioritizes filling the boundaries of a domain first and may leave occasional interior gaps (Camus et al., 2011).

As a theoretical benchmark, the expected coverage radius for N points in a d -dimensional unit cube scales as (Niederreiter, 1992):

$$r_{\text{ref}} \sim N^{-1/d} \quad (5.8)$$

For 50 members in three dimensions, this yields $r_{\text{ref}} = 50^{-1/3} \approx 0.272$. The achieved value of $r = 0.2596$ falls below this theoretical expectation, mathematically confirming that the MDA selection performs at or better than the optimum theoretical spread for this ensemble size.

Figure 5.9 displays the full distribution of minimum distances. The spike at zero corresponds to the 50 selected members themselves. The remaining 4,950 candidates form a near symmetric, bell shaped distribution centered near $\bar{d} = 0.1477$, with the coverage radius sitting safely at the far right tail. A uniform or heavy right tailed distribution would indicate poor spatial coverage; the tight, bell shaped profile observed here confirms that no region of the bounded parameter space is left significantly underrepresented.

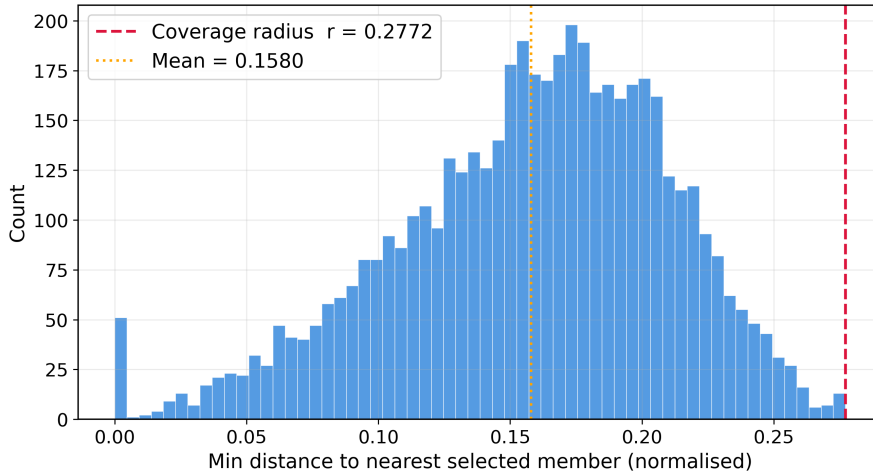


Figure 5.9: Distribution of minimum distances from each of the 5,000 candidates to its nearest MDA selected member in the normalized parameter space. The spike at zero corresponds to the 50 selected members themselves. The dotted orange line marks the mean minimum distance ($\bar{d} = 0.1477$) and the dashed red line marks the coverage radius ($r = 0.2596$). The near symmetric bulk of the distribution confirms that the MDA selection leaves no large unsampled regions.

Final Ensemble Output

The 50 selected combinations establish the final hydrodynamic testing framework. These parameters were exported and are fully listed in Appendix A. Each row represents one discrete ensemble member defined by the triplet $(\Delta T, \Delta S, \Delta \eta)$, which is passed directly to the Delft3D-FM model as the future boundary condition perturbation.

5.5. Formulation of Future Boundary Conditions

5.5.1. Applying the Climate Perturbations

The final step before simulation is translating the 50 selected parameter combinations into functional boundary conditions. The extracted climate deltas (ΔT , ΔS , $\Delta \eta$) were applied to the model using a standard delta-change methodology. This approach superimposes a constant mean shift onto a dynamic historical baseline, preserving the observed high-frequency variability (such as tides and seasonal cycles) while shifting the overall mean state to reflect future climate forcing (Toimil et al., 2020).

Water Level

To represent future mean sea level, the perturbation $\Delta \eta$ was added directly on top of the existing CMEMS tidal and steric signal. In Delft3D-FM, this superposition is achieved by defining a second [Boundary] block for `waterlevelbnd` in the external forcing (.ext) file with the OPERAND = + flag, instructing the solver to sum the two inputs. The auxiliary file `waterlevelbnd_CC.bc` contains a single constant value equal to $\Delta \eta^{(k)}$ that is held constant from $t = 0$ until the end of the simulation:

$$\eta^{(k)}(t) = \eta_{\text{base}}(t) + \Delta \eta^{(k)} \quad (5.9)$$

Figure 5.10 illustrates this application for one example ensemble member ($\Delta T = +1.5^\circ\text{C}$, $\Delta S = -0.3 \text{ psu}$, $\Delta \eta = +0.2279 \text{ m}$). The baseline CMEMS signal preserves all observed seasonal and sub-tidal variability, while the perturbed series is shifted vertically by a constant magnitude across the entire simulation period. The exact same logic applies to temperature and salinity at the open boundary, where the scalars $\Delta T^{(k)}$ or $\Delta S^{(k)}$ are added uniformly to every time step and every vertical layer of the baseline CMEMS profile.

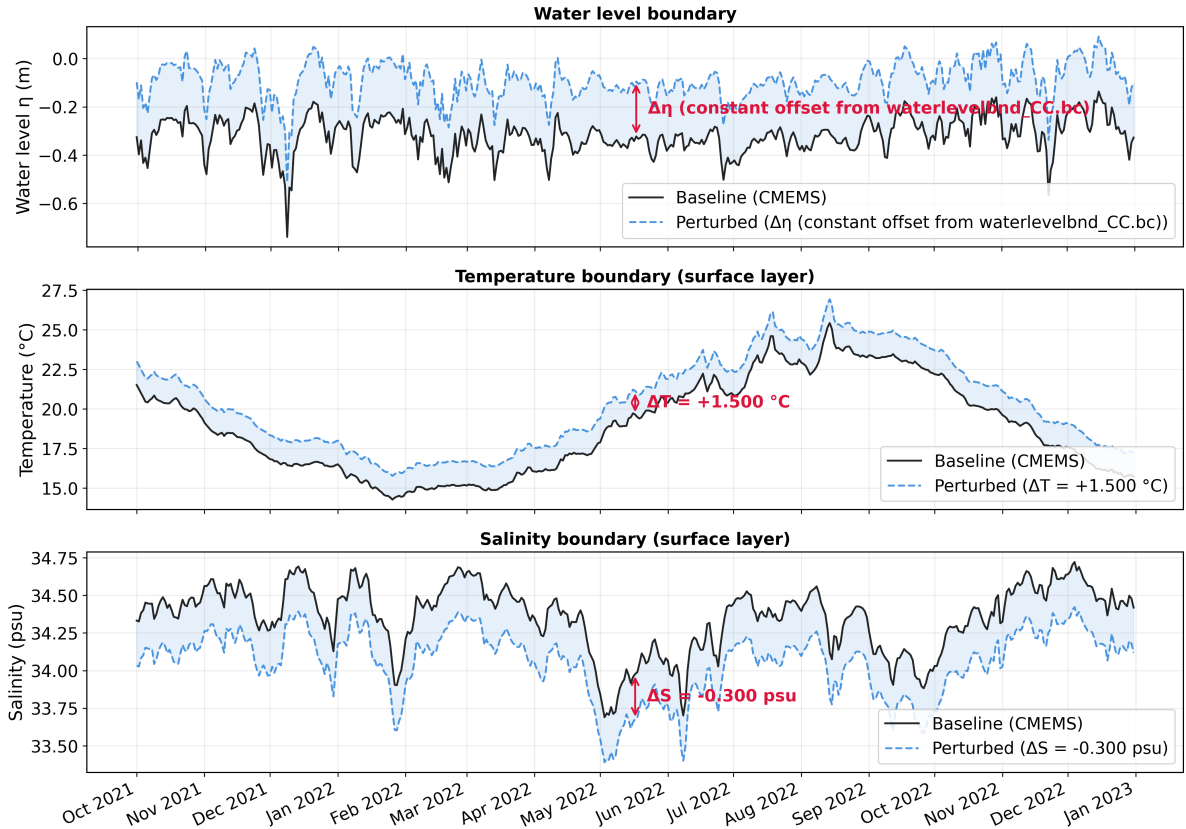


Figure 5.10: Open boundary conditions for one example ensemble member ($\Delta T = +1.5^\circ\text{C}$, $\Delta S = -0.3 \text{ psu}$, $\Delta \eta = +0.2279 \text{ m}$). Black lines show the baseline CMEMS signal; dashed blue lines show the perturbed signal. The shaded area represents the constant delta imposed for each variable. Water level (top), surface temperature (middle), and surface salinity (bottom) are shown for boundary node 1.

5.5.2. Numerical Stability and Nudging

Applying ΔT and ΔS exclusively at the open boundary nodes creates an immediate, artificial spatial gradient. The boundary is instantly shifted to the future climate state, while the rest of the domain initializes from present-day conditions. In early test runs, this unmitigated gradient was large enough to cause numerical instability, causing the model to crash within the first few tidal cycles as the solver struggled to advect the steep tracer fronts inward.

The standard procedure in Delft3D-FM for maintaining internal tracer consistency is to employ a nudge file, which provides a three-dimensional field of target temperature and salinity values that the model interior is gradually relaxed towards (Warner et al., 2005). The nudging equation is defined as:

$$\frac{\partial \phi}{\partial t} = \mathcal{F}(\phi) + \frac{1}{\tau} (\phi_{\text{nudge}}^{(k)} - \phi) \quad (5.10)$$

where ϕ is the modeled temperature or salinity, $\mathcal{F}(\phi)$ represents the internal model dynamics, $\phi_{\text{nudge}}^{(k)}$ is the target field from the nudge file of member k , and τ is the relaxation timescale. A small τ forces the model strongly towards the target field, whereas a large τ allows the interior to evolve dynamically.

During initial testing, the original baseline nudge file was left unmodified, meaning it still pointed to present-day climatology. Consequently, the open boundary was actively pushed towards the future climate state while the interior was simultaneously pulled back towards the historical baseline. This conflicting forcing produced a sharp tracer front that amplified with each tidal cycle until failure. Updating the nudge file by adding $\Delta T^{(k)}$ and $\Delta S^{(k)}$ uniformly to the three-dimensional temperature and salinity fields at every grid cell resolved the most severe instabilities.

However, a subset of ensemble members containing extreme parameter combinations still experienced failure. To guarantee stability across the entire parameter space, two additional numerical safeguards were introduced. First, the maximum timestep (Δt_{max}) was reduced compared to the baseline calibration run to satisfy the Courant-Friedrichs-Lewy (CFL) condition under the steepened interior gradients. Second, the Fourier smoothing parameter (t1fSmo) was set to 86,400 s (one day). This parameter smoothly ramps up the tidal constituent forcing at the start of the simulation, rather than imposing it as an instantaneous shock at $t = 0$ (Deltares, 2025). With these three structural adjustments combined, all 50 ensemble members ran to completion without instability.

5.6. Simulation Workflow

The calibrated baseline Delft3D-FM model, representing the 2022 temporal period, served as the foundational architecture for the entire ensemble. The water level performance of this baseline setup was previously validated against the single available tide gauge in Bantry Bay.

To execute the experiment, an automated Python workflow was developed (Figure 5.11). The baseline directory was duplicated 50 times (Run001 through Run050). A script then iterated over each directory, injecting the specific parameter triplet from the MDA-selected ensemble. Specifically, the script generated the `waterlevelbnd_CC.bc` file with the respective $\Delta \eta^{(k)}$ offset, updated the main temperature and salinity boundary condition files, and applied the corresponding thermal and saline offsets to the full three-dimensional nudge file. The external forcing (`.ext`) and main configuration (`.mdu`) files were concurrently updated to link the correct boundary files, apply the reduced Δt_{max} , and activate the `t1fSmo` smoothing parameter.

All 50 finalized model configurations were subsequently submitted to the High-Performance Computing (HPC) cluster. Each simulation encompassed a three-month spin-up phase followed by a full calendar year of simulation, amounting to 15 months of modeled hydrodynamic time per run.

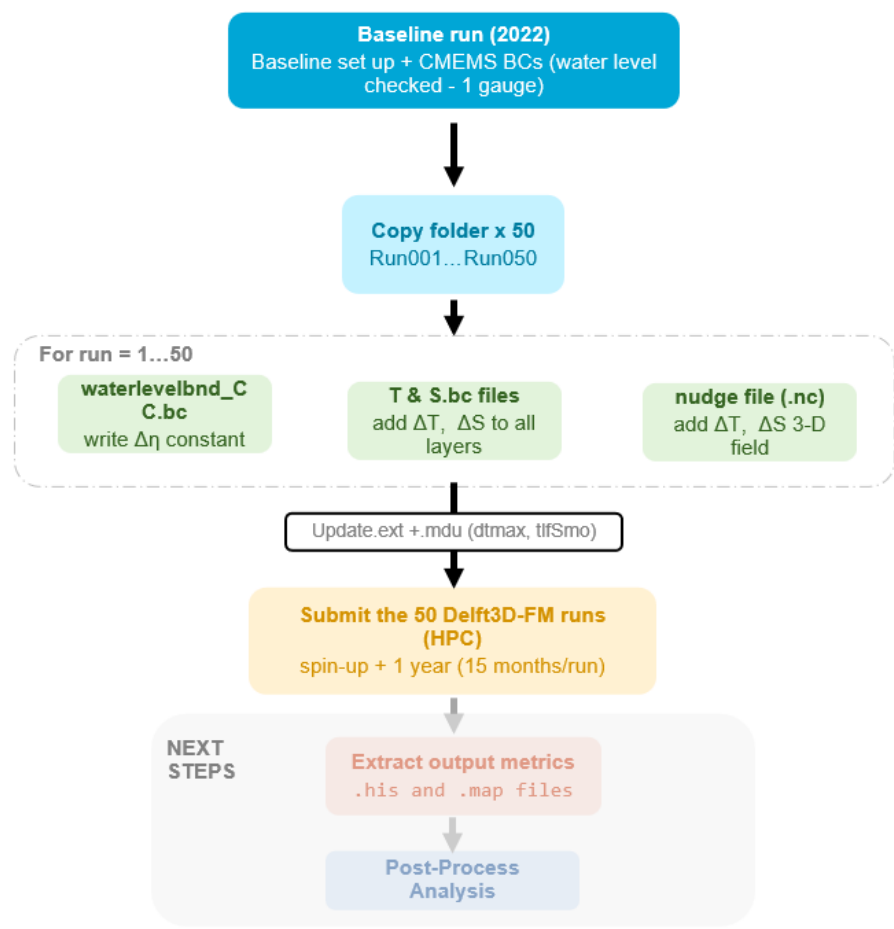


Figure 5.11: Automated simulation workflow for the 50-member ensemble. The baseline folder is duplicated 50 times. A Python script systematically applies the climate perturbations (ΔT , ΔS , $\Delta\eta$) to the specific boundary condition and nudge files of each copy before parallel submission to the HPC cluster.

With the computational execution of the 50-member ensemble complete, the focus shifts to extracting and post-processing the relevant hydrodynamic outputs. The subsequent sensitivity analysis and the formal mapping of the bay's uncertainty bounds are detailed in Chapter 6.

6

Results

6.1. Preamble: Methodological Context and Limitations

Before presenting the results, it is important to clarify the modelling approach adopted in this study and the assumptions that underpin all subsequent analyses. Three consequences follow, fixed 2022 meteorology, spatially uniform boundary offsets (ΔT , ΔS and $\Delta \eta$ each drawn from the 5th–95th percentile range of the projected change), and a 2022 baseline, which together mean the ensemble is best read as the sensitivity of a 2022-like bay to a 2075 boundary envelope rather than a forecast of the bay in 2075. These are revisited in the methodological reflection (Section 7).

6.2. Model Performance Assessment

Prior to analysing the ensemble results, it is necessary to establish that the underlying hydrodynamic model reproduces the observed tidal dynamics at Bantry Bay with sufficient accuracy. Water level observations from the Castletownbere Tide Gauge (operated by the Irish National Tide Gauge Network) were used for this purpose. Comparisons were performed between the modelled and observed water level, salinity and temperature time series over the full 2022 simulation period, following demeaning of both signals to remove the influence of mean sea level offsets.

The semi-diurnal tide is reproduced with high fidelity, and that quality is preserved across the whole ensemble rather than holding only for the baseline run. Pearson correlations stay at 0.995–0.996 and root-mean-square errors at 0.081–0.082 m for every one of the 50 members (Table A.13, Appendix A.5), with an ensemble mean of 0.081 m and 0.996. At three-decimal precision, RMSE and correlation each take only two distinct values across the full ensemble: the climate perturbations sampled here have no discernible effect on the model's tidal-fit skill. The annual overview in Figure 6.1 shows the same point from the other direction: the 50 water-level traces are visually indistinguishable, while the surface-salinity and surface-temperature traces fan out into bands whose width carries the climate signal that the rest of the chapter unpacks. Two members, runs 6 and 7, depart from the ensemble in mean water level specifically rather than tidal-fit skill; this is addressed in Section 6.7.1.

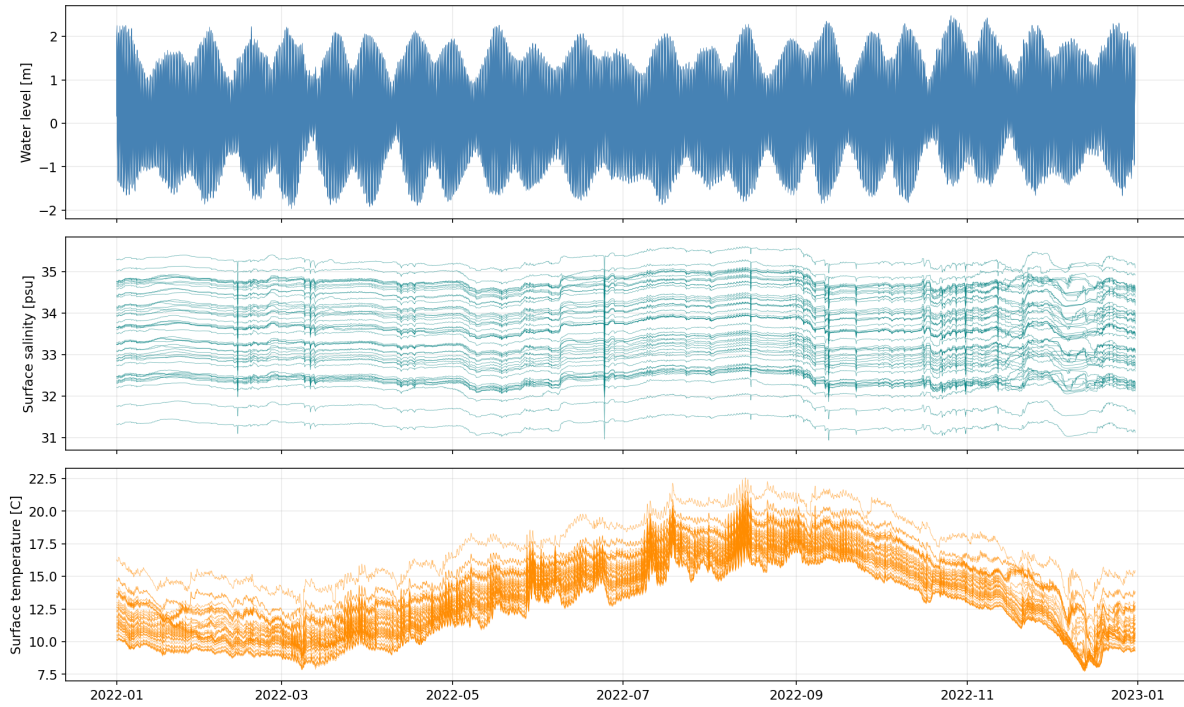


Figure 6.1: Ensemble annual overview of the three parameters

6.3. Parameter Sensitivity

The first research question asks which of the three boundary perturbations, ΔT , ΔS or $\Delta \eta$, exerts the strongest control over the hydrodynamic response of the bay. To answer it, Partial Rank Correlation Coefficients were computed between each input parameter and six scalar response variables, across the 50-member ensemble at all 16 observation stations. PRCC is a well-suited choice here, because it isolates the unique monotonic contribution of one parameter while holding the other two fixed, which is exactly the situation in an ensemble where the three offsets vary together. Significance was assessed with a two-tailed t -test at $\alpha = 0.05$ (S. Marino et al., 2008); coefficients that do not reach that level are drawn as hatched bars. The Partial Rank Correlation Coefficient formulation is given in Section 2.1 (Equation 2.1); Figure 6.2 applies it to the six response variables introduced there.

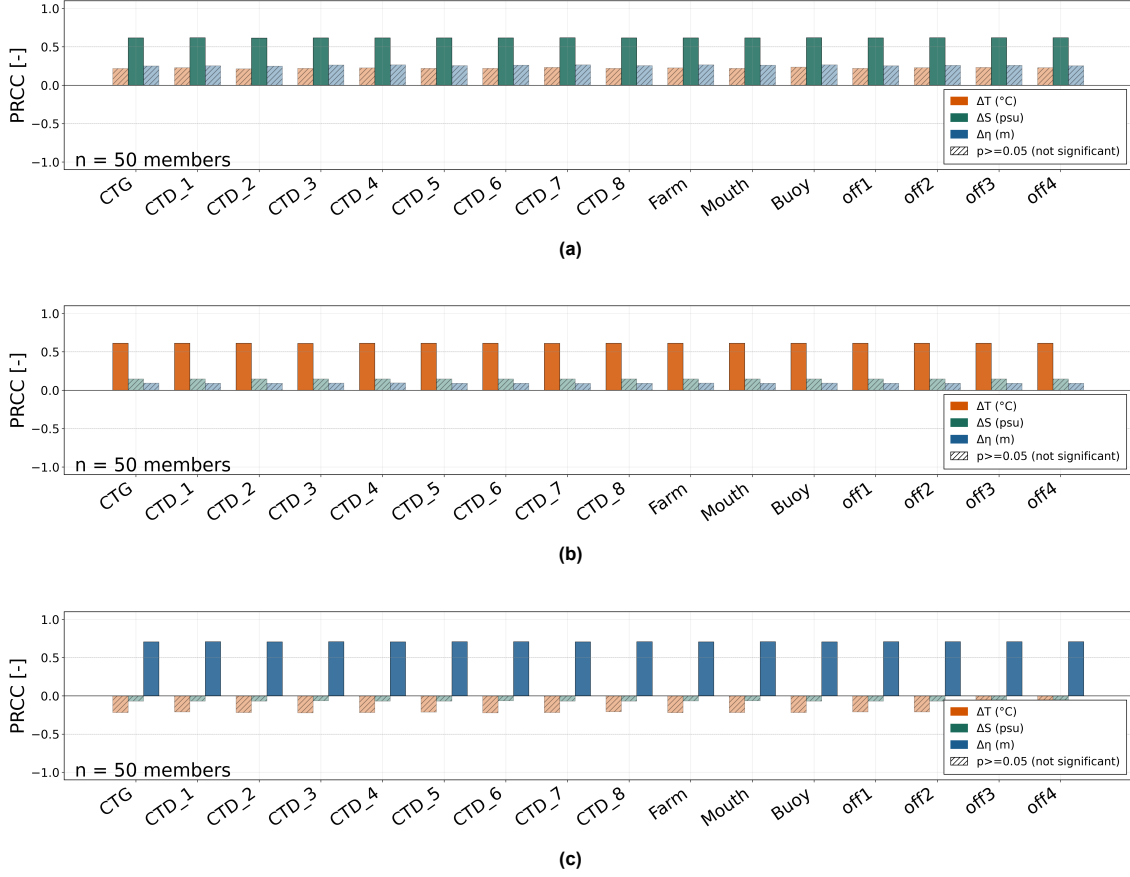


Figure 6.2: Partial Rank Correlation Coefficient (PRCC) sensitivity analysis for (a) Mean Salinity, (b) Mean Temperature, and (c) Mean Water Level.

The PRCC bar charts (Figure 6.2) reveal a clear and physically interpretable pattern of parameter dominance. The mean salinity response is governed almost entirely by ΔS ($\text{PRCC} \approx +0.62$, $p < 0.05$), confirming that the imposed boundary salinity offset propagates directly into the bay: stronger freshening at the open boundary produces correspondingly fresher inner-bay water. Mean surface temperature is most strongly driven by ΔT ($\text{PRCC} \approx +0.53$, $p < 0.05$), consistent with direct thermal forcing from the boundary. Mean water level is most strongly driven by $\Delta \eta$ ($\text{PRCC} \approx +0.65$, $p < 0.05$), reflecting the propagation of the prescribed sea level offset into the bay interior. No response variable is meaningfully driven by more than one parameter.

The sensitivity matrix (Figure 6.3) provides a spatially resolved view of these relationships across all stations and response variables simultaneously and two features stand out. First, ΔT carries a significant *negative* PRCC with tidal range at the inner-bay stations; the mechanism is discussed in Chapter 7. Second, ΔS and $\Delta \eta$ show negligible and largely non-significant PRCC values for mean water level and tidal range respectively, confirming that these responses are genuinely dominated by a single driver each and are not substantially influenced by the other parameters through linear mechanisms.

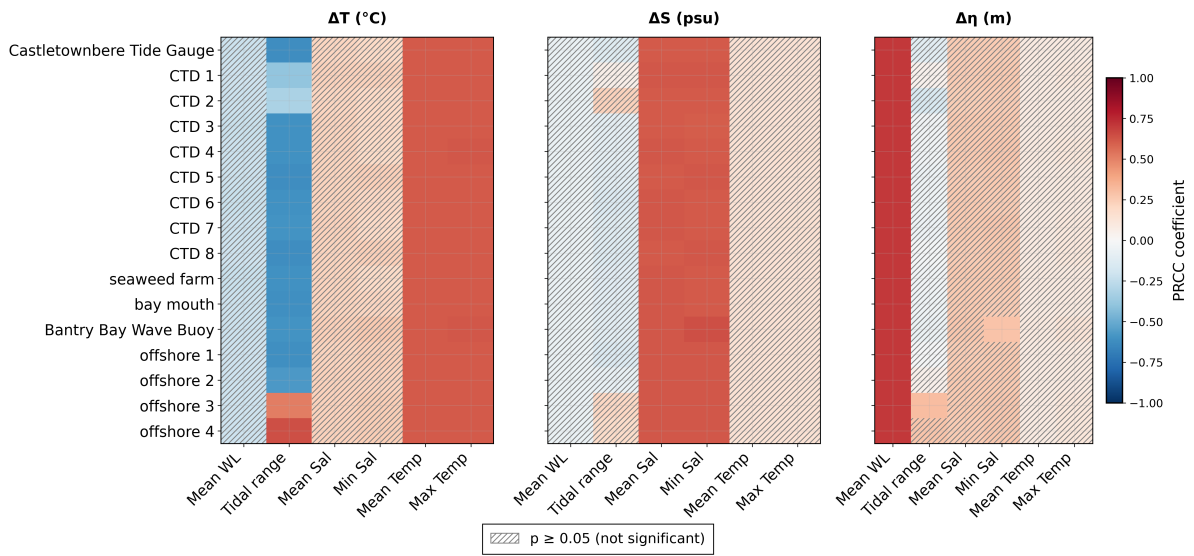


Figure 6.3: PRCC sensitivity matrix showing the influence of boundary parameters (ΔT , ΔS , $\Delta \eta$) on hydrodynamic response variables across all stations. Hatched cells indicate non-significant relationships ($p \geq 0.05$).

It should be noted that PRCC captures monotonic relationships between each individual input and the response (Section 2.1), including nonlinear ones, but is not designed to detect interaction effects between parameters, cases where two or more inputs jointly drive the response in a way not visible when each is considered separately. The implications of this limitation are explored further in Section 6.5.

6.4. Uncertainty Envelopes

The second research question concerns the width of the projection uncertainty for the key response variables. The analysis here focuses on the seaweed-farm station, the primary site of interest in this study. It is where the project's subsequent ecological and aquaculture modules will be applied, so the uncertainty in its physical conditions most directly informs those later stages. Both figures report the *surface* layer, that is, the topmost of the 20 vertical layers. This is the most relevant depth for analysis, as both suspended sugar kelp and blue mussels inhabit the near-surface water column, where they are most sensitive to variations in temperature and salinity.

Figure 6.4 presents the full-year 10/P50/P90 envelopes for water level, surface salinity and surface temperature at the seaweed-farm station, with the 2022 baseline overlaid. Figure 6.5 resolves the temperature and salinity distributions into monthly box plots across the 50 members. The exact ensemble statistics underlying both figures are tabulated in Appendix A.3.

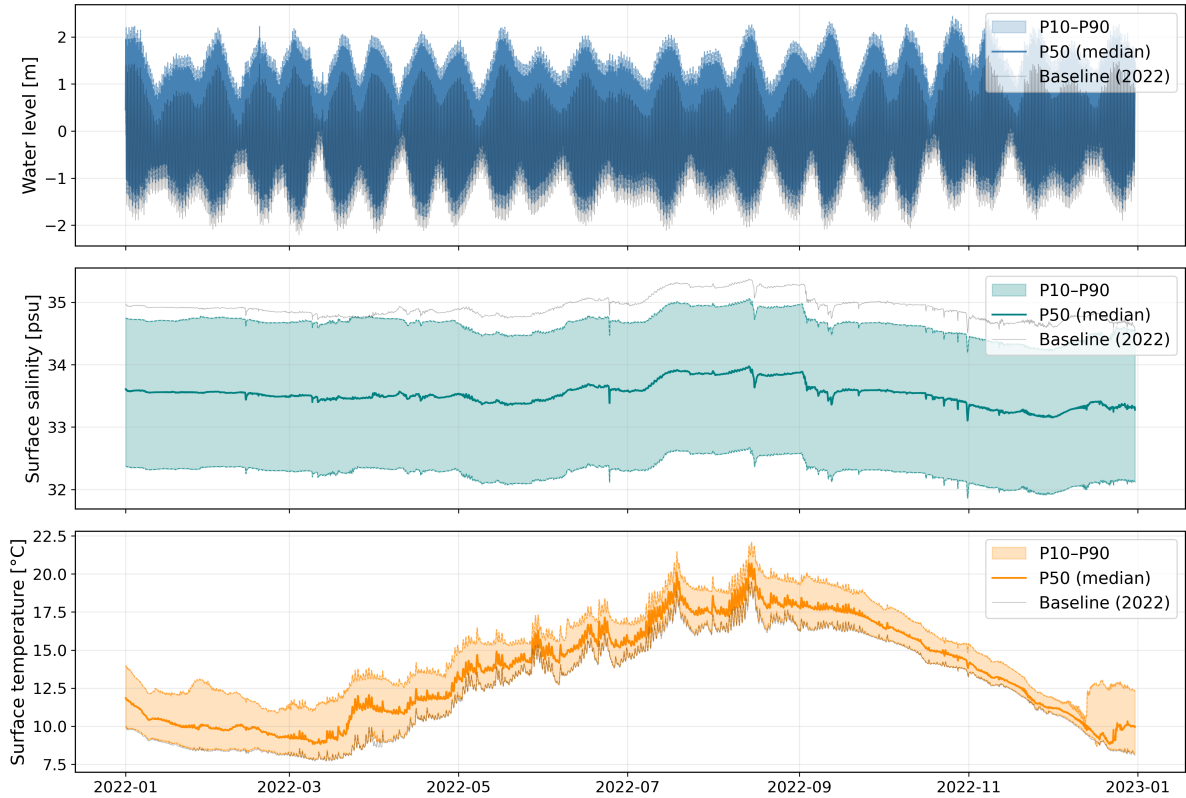


Figure 6.4: Ensemble uncertainty envelope (P10-P90) and median (P50) for surface temperature at the seaweed farm station, with the 2022 baseline shown in black. Every ensemble member warms relative to the baseline, which sits at the lower edge of the band.

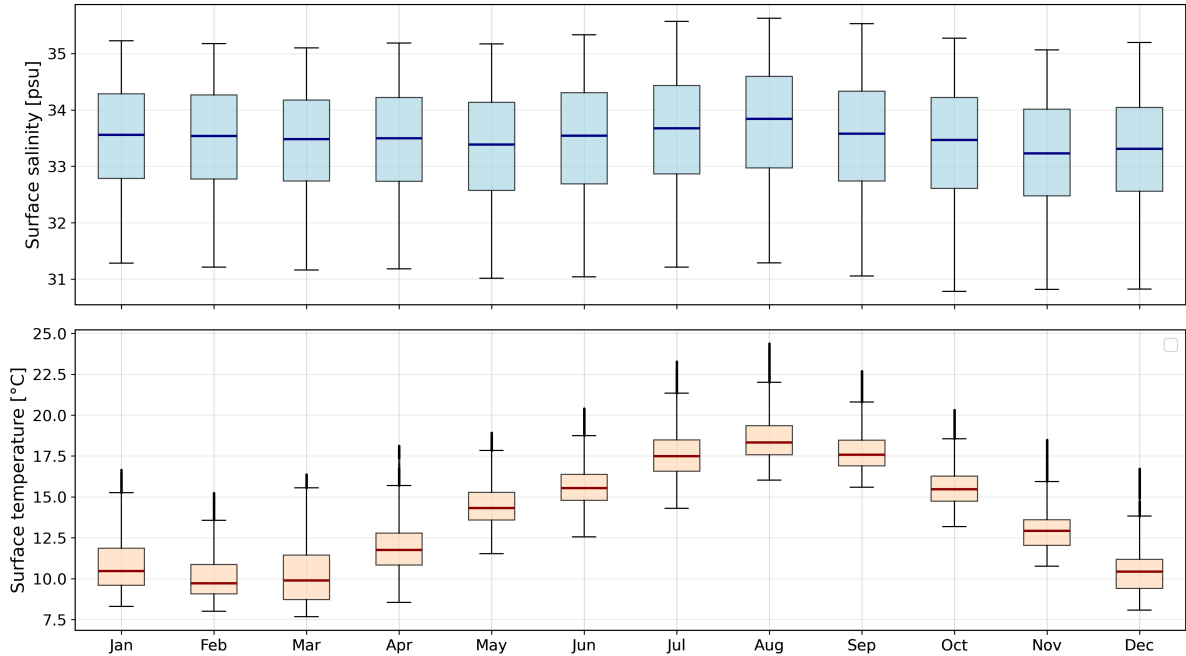


Figure 6.5: Seasonal distribution of ensemble spread for surface temperature and salinity at the seaweed farm station. Boxes show the inter-quartile range across the 50 ensemble members within each season; the temperature spread is largest in summer (June–August) and collapses in winter, whereas the salinity spread remains relatively stable year-round.

The water-level envelope is effectively a single band. The ensemble P10-P90 spread has a median of 0.55 m and a maximum of 0.57 m across the year, matching the prescribed $\Delta\eta$ range almost exactly, small against the roughly 4 m tidal range through which the band oscillates. The baseline runs through the centre of the band. The imposed sea-level offset therefore propagates into the bay as a near-constant mean shift rather than altering the tidal dynamics, consistent with the water-level skill reported in Section 6.2.

The surface-temperature response separates into two distinct signals that the two figures capture in turn, and it is worth keeping them apart. The instantaneous P10-P90 band in Figure 6.4 is in fact widest in winter, with a median spread of 3.5 °C across January-March (reaching 4.8 °C at its maximum), and narrowest in summer, with a median spread of 2.4 °C across July-August. This band width is dominated by short-term variability rather than by the climate signal: in the well-mixed winter column, individual members fluctuate strongly between timesteps, widening the instantaneous envelope, while the seasonal signal is carried by the median and the monthly distributions. This separation is evident in the monthly box-plots (Figure 6.5), where the inter-member spread within each month is far narrower than the instantaneous envelope. The seasonal climate signal, by contrast, is carried by the median and by the monthly distributions. The P50 surface temperature rises from about 10.3 °C in January through 11.7 °C in April to a summer maximum of 20.7 °C, then falls back to 10.0 °C by December. Across the whole ensemble and year the P10 floor is 7.8 °C and the P90 ceiling is 22.1 °C, the latter reached in August. The full monthly statistics underlying this envelope are tabulated in Appendix A.11.

The monthly box plots in Figure 6.5 show that the warmest months are also where the distribution sits highest and reaches furthest. The median monthly surface temperature climbs from around 10 °C in winter to 18.3 °C in August, and the distribution extends to 21.3 °C in July and 22.0 °C in August, against winter whisker maxima below 16 °C. The interquartile range itself is comparable between seasons (1.8-2.7 °C in winter, 1.8-1.9 °C in midsummer), so the distinguishing feature of summer is not a wider box but a higher and longer-tailed one: the upper tail of the ensemble pushes surface temperature furthest above the growth-relevant range precisely in July and August. The baseline lies at or below the ensemble median P50 at every timestep, and below the P10 envelope for 94% of the year. In other words, almost every ensemble member is warmer than 2022 across essentially the entire seasonal cycle, and the strongest warming appears in summer, where the warmest members pull the upper tail of the distribution furthest from the baseline.

The salinity response is, by contrast, seasonally flat in every measure. The P10-P90 envelope spans 2.37 psu in the median and stays within a narrow 2.27-2.50 psu across the entire year, with no summer amplification (the July-August median spread is also 2.37 psu). The ensemble median holds between 33.1 and 34.0 psu through the seasons. The annual P10 floor is 31.9 psu and the P90 ceiling 35.1 psu. The monthly box plots confirm this stability: the interquartile range stays close to 1.5 psu in every month, and the lower bound, the furthest credible excursion of the freshest members, never falls below 30.8 psu (its minimum, in October and November). The baseline lies above the ensemble P90 at every timestep, so every member is fresher than 2022, as expected from the imposed negative ΔS offsets.

Read together, the two figures answer the second research question for the seaweed-farm site. The projection uncertainty in salinity is small (~ 2.4 psu), stable year-round, and confined to a range that poses no stress risk. The temperature uncertainty is larger and structured: the instantaneous envelope is thickest in winter through short-term variability, but the climate-relevant uncertainty, the warming of the seasonal peak, is carried by the upper tail of the summer distribution, where the ensemble reaches 22 °C against a median of 20.7 °C. The physical reasons for this seasonal structure are taken up in Chapter 7.

6.5. Stress Exceedance

6.5.1. Species Selection and Stress Thresholds

The fourth research question moves from continuous responses to thresholds: when and where do conditions cross species-specific stress limits across the bay, and how do compound stress days vary across the ensemble. Answering it requires fixing both *which* species to examine and *where*, and the two choices are linked to the structure of aquaculture in Bantry Bay itself. The analysis centers on the commercial sugar kelp (*Saccharina latissima*) farm, the study's primary site. The bay also supports one

of Ireland's most significant blue mussel (*Mytilus edulis*) industries, whose licensed sites lie elsewhere in the inner bay and do not coincide with the kelp farm. Because the two species occupy different locations and tolerate different thermal and salinity ranges, the stress risk at one is not interchangeable with the other, which is why both are considered separately below.

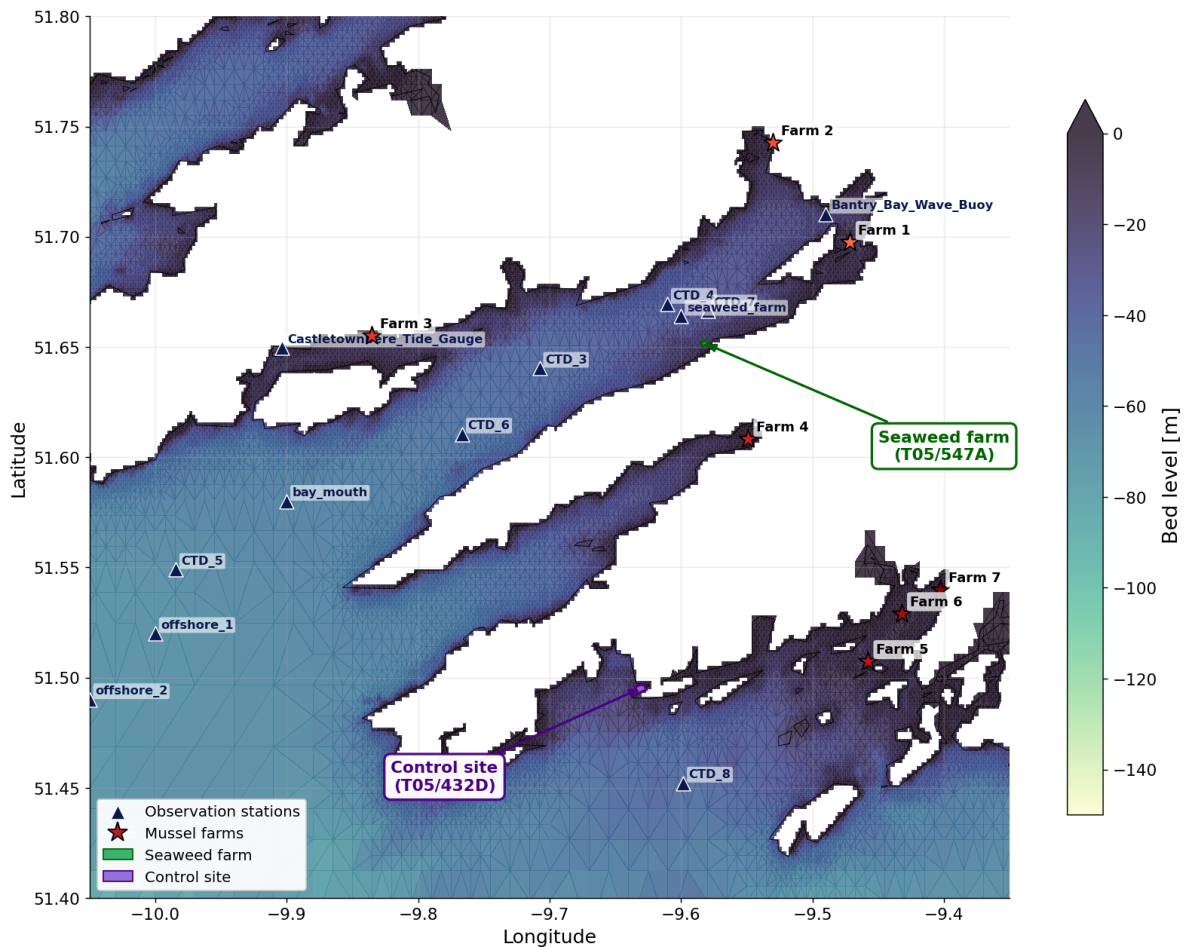


Figure 6.6: Bantry Bay aquaculture sites, observation stations, and model bathymetry. Red stars mark licensed mussel farms; the green and purple polygons mark the seaweed farm (T05/547A) and the Roaringwater Bay control site (T05/432D); navy triangles are the 16 model observation stations.

Figure 6.6 shows the locations that anchor the analysis: the sugar kelp farm on the northern shoreline, the licensed mussel farms (red stars) distributed through the bay, and the model's 16 observation stations (navy triangles). The exceedance analysis is evaluated at the observation stations rather than at the farm coordinates themselves, so for each species a representative station is chosen. For sugar kelp this is the dedicated Seaweed farm station, which sits directly at the kelp farm. The mussel farms have no co-located station, so the Castletownbere tide gauge is used as an indicative proxy: it lies close to Farm 3 and is the nearest station to the inner-bay mussel sites. Thermal and salinity exceedance are therefore computed for sugar kelp at the seaweed-farm station and for blue mussel at Castletownbere, so that both of the bay's cultivation types are represented.

6.5.2. Exceedance Statistics at the Farm Location

The analysis begins at the two representative stations, with the surface temperature and salinity envelopes for each species shown against their stress thresholds in Figure 6.7. Two features are immediately apparent.

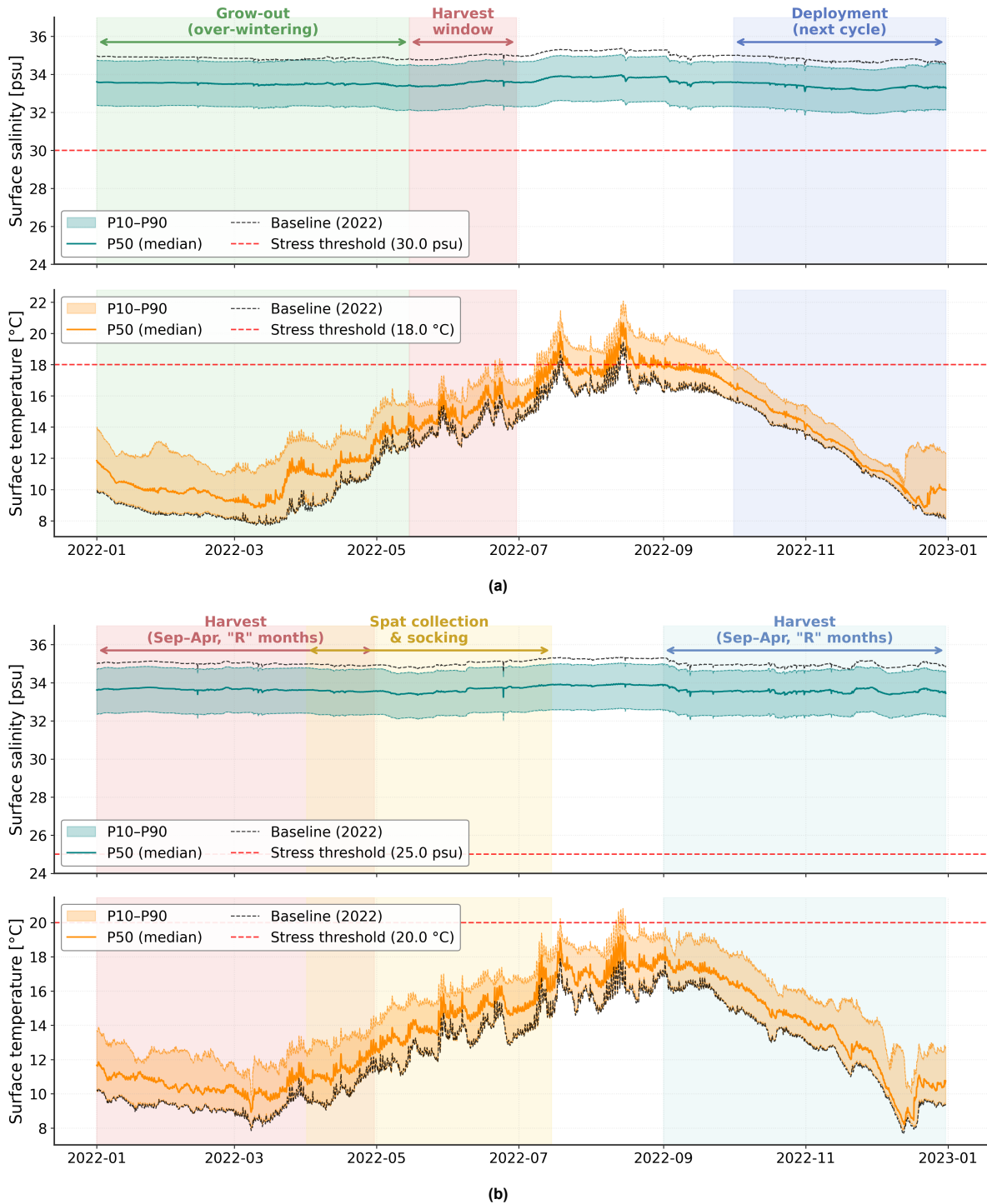


Figure 6.7: Temperature and salinity uncertainty envelopes (P10–P90, with P50 median and 2022 baseline) at the two aquaculture sites, overlaid with species cultivation calendars and growth-impairment thresholds; (a) *Saccharina latissima* at the seaweed farm.; (b) *Mytilus edulis* at Castletownbere.

For surface temperature, exceedance is not confined to the perturbed ensemble: the 2022 baseline itself crosses the *S. latissima* threshold of 18 °C during the summer peak, so thermal stress at the seaweed farm is already a feature of the present-day climate and not solely a projected one. The ensemble shifts the entire summer envelope upward relative to the baseline, so that the P90 members cross the threshold earlier in the season and remain above it for longer, while the median crosses the threshold only around the July–August peak. For *M. edulis* at Castletownbere, the higher 20 °C threshold is not

crossed by the 2022 baseline at any point in the year, and is reached only by the warmer members of the ensemble during midsummer; the present-day mussel site experiences no thermal stress under baseline conditions.

For surface salinity, neither species approaches its threshold at either location. The *S. latissima* limit of 30 psu and the *M. edulis* limit of 25 psu lie well below the full ensemble range at both stations, and no member produces a surface salinity that comes close to either limit at any point in the year. Salinity exceedance is therefore zero across the board, and on this basis salinity is set aside from the remainder of the stress analysis as a non-limiting variable under the scenarios examined; it is returned to only as a candidate for further study (Section 8.2).

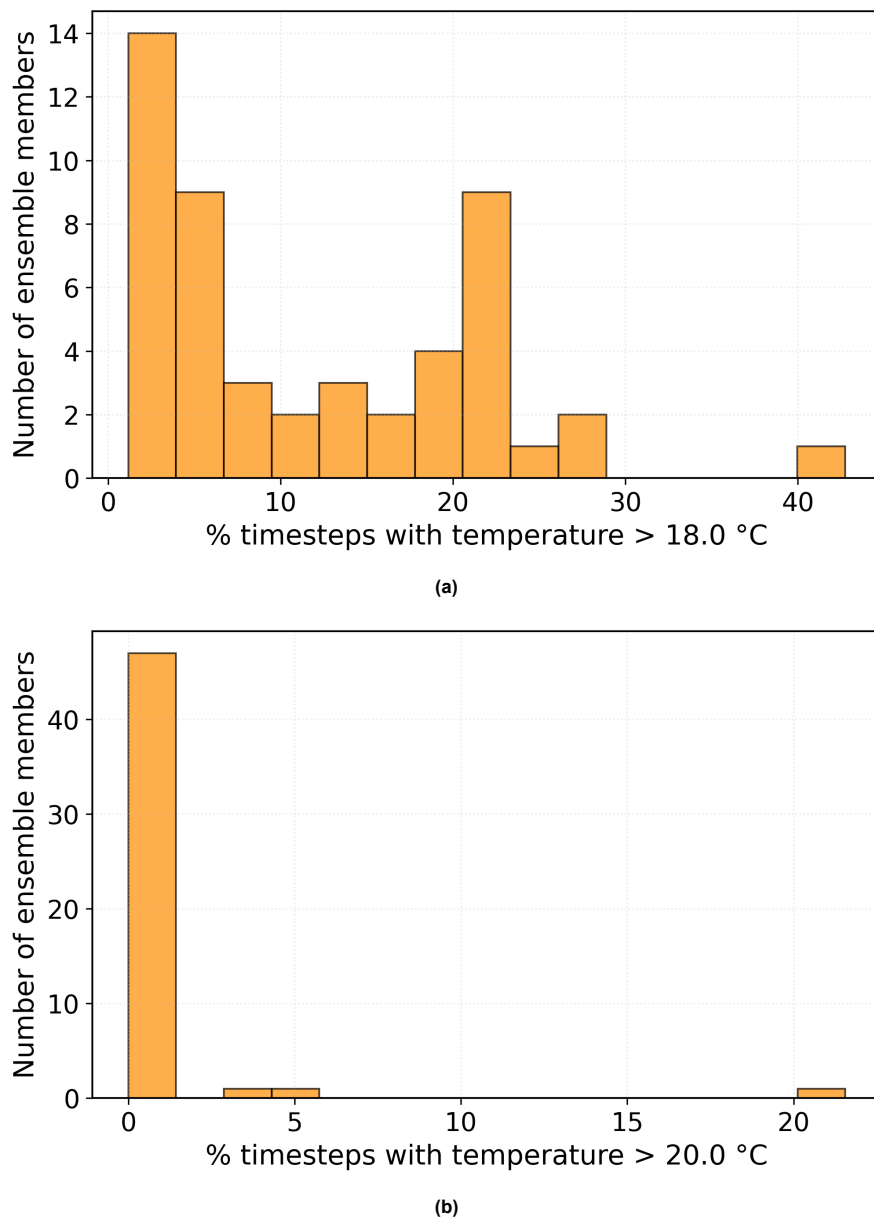


Figure 6.8: Stress exceedance frequency across the 50-member ensemble: distribution of the percentage of timesteps exceeding temperature thresholds; (a) *Saccharina latissima*; (b) *Mytilus edulis*

The exceedance frequencies in Figure 6.8 quantify this across the ensemble. The thermal panels show a broad distribution. For *S. latissima* the fraction of the year above 18 °C ranges widely across members, with a long tail toward high exceedance, whereas for *M. edulis* the distribution is concentrated near zero, with only a minority of members registering any exceedance of the 20 °C threshold at all.

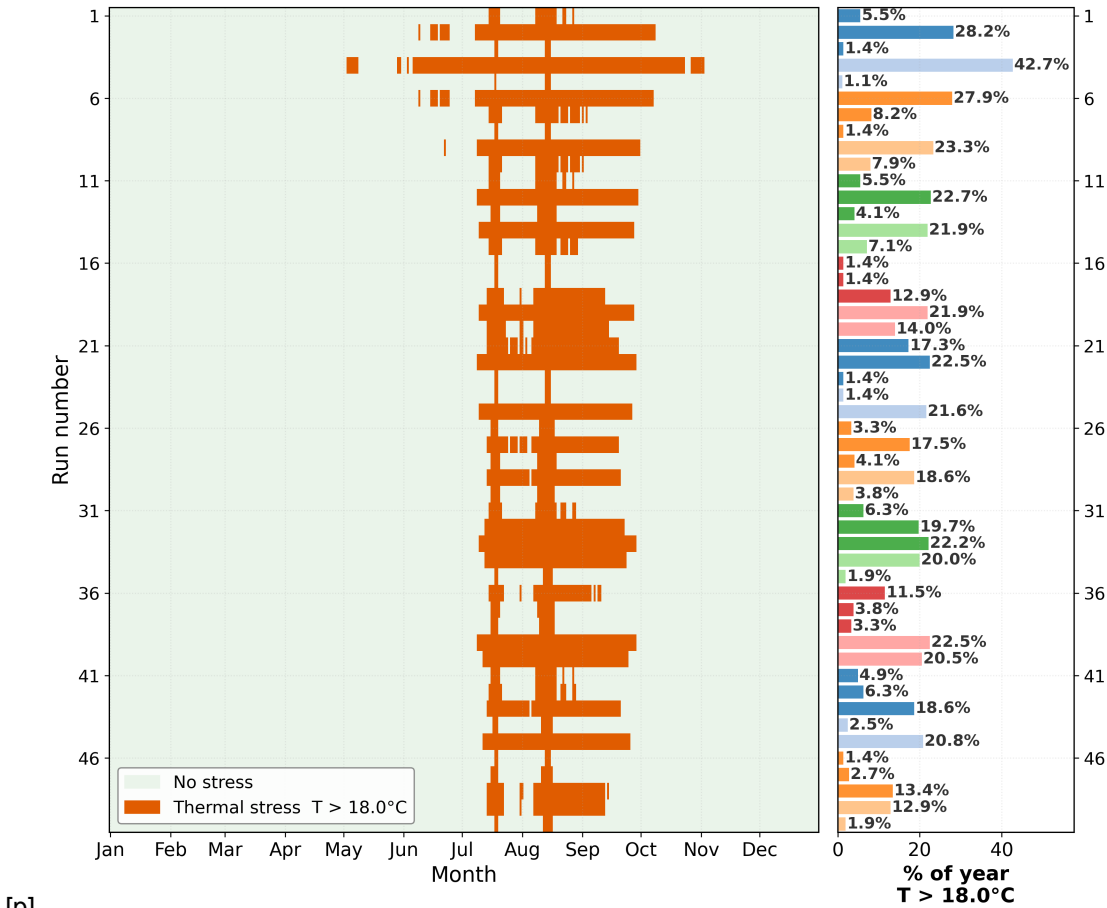
The contrast between the two species follows directly from the 2 °C difference in their thermal limits, and from the fact that the seaweed-farm summer envelope sits close to the kelp threshold while the mussel envelope sits well below the mussel threshold for most of the ensemble.

6.5.3. Compound Stress Calendar

To resolve the timing of exceedance within the year, and not only its annual total, a stress calendar was constructed for each ensemble member: for every day of the simulation year, conditions at the farm station are classified as unstressed, thermally stressed, salinity-stressed, or compound-stressed, and the 50 members are stacked to give the full ensemble view in Figure 6.9.

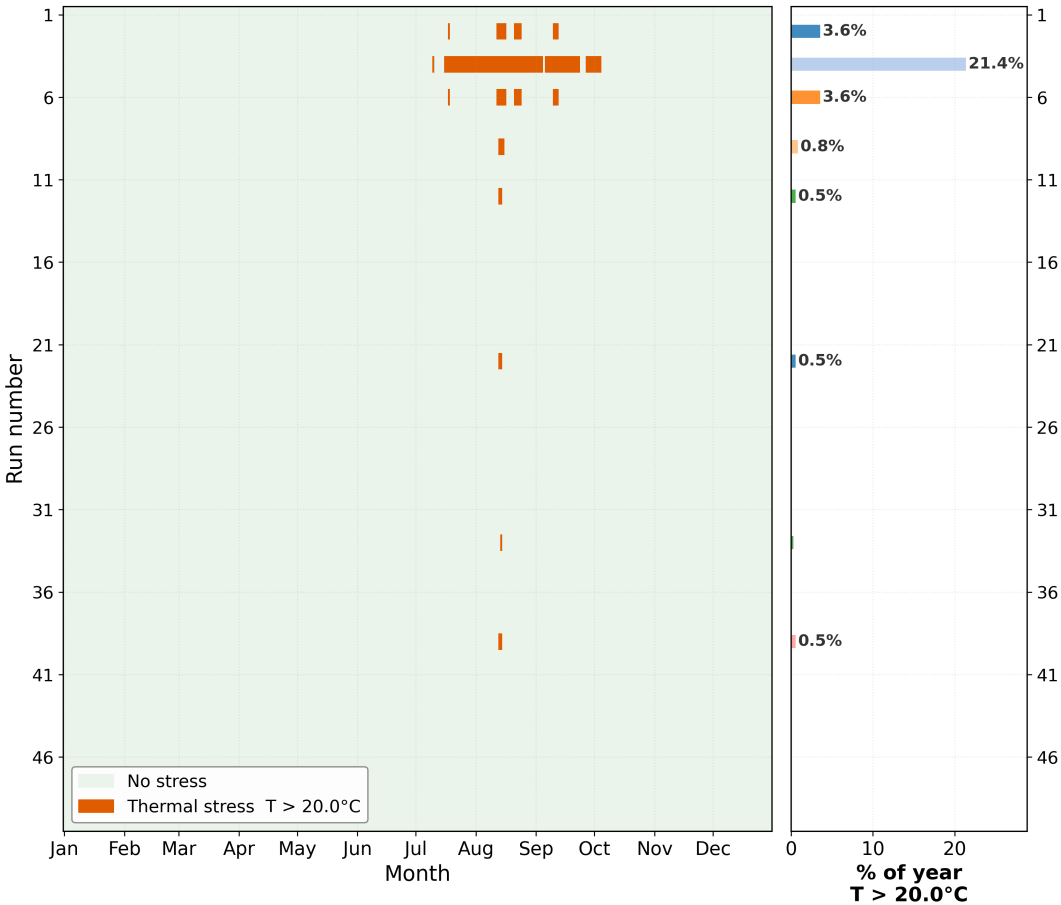
For *S. latissima* the thermal-stress days concentrate in the June–September window and peak in July and August, but the onset varies sharply between members: the high-exceedance runs enter stress as early as late spring, while the low-exceedance runs never cross the threshold at all. The calendar makes plain that the spread in annual exceedance reported above is largely a spread in *onset and duration* of a single summer stress season, rather than scattered isolated events. For *M. edulis* the calendar is almost entirely unstressed, with thermal-stress days appearing only in the warmest members and only at the height of summer, and no salinity-stress or compound-stress days for any member of either species, consistent with the zero salinity exceedance established above.

Restricting the exceedance calculation to the grow-harvest-deploy period, rather than the full calendar year, reduces the median thermal exceedance for *S. latissima* at the seaweed farm from 7.7% of the full calendar year to 0.0% of the in-water cultivation period. Almost all modelled thermal exceedance for this species falls within the June-to-September window, when standing kelp biomass is not in the water under the assumed calendar. This calendar (deployment mid-September to end-December, harvest May to mid-June) represents typical seasonal practice for kelp cultivation at the site rather than a farm-verified operational record, and the exact boundaries of the deployment and harvest windows will shift the precise percentages reported here, though not the qualitative pattern. This median reduction does not mean zero risk for every ensemble member: the 0.0% figure describes typical (median) scenario, whereas the highest-stress member still reaches 23.4% of exceedance its in-water time even once restricted to the cultivation period. In short, a typical projected scenario poses negligible in-water risk to standing kelp biomass, but the warmest projected scenarios remain a meaningful risk even under the current calendar. This calendar-restriction analysis was not repeated for *M. edulis*, whose full-year median exceedance is already effectively zero (Section 6.5.3).



[p]

(a)



(b)

Figure 6.9: Compound stress calendar across the 50-member ensemble. For each run (row) and day of year (column), the left panel shows whether conditions are unstressed, thermally stressed, salinity-stressed, or compound-stressed; the right panel ranks per-run thermal exceedance; (a) *Saccharina latissima* at the seaweed farm ($T > 18^{\circ}\text{C}$, $S < 30$ psu).; (b) *Mytilus edulis* at Castletownbere ($T > 20^{\circ}\text{C}$, $S < 25$ psu).

6.5.4. Spatial Distribution Across the Bay

The results so far describe the two farm stations. But since the bay's hydrodynamic response varies spatially, the stress experienced at a given location does not represent the bay as a whole. This fact creates the need for further representation because the siting of future cultivation depends on knowing where thermal risk concentrates. To map this, the median thermal exceedance across the 50 members was computed at every one of the 16 observation stations and is shown in Figure 6.10, with the licensed farm locations overlaid.

The exceedance is not spatially uniform. For *S. latissima* the inner-bay stations carry high median exceedance, which decreases towards the bay mouth before rising again at the further offshore stations, where it reaches its network peak. The most exposed station is CTD 8 in the southern inner bay, which records the highest median exceedance in the network and flags that part of the bay as the most thermally stressed for kelp cultivation. For *M. edulis* the same spatial pattern holds at much lower absolute levels, with even the most exposed stations registering only limited exceedance of the higher mussel threshold. Restricting attention to locations that are realistic for cultivation, that is, the sheltered inner- and mid-bay sites rather than the exposed offshore stations, the highest thermal risk concentrates at the inner of Bantry Bay and at the souther inner bay (Dunmanus Bay) around CTD 8, identifying that part of that bay as the most thermally stressed for kelp cultivation.

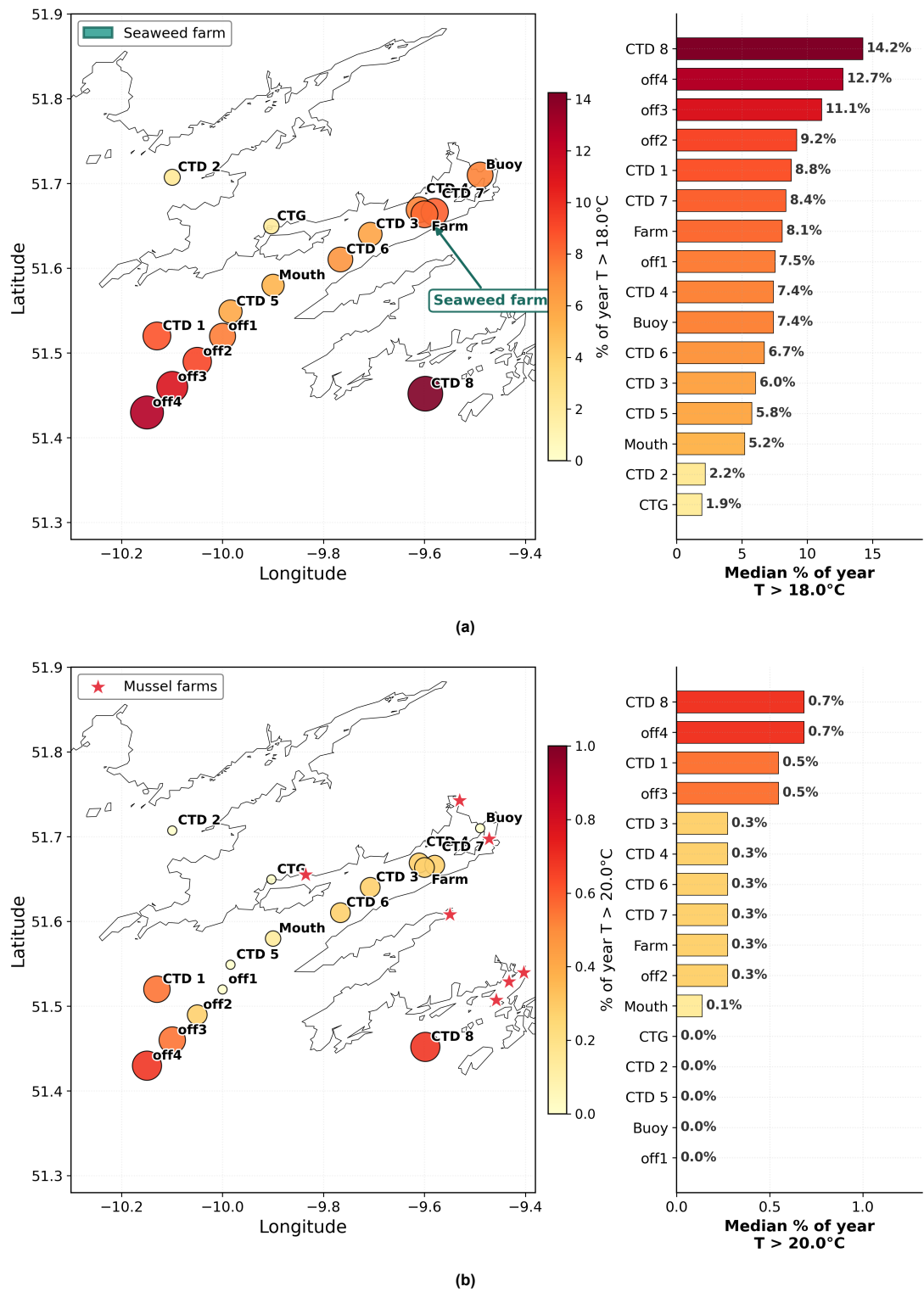


Figure 6.10: Spatial distribution of thermal stress exceedance across Bantry Bay observation stations (median % of year above the species temperature threshold across the 50-member ensemble). Bubble size and colour encode exceedance at each monitored station; aquaculture site markers indicate farm locations. The bar chart ranks stations by exceedance. (a) *Saccharina latissima*, thermal threshold $T > 18^{\circ}\text{C}$. The seaweed farm and Roaringwater Bay control site are marked; (b) *Mytilus edulis*, thermal threshold $T > 20^{\circ}\text{C}$. Licensed mussel farm locations are marked.

6.5.5. Thermal Exceedance and Parameter Interdependency

The sensitivity analysis of Section 6.3 identified ΔT as the dominant driver of mean surface temperature, which would lead one to expect thermal exceedance to follow the imposed warming. It does not. When exceedance at the seaweed farm is plotted against ΔT across the ensemble (Figure 6.11a), the relationship is weak: a linear fit explains only a small fraction of the variance ($R^2 = 0.26$), and members with very different ΔT produce similar exceedance while members with similar ΔT scatter widely. Because exceedance is a threshold-crossing rather than continuous quantity, a linear fit is not well suited to describing this relationship, and R^2 correspondingly understates how much of the response ΔT actually organises. Two alternative measures confirm this: Spearman's rank correlation, which does not assume linearity, returns $\rho = 0.59$ ($p < 0.001$), and a sigmoid fit to the same data captures the shape of the response more closely (pseudo- $R^2 = 0.32$; Figure 6.11c), rising from a low, near-flat baseline below $\Delta T \approx 2^\circ\text{C}$ to a higher, near-flat plateau above $\Delta T \approx 3.5^\circ\text{C}$. Even under the better-fitting sigmoid, four ensemble members remain substantial outliers, each reaching an exceedance level far from what its ΔT value alone would predict; these are runs 2, 4, 5, and 9. The bulk of the remaining variance, and the behaviour of these four runs specifically, is carried by ΔS and $\Delta\eta$, acting individually or together, shown in Figures 6.11b and 6.11c.

Figure 6.11 presents this as three panels. All three show the same scatter of the 50 members, exceedance on the vertical axis against the ΔT perturbation on the horizontal axis; what changes between panels is only the colour of the points. In panel (a) the points are coloured by ΔT , in panel (b) by ΔS , and in panel (c) by $\Delta\eta$. The purpose of re-colouring the same scatter three times is to reveal which parameter organises the vertical spread: if exceedance were set by ΔT alone, panel (a) would show a tight rising band and the colours in (b) and (c) would be arranged randomly. Instead the scatter against ΔT is loose, while the ΔS and $\Delta\eta$ colourings in (b) and (c) separate the high- from the low-exceedance members, which is the visual signature of exceedance being controlled by the other two parameters rather than by warming. The labelled points mark the outlier runs discussed below. Two groups of outliers carry the result. The first are members that reach high exceedance despite little or no warming. Run 9 produces 23.7% exceedance with a slightly negative ΔT of -0.19°C ; run 14 produces 22.3% with $\Delta T = -0.03^\circ\text{C}$; and run 40 produces 20.8% with only $\Delta T = +0.18^\circ\text{C}$ but the largest sea-level offset in this group ($\Delta\eta = +0.85\text{ m}$). These are cases where stress arises without direct thermal forcing. The second group are members that produce almost no exceedance despite strong warming, and all of them share strong freshening: run 26 reaches only 3.4% exceedance with $\Delta T = +4.78^\circ\text{C}$ and $\Delta S = -2.69\text{ psu}$, and run 16 only 1.3% with $\Delta T = +2.32^\circ\text{C}$ and the same strong freshening. The single highest exceedance in the ensemble at this station, 42.7%, is run 4, which combines strong warming, strong freshening and a moderate sea-level rise ($\Delta T = +4.92^\circ\text{C}$, $\Delta S = -2.69\text{ psu}$, $\Delta\eta = +0.61\text{ m}$). The parameter triplets for all labelled runs are listed in Appendix A.1 and their exceedance values in Appendix A.4.

Before these cases are taken further, it was confirmed that they are physical rather than numerical. The water-level series of the outlier runs were compared against the Castletownbere tide gauge and against the baseline simulation, the tidal phase and amplitude in every case remain consistent with the rest of the ensemble, so the unusual exceedance values are genuine responses to the boundary perturbations and not model artefacts. The mechanism that links sea-level rise, freshening and stratification to these compound effects, and what it implies for how climate scenarios should be ranked, is examined in Chapter 7.

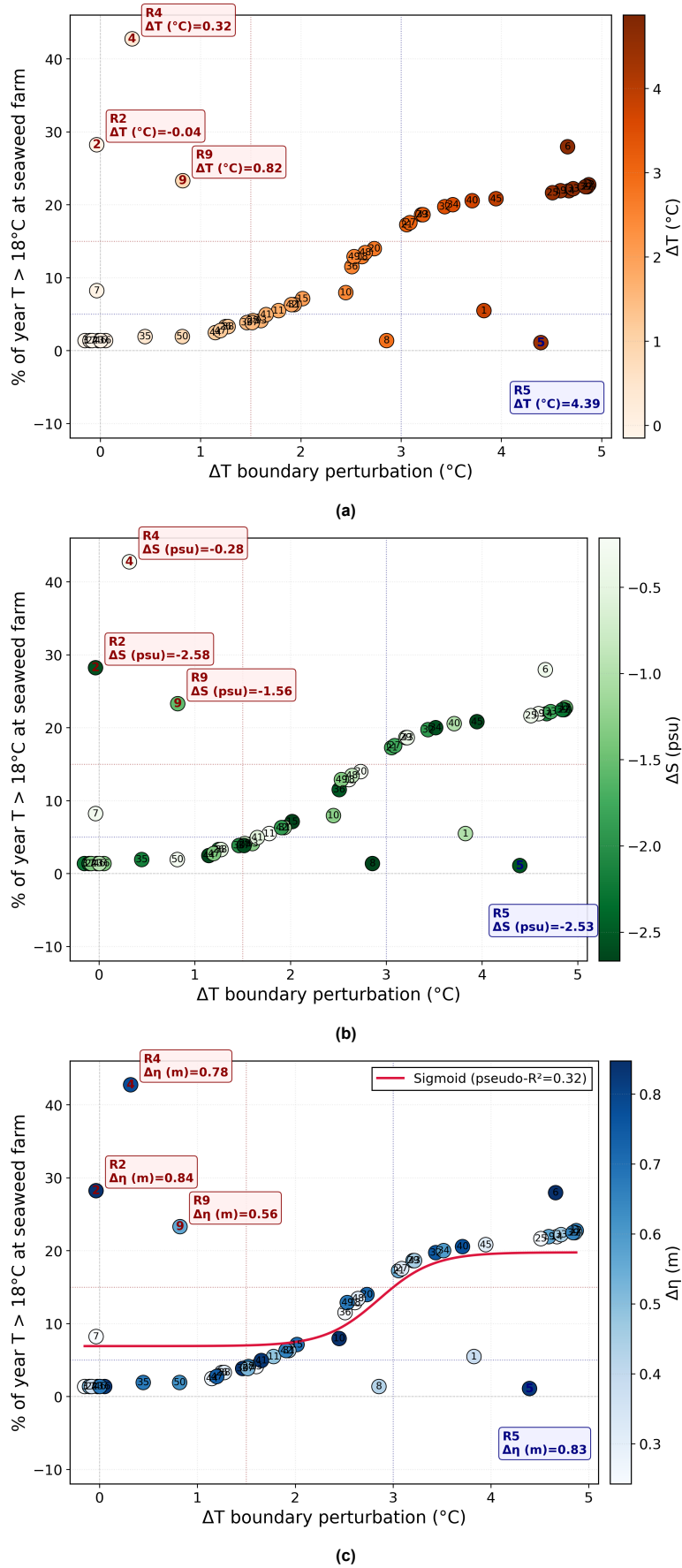


Figure 6.11: Thermal exceedance (% of year with $T > 18^{\circ}\text{C}$ at the seaweed farm) versus the ΔT boundary perturbation across the 50-member ensemble, with points coloured by each of the three perturbation parameters in turn. The weak scatter against ΔT , and the structure revealed by the ΔS and $\Delta \eta$ colourings, illustrate that exceedance is governed by parameter interactions rather than ΔT alone. Run numbers label each point; highlighted outliers (red: high exceedance at low ΔT ; blue: low exceedance at high ΔT) identify the compound-effect cases; (a) Points coloured by ΔT ($^{\circ}\text{C}$); (b) Points coloured by ΔS (psu); (c) Points coloured by $\Delta \eta$ (m).

6.6. Spatial Distributions

The third research question asks how the spatial distribution of surface temperature and salinity across the bay differs between ensemble members, and where the spatial gradients are largest. Unlike the preceding questions, which were evaluated from the full 50-member ensemble at the station network, this question relies on the gridded map output of the model. Storing the three-dimensional map fields for all 50 runs was not feasible within the available storage budget, so the analysis here is based on a representative subset of four runs together with the unperturbed 2022 baseline. The results are therefore read qualitatively, as a comparison of spatial patterns across a small set of contrasting scenarios, rather than as ensemble statistics.

6.6.1. Selection of Representative Runs

The four runs were chosen to span the thermal-exceedance distribution established in Section 6.5 rather than at random. Run 046 sits at the low end of that distribution (1.4% of the year above the kelp threshold), corresponding to the lower envelope (P10), run 015 near the median (7.1% P50), and run 039 near the upper end (22.5% P90). Run 004 was added as the extreme case (42.7%), the sea-level-driven compound member already identified in Section 6.5.5. Taken together the four sample the ensemble's thermal response from near-unperturbed to extreme. Their full parameter triplets are listed in Appendix A.1.

6.6.2. Difference From the Baseline

Because the absolute fields are dominated by the seasonal-mean pattern, the climate signal is seen more clearly once the baseline is subtracted. Figures 6.12 and 6.13 show each run as a departure from the 2022 baseline, on a shared diverging scale centred on zero.

The warming is spread fairly evenly across the bay. It enters from the open Atlantic boundary, so where any difference shows, the outer bay and offshore water warm slightly more than the sheltered inner-bay arms. The size of the warming grows from run 046 to run 015 to run 039, following the imposed ΔT .

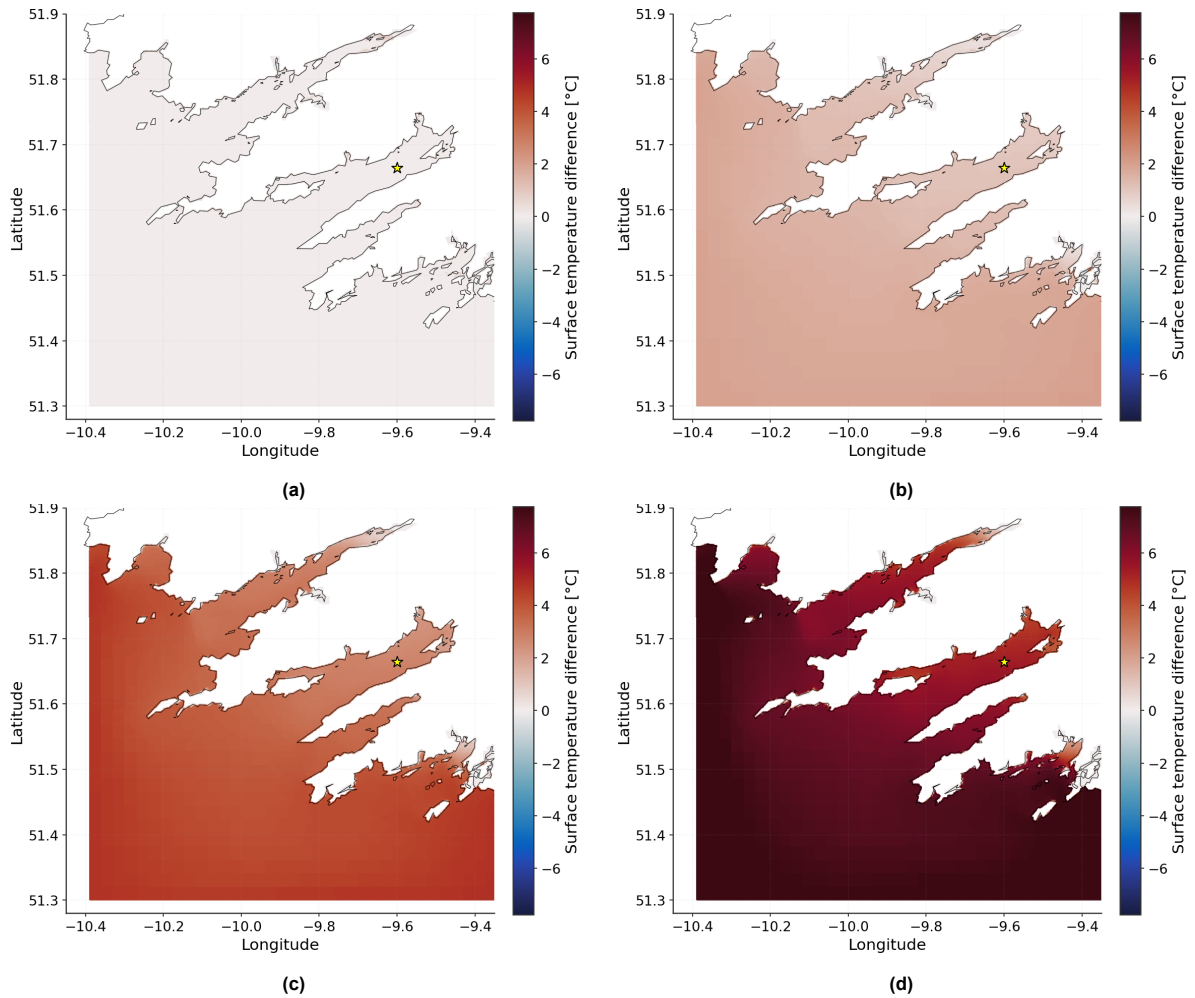


Figure 6.12: Surface temperature difference from the 2022 baseline for four representative ensemble members; (a) P10; Run 046 - Baseline, (b) P50; Run 015 (median) - Baseline, (c) P90; Run 039 - Baseline, and (d) the extreme member; Run 004 - Baseline. Warming propagates inward from the open Atlantic boundary with limited attenuation and is close to spatially uniform across the bay, scaling in magnitude with the imposed ΔT from (a) to (d). The yellow star marks the seaweed farm.

The salinity difference is spatially uniform across the bay, with no meaningful inner-to-outer gradient. Its magnitude reflects the imposed boundary offset almost directly, deepening from roughly -1 psu in run 046 to about -2.8 psu in the strongest-freshening member, and no run produces a sharp spatial structure. Like the temperature signal, the freshening therefore propagates inward at close to its full imposed strength, consistent with the boundary-controlled, single-driver response identified by the PRCC analysis.

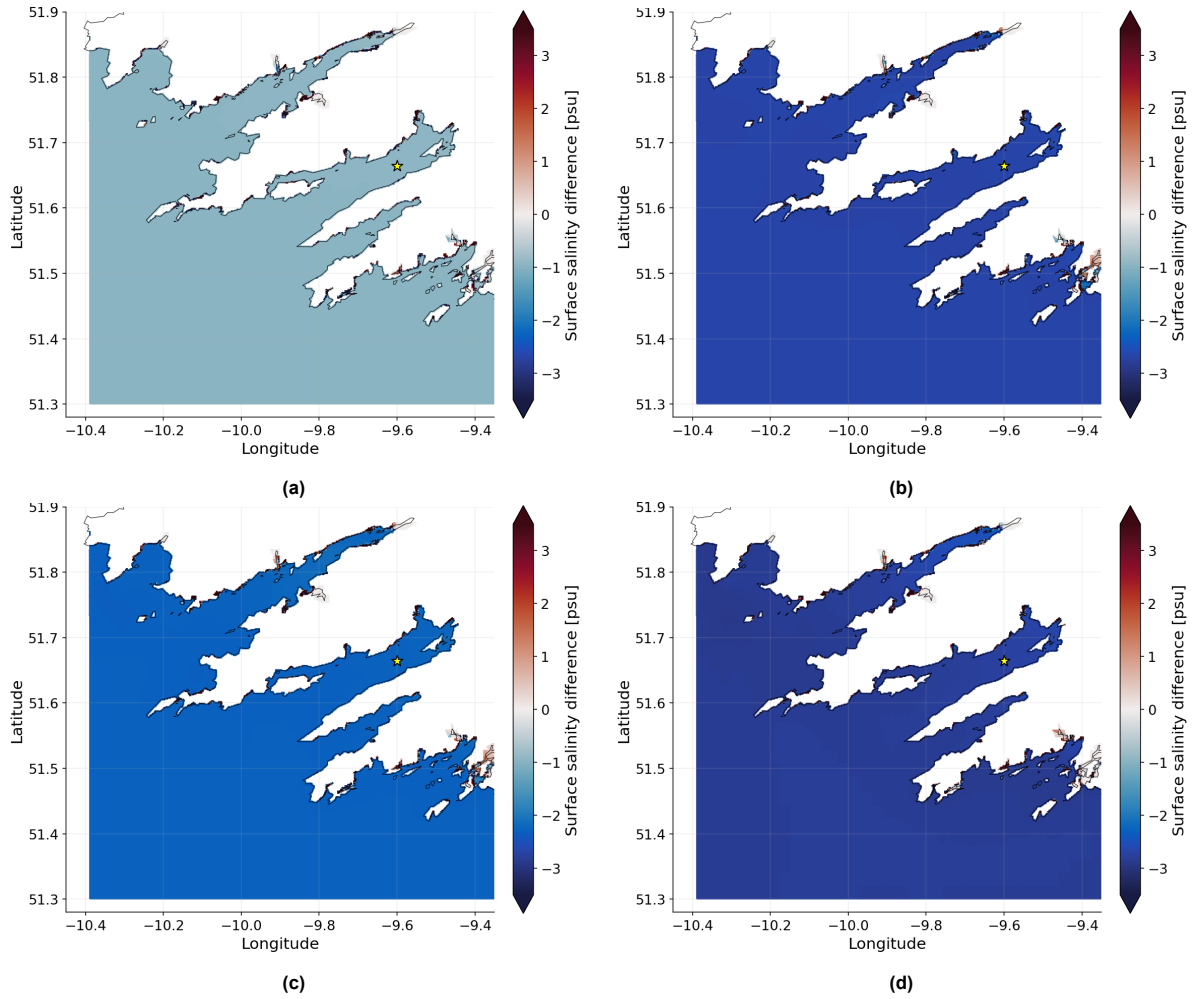


Figure 6.13: Surface salinity difference (member minus baseline) for the four selected members; (a) P10; Run 046 - Baseline, (b) P50; Run 015 (median) - Baseline, (c) P90; Run 039 - Baseline, and (d) the extreme member; Run 004 - Baseline. Negative values (blue) indicate freshening relative to the 2022 baseline, positive values (red) indicate increased salinity. The freshening signal is spatially uniform across the bay, with no meaningful inner-to-outer gradient, and its magnitude tracks the imposed ΔS almost directly from (a) to (d). The yellow star marks the seaweed farm.

6.6.3. Summer Thermal and Haline Stratification

The vertical structure of the water column is summarised in Figures 6.14 and 6.15, which map the summer surface-minus-bottom temperature and the corresponding surface-minus-bottom salinity for each run. Summer is chosen because it is the season of strongest stratification and largest inter-member temperature spread, making it the period in which water-column structure is most sensitive to the imposed warming and therefore most diagnostic of the ensemble's spatial response. A positive surface-minus-bottom temperature indicates a warm surface layer overlying cooler deep water, that is, thermal stratification.

In the baseline and the low-response run 046, summer thermal stratification is concentrated in the deep central basin and the outer bay, where a warm surface layer overlies cooler deep water, while the shallow inner-bay arms remain weakly stratified. As the imposed warming increases through run 015 to run 039 and the extreme run 004, the inner bay becomes less vertically differentiated. The well-mixed (low-contrast) zone expands inward, so the strongest warming members show the weakest inner-bay stratification.

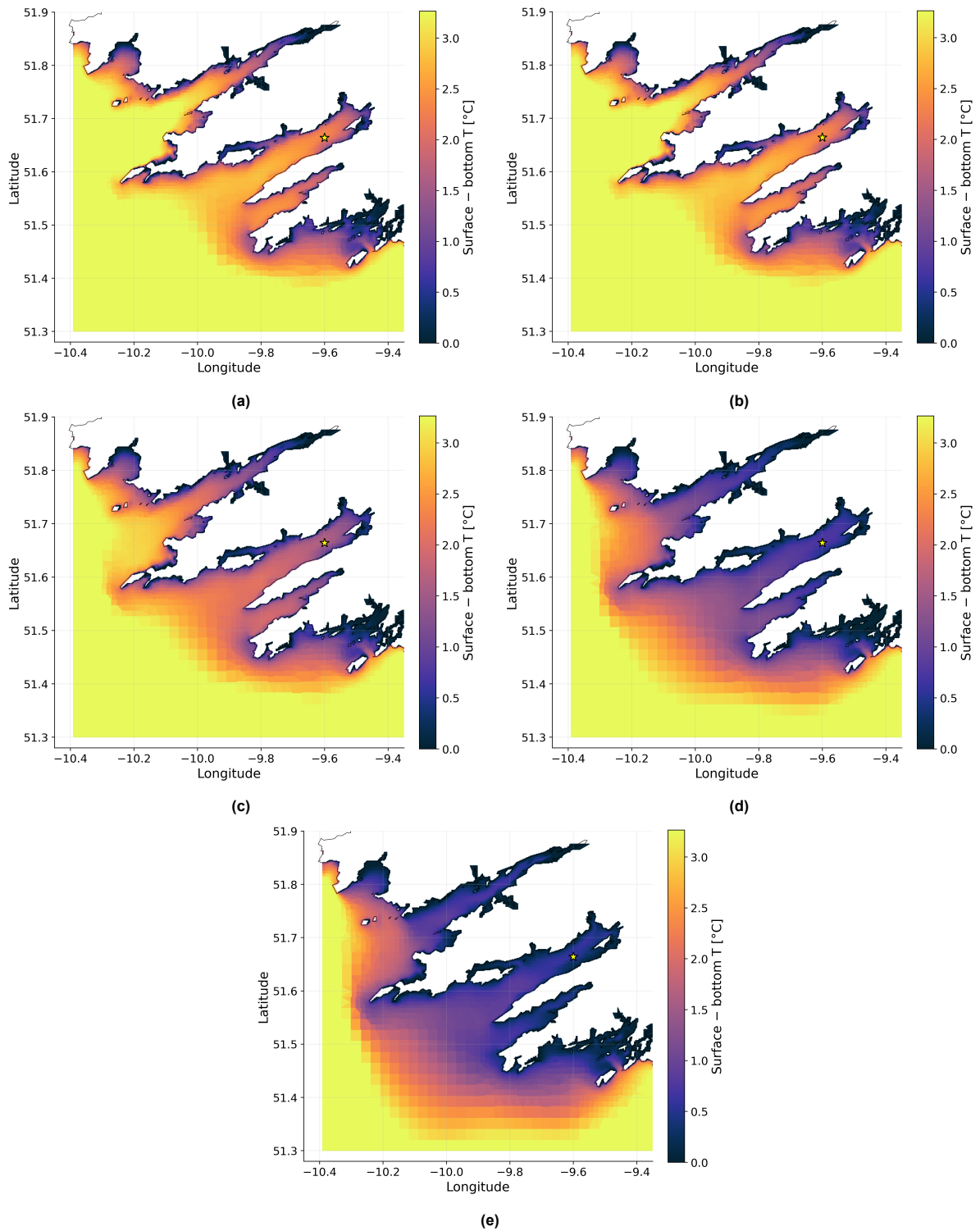


Figure 6.14: Summer thermal stratification (surface-minus-bottom temperature) for (a) the 2022 baseline, and ensemble members (b) P10 - Run 046, (c) P50 - Run 015 (median), (d) P90 - Run 039, and (e) the extreme member - Run 004. Larger positive values (yellow) indicate stronger thermal stratification. Stratification is strongest in the deep central basin and the outer bay and weakest in the shallow inner-bay arms, the seaweed farm (star) is only moderately stratified. As the imposed warming increases, the inner bay becomes *less* vertically differentiated, because the warming reaches through the shallow column. The yellow star marks the seaweed farm.

The haline stratification shows a comparable pattern, the surface-to-bottom salinity contrast is largest along the outer and offshore boundary and weak in the well-mixed inner-bay arms, and it does not in-

intensify with increased freshening; if anything, the inner-bay contrast is slightly reduced in the strongest-freshening members.

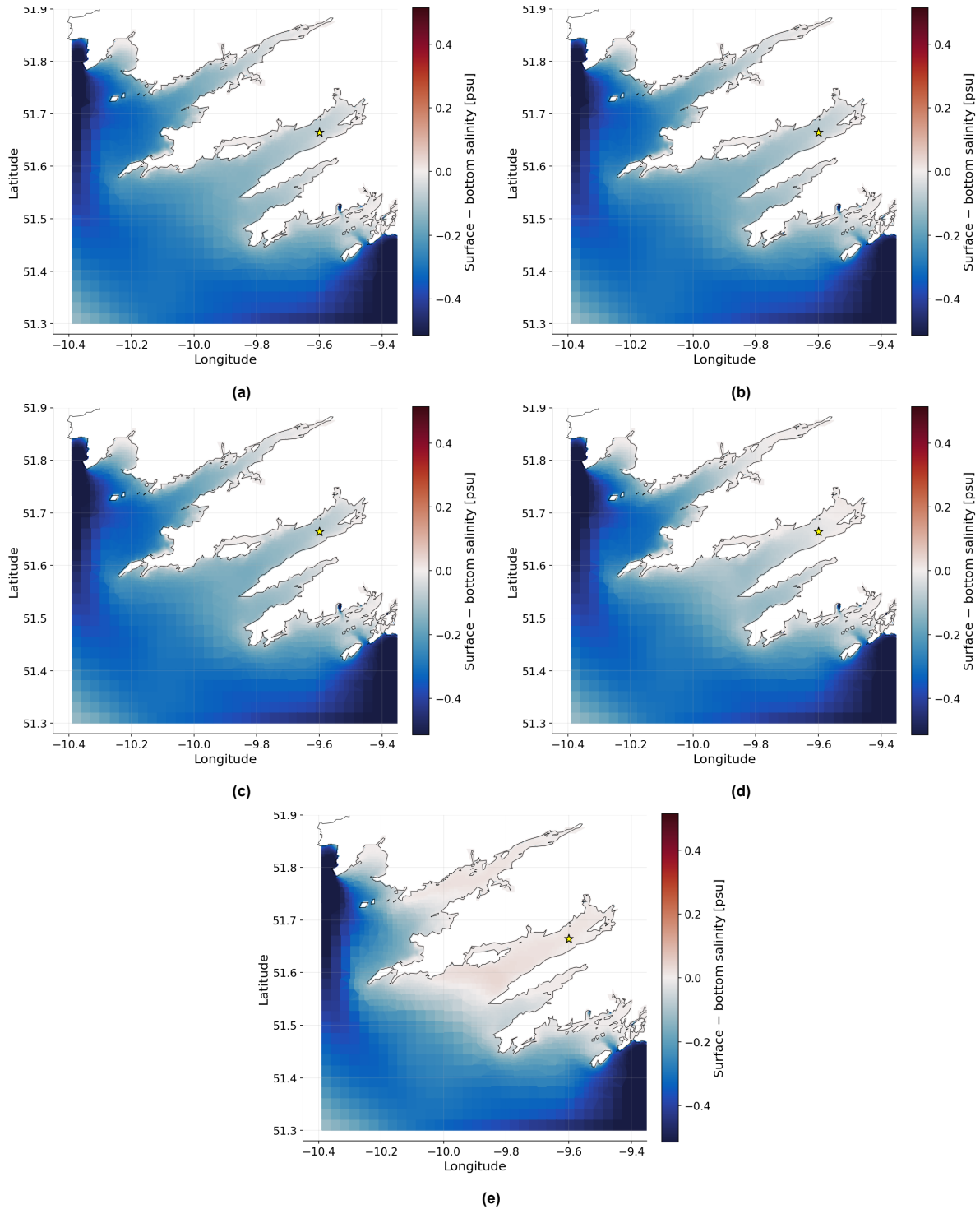


Figure 6.15: Summer haline stratification (surface-minus-bottom salinity) for (a) the 2022 baseline, and ensemble members (b) P10 - Run 046, (c) P50 - Run 015 (median), (d) P90 - Run 039, and (e) the extreme member - Run 004. The strongest haline stratification contrast occurs along the outer and offshore boundary, while the shallow inner-bay arms remain weakly stratified and close to vertically uniform. The contrast does not intensify with increased boundary freshening; if anything, the inner-bay difference is slightly reduced in the strongest-freshening members (P90, Extreme) relative to the baseline and P50. The yellow star marks the seaweed farm.

6.6.4. Summary

Across the four runs, the spatial pattern of the temperature and salinity fields is broadly conserved while their magnitude scales with the imposed forcing. The warming is close to spatially uniform, marginally stronger in the outer bay and offshore than in the sheltered inner-bay arms, with no sharp internal gradient. The salinity field is likewise spatially uniform but perturbed at close to its full imposed magnitude, not weakly.

The clearest pattern from the map analysis, however, concerns the vertical dimension: stratification, both thermal and haline, is governed by bathymetry and mixing rather than by the magnitude of the imposed offsets. It concentrates in the deep outer bay and collapses in the shallow, tidally mixed inner arms, and increased warming or freshening at the boundary does not build inner-bay stratification but tends to homogenise it further. The physical interpretation of this pattern is taken up in Section 7.

The compound run 004 reaches high thermal exceedance despite a small imposed temperature offset, the spatial counterpart of the parameter-interaction effect quantified in Section 6.5.5; this member-specific reading is provisional pending the run-verification noted in Section 7.7.

6.7. Tidal Range and Sea Level Rise

The fifth research question has two parts: how the prescribed sea-level rise influences the mean water level in the bay, and whether it reshapes the tidal range. Both are examined at the Castletownbere station, where the continuous tide-gauge record provides the reference signal. This question is motivated by the established sensitivity of tidal dynamics to changes in water depth and bay geometry, and by the finding from the PRCC matrix that ΔT shows a statistically significant negative correlation with tidal range at inner bay stations.

6.7.1. Mean Water Level Response

Figure 6.16 plots the simulated mean water level at Castletownbere against the imposed $\Delta\eta$, with each point coloured by ΔT . The relationship is strong and positive (Pearson $r = 0.736$, $p < 0.001$): the sea-level offset prescribed at the open boundary propagates into the bay interior and raises the mean level by close to the imposed amount. The fit is tight but not exact, and the residual scatter is not clearly organised by ΔT .

Two members depart from the trend and stand out as outliers in the scatter. Run 7 produces a high mean water level of 0.51 m despite carrying the lowest imposed $\Delta\eta$ in the ensemble (0.24 m) and a near-zero ΔT , while run 6 produces a negative mean water level of -0.12 m despite carrying the highest offset (0.85 m) and a comparatively strong ΔT . The two therefore runs counter to the prescribed forcing rather than scattering around it. Both carry near-zero salinity perturbations ($\Delta S \approx -0.3$ psu), placing them among the least-freshened members of the ensemble. Their demeaned water-level skill is indistinguishable from the rest of the ensemble (Section 6.2), so the departure is confined to the mean level and does not reflect any loss of tidal performance; their full parameter values are listed in Appendix A.1. This phenomenon is discussed further in Chapter 7.

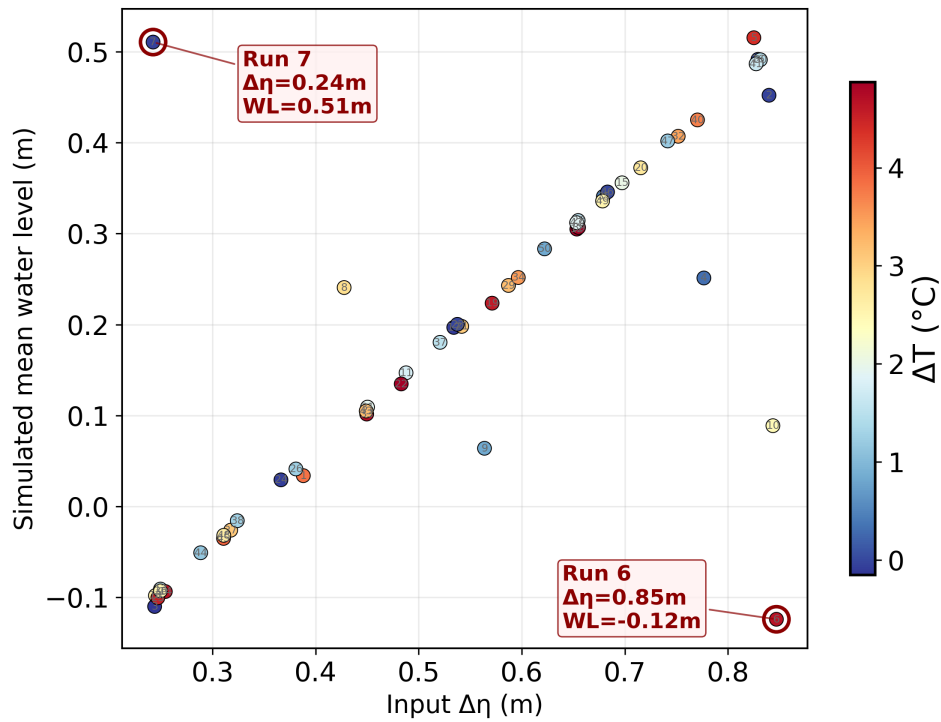


Figure 6.16: Simulated mean water level at Castletownbere against the prescribed sea-level offset $\Delta\eta$ across the 50-member ensemble, with each point coloured by its temperature offset ΔT . The strong positive relation ($r = 0.736$, $p < 0.001$) confirms that the imposed offset propagates into the bay and raises the mean level; the residual scatter is partly organised by ΔT , reflecting a secondary steric contribution. Runs 6 and 7 (labelled) depart from the trend and are discussed in the text.

6.7.2. Tidal Range Response

The mean tidal range at Castletownbere was extracted for each member by peak detection of high- and low-water events in the modelled water-level series, with the mean range taken as the difference between mean high water and mean low water over all detected events. Harmonic analysis with the UTide package was attempted first as the more rigorous route, but a confirmed amplitude-scaling defect in UTide v0.3.1 under NumPy ≥ 2.0 produced non-physical constituent amplitudes, so the peak-detection approach was adopted as a validated alternative.

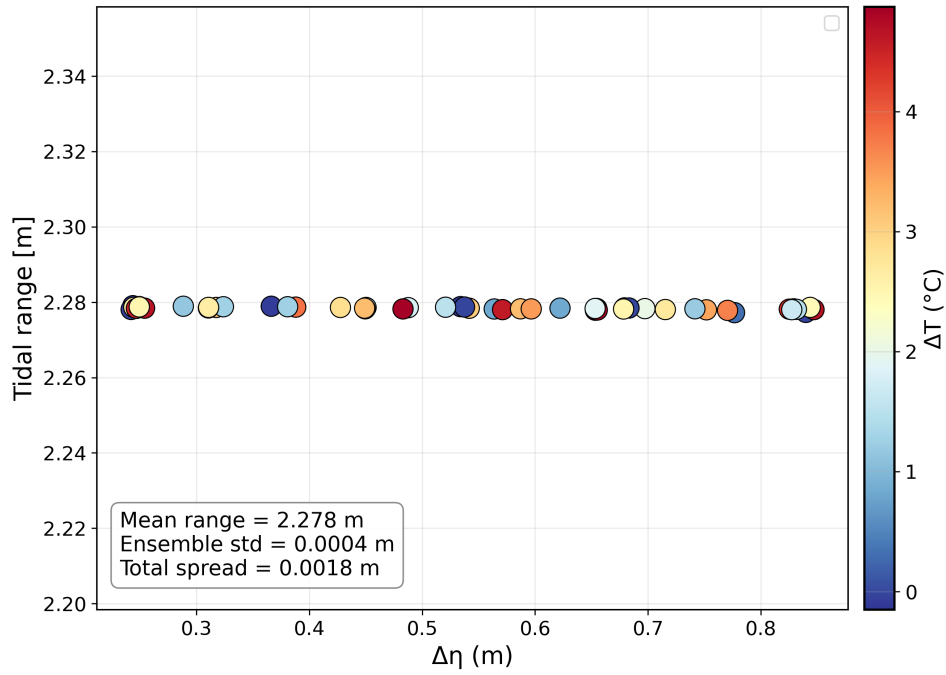


Figure 6.17: Mean tidal range at Castletownbere against the sea-level offset $\Delta\eta$, with points coloured by ΔT . The dashed line is the linear fit and the shaded band its $\pm 1.96\sigma$ residual envelope. The fit is statistically significant ($R^2 = 0.423$, $p < 0.001$) but the slope is only -0.0012 m per metre of $\Delta\eta$, equivalent to a change of about -0.7 mm across the full sampled range: the tidal range is effectively unchanged by sea-level rise. The ΔT colouring reveals the weak secondary association between warming and reduced tidal range discussed in the text.

The mean tidal range across the 50 members clusters tightly around 2.278 m, with an ensemble standard deviation of 0.0004 m and a total spread of only 0.0018 m, equivalent to 0.08% of the mean range. Figure 6.17 plots the same tidal range against $\Delta\eta$, coloured by ΔT .

This scatter is coloured by ΔT specifically to investigate the weak negative rank correlation between tidal range and ΔT already identified in the PRCC matrix (Figure 6.3: $\rho = -0.35$, $p = 0.012$). However, no clear visual pattern emerges from the colouring itself: members with stronger warming are not consistently distinguishable from the rest of the scatter. The association, while statistically detected by PRCC, is too weak or too diffuse to confirm visually at this scale, and sits at the threshold of the peak-detection method's resolution; establishing it conclusively would require dedicated further analysis, addressed in 7.6

7

Discussion

7.1. Introduction

This thesis set out to address three connected axes at once: the *sensitivity* of the bay's hydrodynamics to its open-boundary forcing, the *uncertainty* attached to that forcing under a late-century climate scenario, and the *application* of the resulting envelope to a concrete aquaculture question. The first two axes are methodological and are where the main contribution of the work lies. The third is included because grounding sensitivity and uncertainty analyses in a tangible, real-world impact is essential to keeping the modeling process relevant. By framing the aquaculture stress analysis as an illustrative end-to-end application, this work demonstrates how boundary-uncertainty envelopes can be translated into spatial risk indicators. This approach highlights both the potential for actionable insight and the inherent limitations of the results, ensuring the research remains anchored in the applied objectives of the PHAROS project rather than claiming to be a finished decision-support tool.

7.2. Dominant boundary control and what it implies

The PRCC analysis returns a clean and physically interpretable result for the mean state specifically: each of the three response variables is governed by its own boundary driver, and by essentially only that driver. Mean surface salinity follows ΔS , mean surface temperature follows ΔT , and mean water level follows $\Delta \eta$, with no response variable meaningfully controlled by more than one parameter at the level of the mean. This separation is consistent with the way a small, transport-driven bay communicates with the open ocean: the water masses arriving at the mouth set the interior state, and a uniform offset at the boundary propagates inward with limited attenuation. The result supports the central premise of the study, namely that in a data-scarce embayment the open boundary, rather than the internal parameterisation, is the dominant source of predictive uncertainty, and it is in agreement with the broader literature on boundary-forced coastal systems (Hendrickx et al., 2023; Olbert et al., 2012).

The more interesting result sits one level below the mean. Although ΔT dominates mean temperature, it is a poor predictor of thermal stress *exceedance* at the seaweed farm: a linear fit of exceedance against ΔT explains only a small fraction of the variance ($R^2 = 0.26$), and because exceedance is a threshold-crossing quantity rather than a continuous one, a linear R^2 understates how weak this relationship actually is (Section 6.5). A rank-based measure and a saturating (sigmoid) fit, reported in Section 6.6, both confirm the same qualitative picture: members with very different ΔT produce similar exceedance, while members with similar ΔT scatter widely. The exceedance outcome is instead organised by ΔS and $\Delta \eta$ acting together. ΔT being the dominant driver of the mean, in other words, does not make it the dominant driver of everything; which parameter matters depends on which property of the response is being asked about.

7.3. Projection uncertainty in the seaweed-farm envelope

That temperature and salinity uncertainty differ much in shape, not merely in magnitude, follows directly from the single-driver structure established in Section 7.2. ΔS enters as a comparatively small perturbation on a bay whose interior salinity is already tightly constrained by strong Atlantic exchange; the boundary signal has correspondingly little room to reshape the salinity envelope's seasonal pattern, only its overall level. ΔT behaves differently, though not simply as compounding with the seasonal cycle in a way that makes winter and summer symmetric: the instantaneous envelope is in fact widest in winter, driven by short-term mixing variability rather than by the imposed climate signal itself (Section 6.4). The climate-relevant part of the envelope is instead carried by the seasonal median and by the upper tail specifically in summer, when the ensemble's warmest members push furthest above the baseline and approach or cross the thresholds that matter for cultivation. The consequence of a given ΔT offset is therefore not mechanically larger in summer; it is more biologically and operationally significant in summer, because that is when the resulting temperatures approach the range that matters.

Worth mentioning that this reading of salinity as a low-risk variable should be taken with one caveat: the model has no gauged river discharge forcing (Section 3.1), so any localised freshening from ungauged streams entering the inner bay is not represented, and the salinity envelope reported here reflects oceanic boundary variability only, not the full range of freshwater input the bay may actually experience.

7.4. The aquaculture stress envelope

Before turning to what the ensemble shows, it is worth being explicit about what this application can and cannot claim. The stress thresholds used throughout this section are deliberately simplified: for *S. latissima*, sustained surface temperatures above roughly 18 °C and salinities below about 30 psu are associated with reduced growth (Sæther et al., 2024); for *M. edulis*, thermal stress is associated with temperatures above about 20 °C and salinity stress with values below about 25 psu (Kamermans et al., 2022). Real physiological outcomes depend on acclimation history, exposure duration, life stage, and on stressors this study does not resolve at all, dissolved oxygen, ocean acidification, food availability, any of which can compound with thermal or osmotic stress in ways a single-variable threshold cannot represent. The results below should accordingly be read as a first-order screening of physical risk, not a biological verdict, and the thresholds themselves as a starting point to be revised as better site-specific data become available, rather than as fixed management prescriptions.

The first result worth discussing is salinity: across every ensemble member, at every station, surface salinity never approaches the growth-impairment threshold for either species. This is a robust finding in the sense that even the strongest freshening sampled here keeps the bay's salinity comfortably within the range both species tolerate, but it should be read as a statement about the boundary-driven uncertainty sampled here, not a guarantee against all freshwater-related risk. The ensemble does not include riverine discharge as a forcing input (Section 4.4); any localised freshening from ungauged streams entering the inner bay, particularly during storm events, is therefore not represented. The salinity result should accordingly be read as "boundary-driven freshening does not threaten cultivation," not as "the bay faces no salinity risk under any circumstance."

The second result concerns thermal stress, and here the picture is less reassuring. Thermal stress is already present at the seaweed farm in the 2022 baseline at the height of summer, and the ensemble shifts the entire summer envelope upward, so that warmer members cross the kelp threshold earlier in the season and remain above it for longer; the higher mussel threshold is not crossed by the baseline at all and is reached only by the warmer members in midsummer. Spatially, this exceedance concentrates in the inner bay: for *S. latissima* it peaks at the sheltered southern station CTD 8, identifying that part of the bay as the most thermally stressed for kelp.

Read at face value, this result appears almost reassuring once the kelp farm's own operational calendar is taken into account. Kelp in Bantry Bay is deployed over winter, harvested by late June, and redeployed the following autumn, so the period of greatest modelled thermal stress, concentrated between June and September, falls largely outside the window in which standing biomass is in the water; restricting the exceedance calculation to the cultivation period rather than the full year drops the median exposure for *S. latissima* close to zero (Section 6.5.4). That reassurance, however, is narrow, and should not be read past what it actually shows. For example it says nothing about the wild kelp

populations occupying the same water during the same months, which are not harvested away from the stress the way the cultivated crop is, these populations remain exposed to the full summer thermal signal regardless of the farm's own calendar. Likewise it neglects important facts concerning the *M. edulis* as well. Their calendar offers no comparable protection: mussel cultivation follows the traditional harvest window of September to April, with standing biomass remaining in the water continuously through the warm season across a production cycle that runs well over a year from seed to harvest. Even the comparatively modest thermal exceedance found for mussels in Section 6.5 therefore represents a genuine, sustained exposure rather than one a harvest calendar removes by construction, and the threshold-crossing frequency alone may understate what this exposure means in practice, since sub-lethal, cumulative effects on condition or growth can occur well below the hard exceedance threshold used here. This is particularly consequential because for instance, spat collection itself falls in spring and early summer, at the edge of the warm season rather than safely outside it. In reality, farmed *M. edulis* in Bantry Bay depends on natural spat supply rather than hatchery stock, so farm viability depends not only on adult mussels tolerating summer conditions but on wild populations successfully spawning during that same window. This connects to the coupling between reduced warming and freshening introduced in the theoretical framework: a weakening AMOC tends to deliver both a suppressed temperature signal and a stronger freshening signal simultaneously (Caesar et al., 2021; Holliday et al., 2020), so a scenario that eases adult thermal exposure through the summer could still plausibly disrupt spring recruitment conditions, a combination the exceedance statistics for farmed biomass alone would read as low risk.

The third result concerns how thermal exceedance is actually driven. Section 6.5.5 showed that exceedance at the seaweed farm is not well explained by ΔT alone: the members posing the greatest risk are not simply the warmest, but those combining moderate-to-strong warming with pronounced freshening and elevated sea level. The practical consequence is direct: a risk assessment that ranked ensemble members by projected warming alone, treating the warmest members as the scenarios of greatest concern, would misidentify which future conditions actually threaten the farm. Screening future climate scenarios for aquaculture risk in Bantry Bay, or in comparable data-scarce embayments, cannot be reduced to a temperature-only exercise, however convenient that simplification is when a single variable is easiest to communicate to a non-specialist audience.

7.5. Spatial and vertical structure across the bay

The spatial map analysis sharpens, and also complicates, the physical reading of the results above. At the surface, the imposed warming and freshening propagate inward with limited attenuation and are close to spatially uniform: warming is, if anything, marginally stronger in the outer bay and offshore than in the sheltered inner-bay arms, consistent with the inner bay's longer flushing time buffering the imposed offset before it is fully expressed. The salinity difference from baseline is spatially uniform at close to its full imposed magnitude, with no comparable inner-to-outer gradient, reinforcing the boundary-controlled, single-driver reading of Section 7.2.

The vertical structure does not follow this same uniform pattern, and does not simply scale with the strength of the boundary forcing. Thermal and haline stratification both concentrate in the deep central basin and outer bay, while the shallow inner-bay arms remain comparatively well mixed regardless of how strong the imposed perturbation is. As the ensemble's imposed warming increases, the inner bay if anything becomes less stratified rather than more, because the added heat penetrates a shallow water column more completely than it does the deeper outer basin. A possible explanation, rather than a confirmed mechanism, is that bathymetry and local mixing regime govern where vertical structure forms in the bay more strongly than the magnitude of the boundary signal does: the shallow, well-mixed inner arms may simply not retain added heat or freshwater long enough to build stratification, regardless of how strong the imposed offset is, whereas the deeper, more sheltered outer-bay waters can. This reading is consistent with the broader estuarine mixing literature, where the balance between tidal stirring and buoyancy input, rather than the buoyancy input's magnitude alone, is understood to control where stratification develops and persists (Simpson et al., 1990). It remains a plausible reading of the spatial pattern rather than a confirmed mechanism for Bantry Bay specifically: the summer-mean maps used here were not designed to isolate the relative roles of depth, residence time, and tidal mixing intensity against one another, and a dedicated vertical-mixing analysis would be needed to establish

which of these actually dominates. What the maps do establish is that the concentration of thermal stress at the southern inner bay (Section 6.5 cannot be read as a simple consequence of stronger local warming, since the warming itself is not spatially concentrated there; shallow depth and long residence time are the more likely candidates, and are identified here as an open question for dedicated follow-up work.

7.6. Sea-level rise and the tidal response

The tidal-range result is essentially a null result. Across the full sampled range of $\Delta\eta$, the mean tidal range at Castletownbere changes by less than a millimetre. Sea-level rise of the projected scale therefore propagates into the bay as a near-constant lift of the mean level, raising the water level by close to the imposed amount, without measurably reshaping the tidal dynamics. This is consistent with shelf-scale estimates that the tidal response to sea-level rise in this region is small by 2075 (Pickering et al., 2017), and it means that for the purposes of the later aquaculture modules the sea-level signal can be treated as a mean shift rather than as a change in tidal energy.

A related observation concerns the two outlier members identified in the mean water-level analysis (Section 6.7). Run 7, the coldest member in the ensemble, produces the highest anomalous mean water level; run 6, a comparatively warm member, produces the lowest, even negative. This runs counter to what a simple steric (thermal-expansion) mechanism would predict, which would expect the reverse. Both members carry near-zero salinity perturbations, ruling out freshening as an explanation, but beyond that the reversal is not explained by the present analysis. Why these two members specifically depart from the expected $\Delta\eta$ relationship, and whether the cause is physical or an artefact of sampling at the extremes of the ensemble's range, is identified here as a specific open question, distinct from the tidal-range null result discussed above.

7.7. Methodological reflection

The shift from deterministic calibration to an ensemble-based uncertainty framework was forced by the data situation, but it is defensible on its own terms. With only a single tide gauge available and no ADCP, continuous CTD, or gauged river discharge, a full three-dimensional calibration could not be constrained, and tuning the interior parameters against the data that did exist would have produced a fragile baseline rather than a reliable one. Reframing the question around how the interior responds to plausible variation at the boundary makes the limits of the model explicit instead of hiding them inside a single tuned run, which is the more honest position in a data-scarce setting (Pianosi et al., 2016; Beven et al., 2001).

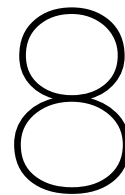
This reframing shaped several specific choices about how the model itself was configured, each worth scrutiny in turn. The decision to keep Manning's n uniform across the domain was reasonable given the absence of spatially distributed velocity data to constrain a zoned roughness field; the screening identified Manning's n as the dominant internal control, so it is the parameter that would most reward refinement, and a zoned field, lower in the deep outer channels, higher in the structurally rough inner bay, is a natural next step once observations exist to support it. The same logic applies to the uniform boundary offsets: applying ΔT , ΔS , and $\Delta\eta$ as constant shifts along the open boundary is consistent with the coarse resolution of the CMIP6 cells, which collapse to a single value at this scale, but it cannot represent a spatial gradient in oceanic change that would reach the mouth and the inner bay differently. A related choice was holding the 2022 meteorological forcing fixed across all members, which isolates the oceanic signal cleanly at the cost of excluding any change in storminess, seasonal wind pattern, or rainfall that a warmer climate might bring; taken together, these three choices mean the ensemble is best read as the sensitivity of a 2022-like bay to a 2075 boundary envelope, not as a forecast of the bay in 2075.

Given these constraints on how the model represents the physical system, it is worth asking whether the model's three-dimensional complexity was itself necessary, given the computational cost an ensemble approach imposes. The central finding of Sections 7.4 and 7.5, that thermal stress concentrates where shallow depth and long residence time allow an imposed surface warming to raise near-surface temperature efficiently, and that this is not straightforwardly predicted by warming alone, is fundamentally a three-dimensional result. A depth-averaged two-dimensional model, by construction, cannot resolve

the surface-bottom decoupling this mechanism depends on, and could not have produced the compound stress-exceedance finding that is the central contribution of this thesis. Questions governed principally by depth-averaged dynamics, such as the boundary-driven mean state (Section 7.2) and the tidal-range response (Section 7.6), could plausibly have been answered with a simpler model; the vertical-structure results could not. The added computational cost of the three-dimensional approach, which limited the ensemble to 50 members rather than the several hundred a two-dimensional model might have afforded, is therefore read as a deliberate trade-off in service of the thesis's central result, not an unexamined default.

A second set of choices concerns how the ensemble itself was designed, independently of the model configuration above. The ensemble was generated by drawing a large candidate pool through inverse-transform sampling from the marginal distributions and reducing it to a space-filling 50-member subset with the Maximum Dissimilarity Algorithm. The three boundary parameters were treated as statistically independent during sampling, a deliberate first-approach simplification, grounded in the weakness of the empirical correlation between the temperature and salinity deltas ($r = -0.24$; $r^2 \approx 0.06$, so the shared variance is small) rather than a claim that the correlation is negligible or physically meaningless, and independence cleanly satisfies the input-independence assumption of the PRCC method used downstream. It is worth noting that this design is not strictly conservative with respect to compound extremes: were the drivers genuinely correlated, the probability of their joint extreme occurrence would be higher than under the independence assumption. Testing the ensemble's sensitivity to imposing this correlation explicitly is identified as a recommended extension in Chapter 8.2.

The final set of choices concerns the analysis methods applied to the ensemble output once generated. Model skill was assessed with demeaned RMSE, bias, and Pearson correlation against the tide-gauge record, Pearson's r chosen specifically because the claim being tested there is linear covariation on the raw scale. Sensitivity was quantified with PRCC, chosen over a variance-based method such as Sobol because it captures monotonic relationships at a fraction of the computational cost, which matters when each member is a full three-dimensional run, and because the independent sampling design satisfies its assumption of uncorrelated inputs. Its principal limitation is that it evaluates each input's contribution individually while holding the others fixed, and so cannot detect interaction effects between parameters, precisely why the exceedance result in Section 7.4 could not have been anticipated from the PRCC ranking alone, and why rank-correlation screening should be paired with direct inspection of the response of interest rather than relied on in isolation. Where the question instead concerned monotonicity or robustness on a near-zero-variance response, as with the tidal-range trend against $\Delta\eta$ (Section 7.6), Spearman's rank correlation was used instead of Pearson's; the two measures are matched to the specific claim being tested in each case, not used interchangeably. The peak-detection route for tidal-range extraction was itself a methods choice forced by circumstance: it was adopted only after a confirmed defect in the harmonic-analysis package produced non-physical amplitudes, and its resulting mean range was checked for internal consistency across the ensemble; a direct comparison against an independently published tidal-range value for Bantry Bay remains an outstanding verification step and is not yet included in this thesis.



Conclusions & Recommendations

8.1. Conclusions

This thesis set out to answer the following main research question: **Which projected climate variables, ocean temperature change, salinity change, or sea level rise, most strongly drive the hydrodynamic response of Bantry Bay under SSP5-8.5 for the 2075 horizon, and what are the implications for aquaculture conditions in the bay?** This question was addressed through five research sub-questions, each addressed in turn below, followed by a closing synthesis and the recommendations that follow from it.

Research Question 1: How do the individual oceanic boundary perturbations (ΔT , ΔS , and $\Delta \eta$) govern the hydrodynamic response of Bantry Bay, and what is their relative importance as evaluated through PRCC analysis? The bay is boundary-controlled: mean surface salinity, mean surface temperature, and mean water level are each governed almost exclusively by their corresponding boundary driver (ΔS , ΔT , and $\Delta \eta$ respectively), with no response variable meaningfully controlled by more than one parameter at the level of the mean. This confirms that in a data-scarce, transport-driven embayment, the open boundary, rather than the internal model parameterisation, is the dominant source of predictive uncertainty. This single-driver dominance holds for the mean state specifically and does not extend to the extremes, as Research Question 4 below shows.

Research Question 2: How uncertain are future hydrodynamic conditions in the bay, and how wide are the P10/P50/P90 ensemble envelopes for the key response variables? The projection uncertainty differs between variables. The salinity envelope is narrow (of order 2.4psu), stable through the year, and confined to a range that poses no stress risk. The temperature uncertainty is larger and seasonally structured: the instantaneous spread is widest in the well-mixed winter, driven by short-term variability, while the climate-relevant uncertainty is carried by the upper tail of the summer distribution, where the ensemble reaches about 22°C against a median summer peak near 20.7°C . As imposed, every member is warmer than the 2022 baseline across essentially the whole year, and fresher across the whole year.

Research Question 3: How do temperature, salinity, and mean water level distributions across the bay differ between extreme and median ensemble members, and where are the spatial gradients largest? Spatially, the imposed surface fields propagate inward with limited attenuation and are close to uniform, with the warming, if anything, marginally weaker in the sheltered inner bay than offshore. This picture is based on summer conditions across the five representative ensemble members analysed spatially (Section 6.6). Thermal exceedance nonetheless concentrates at the shallow inner-bay stations, with CTD 8 in the southern inner bay the most exposed cultivation-relevant site. The summer maps show the inner bay to be relatively well mixed rather than strongly stratified, so this concentration is not explained by enhanced inner-bay stratification; its likely origin is the shallow depth

and long residence time of the inner bay, and the detailed mechanism is left as an open question for the vertical analysis recommended below.

Research Question 4: When and where do physical conditions exceed species-specific stress thresholds at the seaweed farm location in the inner bay, and how do compound stress days vary across the ensemble? Thermal stress at the seaweed farm is not only a future phenomenon. The 2022 baseline already crosses the kelp threshold at the summer peak, and the ensemble extends both the onset and the duration of that summer stress season under the simplified case examined. Salinity stress does not occur for either species, at any station, in any member.

The thermal exceedance is not predicted by the imposed warming alone. It is governed by the joint action of freshening and sea-level rise together with temperature, so that some members reach high exceedance with little or no warming while others reach almost none despite strong warming. This interaction, rather than warming on its own, is the principal control on surface thermal stress in the ensemble, and it is the reason a scenario ranking based on ΔT alone would misclassify the members that matter most.

Research Question 5: How sea level rise modifies the tidal range distribution across Bantry Bay under future climate scenarios? The sea level rise does not modify the tidal range distribution. Across the full sampled range of sea-level rise, the ensemble spread in mean tidal range is under two-tenths of a millimetre at station Castletownbere, a magnitude too small to support a meaningful trend test. Sea-level rise instead manifests as a near-constant lift of the mean water level, not a change in the bay's tidal energy.

The central message of this thesis is that in a data-limited coastal system, boundary-condition uncertainty dominates the predictive landscape, and climate-risk assessment for surface aquaculture cannot rely on temperature projections alone. The conditions most likely to cause biological stress arise from the combined interplay of multiple physical drivers rather than from any one of them in isolation, and this distinction is only visible once the analysis moves past mean-state sensitivity to examine the extremes directly.

8.2. Recommendations

Several directions for future work follow from this study, from immediate data-driven refinements to wider ecological extensions.

The first priority is in-situ observational data. The absence of ADCP current profiles, continuous CTD records, and gauged river discharge at the bay head was the main constraint on this work, and it is what forced the shift from calibration to a sensitivity-based framework. With these data, the model could be returned to a constrained three-dimensional calibration. Bottom friction, which the screening identified as the dominant internal control, is the parameter that would gain most: it could be moved from a uniform value to a spatially zoned field, lower in the deep outer channels and higher in the rougher inner bay.

The 50-member ensemble was a practical compromise between statistical robustness and the available computing budget. A larger ensemble would resolve the tails of the uncertainty envelope and the parameter interactions that drive stress exceedance more sharply. One way to reach that without a proportional increase in simulation cost is to train a machine-learning emulator on the existing model output and use it to explore the $(\Delta T, \Delta S, \Delta \eta)$ space far more densely. An emulator would also make variance-based methods such as Sobol indices tractable, which would capture the non-linear interactions that the PRCC method used here cannot see, and that the exceedance result showed to be important. A related refinement concerns tidal-range extraction itself. The weak association between ΔT and tidal range identified in Section 7.6 sits close to the resolution limit of the peak-detection method used in this study, adopted after a confirmed defect in the available harmonic-analysis tooling prevented its use. Repeating the tidal-range extraction with a validated harmonic analysis, once this tooling issue is resolved or an alternative package is adopted, would allow this weak signal to be resolved at the level of individual tidal constituents rather than bulk range alone, and would confirm whether it reflects a genuine, if minor, physical process or a resolution artefact of the current method.

The boundary and atmospheric forcing could also be refined. Replacing the uniform offsets with boundary conditions that vary along the open boundary and through the seasons would let the model represent how oceanic change reaches the mouth and the inner bay differently. Coupling the ensemble to downscaled atmospheric projections, rather than holding the 2022 meteorology fixed, would turn this sensitivity analysis into a genuine future projection, at the cost of adding atmospheric uncertainty to the chain.

Finally, the analysis would benefit from a closer link between the physical model and biological management. The present stress analysis treats physical thresholds in isolation. Weighting the exceedances by the growth and harvest windows of *Saccharina latissima* and *Mytilus edulis* would make the results more useful to farm operators, since stress that falls outside the active cultivation period matters less than stress during it. Connecting the physical output to the ecological and aquaculture growth modules planned for the later stages of the PHAROS project would move the focus from threshold exceedance toward direct estimates of biomass and mortality. Extending the analysis through the full water column, rather than the near-surface layer alone, would also make it relevant to deeper-dwelling species and is a natural follow-up to the unresolved question of how the inner-bay stress concentration arises. Taken together, these four steps chart a path from a sensitivity tool to genuine decision support: a workflow transferable across the PHAROS network and beyond, moving from a sensitivity study toward operational guidance for aquaculture planning under climate change.

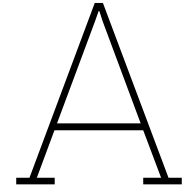
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Supplementary Tables

A.1. Ensemble Parameter Combinations

Table A.1: Full 50-member climate ensemble: imposed open-boundary deltas for temperature (ΔT), salinity (ΔS), and water level ($\Delta \eta$). Member numbering matches the results chapters.

Run	ΔT ($^{\circ}\text{C}$)	ΔS (psu)	$\Delta \eta$ (m)
1	3.827	-1.010	0.388
2	-0.035	-2.579	0.840
3	-0.151	-2.248	0.244
4	0.318	-0.279	0.777
5	4.394	-2.531	0.825
6	4.661	-0.357	0.847
7	-0.035	-0.321	0.242
8	2.856	-2.656	0.428
9	0.823	-1.557	0.564
10	2.449	-1.286	0.844
11	1.779	-0.214	0.488
12	4.872	-1.507	0.653
13	1.603	-1.315	0.249
14	4.675	-2.108	0.254
15	2.019	-2.668	0.697
16	0.053	-1.373	0.829
17	-0.102	-2.567	0.534
18	2.610	-0.254	0.244
19	4.591	-0.342	0.571
20	2.733	-0.226	0.715
21	3.057	-1.744	0.542
22	4.857	-2.564	0.483
23	-0.020	-0.642	0.537
24	-0.081	-1.381	0.366
25	4.511	-0.374	0.247
26	1.250	-2.071	0.381
27	3.088	-1.756	0.318
28	1.522	-0.823	0.655
29	3.205	-0.887	0.587
30	1.463	-2.003	0.832
31	1.934	-1.043	0.450
32	3.436	-1.917	0.752

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Table A.1 – *continued from previous page*

Run	ΔT (°C)	ΔS (psu)	$\Delta \eta$ (m)
33	4.717	-1.774	0.450
34	3.516	-2.574	0.597
35	0.447	-2.167	0.679
36	2.509	-2.511	0.249
37	1.515	-2.611	0.521
38	1.275	-0.555	0.324
39	4.840	-2.285	0.655
40	3.710	-1.017	0.770
41	1.654	-0.545	0.827
42	1.907	-1.900	0.653
43	3.219	-0.412	0.449
44	1.148	-2.645	0.288
45	3.947	-2.647	0.311
46	0.004	-0.958	0.683
47	1.198	-1.368	0.742
48	2.642	-0.850	0.311
49	2.532	-1.337	0.678
50	0.819	-0.275	0.622

A.2. Full PRCC Sensitivity Coefficients

Table A.2: PRCC coefficients for Mean salinity [psu]. Asterisk denotes significance at $\alpha = 0.05$.

Station	ΔT		ΔS		$\Delta \eta$	
	PRCC	p	PRCC	p	PRCC	p
Castletownbere TG	+0.217	0.138	+0.616*	<0.001	+0.252	0.084
CTD 1	+0.229	0.117	+0.619*	<0.001	+0.254	0.081
CTD 2	+0.213	0.146	+0.616*	<0.001	+0.250	0.087
CTD 3	+0.221	0.131	+0.616*	<0.001	+0.264	0.070
CTD 4	+0.226	0.122	+0.618*	<0.001	+0.265	0.068
CTD 5	+0.220	0.133	+0.617*	<0.001	+0.255	0.080
CTD 6	+0.221	0.131	+0.617*	<0.001	+0.262	0.073
CTD 7	+0.232	0.112	+0.618*	<0.001	+0.266	0.068
CTD 8	+0.220	0.133	+0.617*	<0.001	+0.255	0.080
Seaweed farm	+0.226	0.122	+0.618*	<0.001	+0.265	0.068
Bay mouth	+0.221	0.131	+0.617*	<0.001	+0.262	0.073
Bantry Bay Buoy	+0.237	0.104	+0.619*	<0.001	+0.267	0.067
offshore 1	+0.220	0.133	+0.618*	<0.001	+0.254	0.082
offshore 2	+0.228	0.119	+0.619*	<0.001	+0.260	0.074
offshore 3	+0.232	0.113	+0.619*	<0.001	+0.260	0.074
offshore 4	+0.229	0.117	+0.619*	<0.001	+0.254	0.081

Table A.3: PRCC coefficients for Min salinity [psu]. Asterisk denotes significance at $\alpha = 0.05$.

Station	ΔT		ΔS		$\Delta \eta$	
	PRCC	p	PRCC	p	PRCC	p
Castletownbere TG	+0.199	0.176	+0.610*	<0.001	+0.254	0.081
CTD 1	+0.232	0.113	+0.619*	<0.001	+0.262	0.072
CTD 2	+0.201	0.171	+0.614*	<0.001	+0.252	0.084
CTD 3	+0.196	0.182	+0.606*	<0.001	+0.258	0.077
CTD 4	+0.192	0.191	+0.616*	<0.001	+0.266	0.068
CTD 5	+0.238	0.103	+0.620*	<0.001	+0.263	0.071
CTD 6	+0.206	0.160	+0.612*	<0.001	+0.253	0.083
CTD 7	+0.201	0.172	+0.614*	<0.001	+0.272	0.061
CTD 8	+0.236	0.106	+0.620*	<0.001	+0.261	0.073
Seaweed farm	+0.194	0.187	+0.617*	<0.001	+0.264	0.070
Bay mouth	+0.218	0.137	+0.617*	<0.001	+0.254	0.082
Bantry Bay Buoy	+0.263	0.070	+0.646*	<0.001	+0.288*	0.047
offshore 1	+0.237	0.104	+0.620*	<0.001	+0.264	0.070
offshore 2	+0.228	0.119	+0.619*	<0.001	+0.260	0.074
offshore 3	+0.242	0.097	+0.620*	<0.001	+0.267	0.066
offshore 4	+0.248	0.089	+0.620*	<0.001	+0.266	0.068

Table A.4: PRCC coefficients for Mean temperature [C]. Asterisk denotes significance at $\alpha = 0.05$.

Station	ΔT		ΔS		$\Delta \eta$	
	PRCC	p	PRCC	p	PRCC	p
Castletownbere TG	+0.613*	<0.001	+0.148	0.315	+0.093	0.530
CTD 1	+0.613*	<0.001	+0.148	0.315	+0.092	0.534
CTD 2	+0.613*	<0.001	+0.148	0.315	+0.092	0.534
CTD 3	+0.612*	<0.001	+0.148	0.315	+0.094	0.526
CTD 4	+0.613*	<0.001	+0.148	0.314	+0.096	0.519
CTD 5	+0.613*	<0.001	+0.148	0.315	+0.092	0.534
CTD 6	+0.613*	<0.001	+0.148	0.315	+0.092	0.534
CTD 7	+0.612*	<0.001	+0.148	0.316	+0.089	0.545
CTD 8	+0.613*	<0.001	+0.148	0.315	+0.092	0.534
Seaweed farm	+0.613*	<0.001	+0.148	0.315	+0.094	0.526
Bay mouth	+0.613*	<0.001	+0.148	0.315	+0.092	0.534
Bantry Bay Buoy	+0.613*	<0.001	+0.147	0.319	+0.094	0.524
offshore 1	+0.613*	<0.001	+0.148	0.315	+0.092	0.534
offshore 2	+0.613*	<0.001	+0.148	0.315	+0.092	0.534
offshore 3	+0.613*	<0.001	+0.148	0.315	+0.092	0.534
offshore 4	+0.613*	<0.001	+0.148	0.315	+0.092	0.534

Table A.5: PRCC coefficients for Max temperature [C]. Asterisk denotes significance at $\alpha = 0.05$.

Station	ΔT		ΔS		$\Delta \eta$	
	PRCC	p	PRCC	p	PRCC	p
Castletownbere TG	+0.612*	<0.001	+0.144	0.327	+0.092	0.532
CTD 1	+0.612*	<0.001	+0.146	0.322	+0.104	0.481
CTD 2	+0.612*	<0.001	+0.144	0.328	+0.091	0.539
CTD 3	+0.613*	<0.001	+0.148	0.314	+0.094	0.526
CTD 4	+0.622*	<0.001	+0.154	0.294	+0.115	0.435
CTD 5	+0.612*	<0.001	+0.144	0.329	+0.098	0.508
CTD 6	+0.613*	<0.001	+0.148	0.314	+0.094	0.526
CTD 7	+0.611*	<0.001	+0.154	0.296	+0.103	0.487
CTD 8	+0.611*	<0.001	+0.144	0.328	+0.114	0.443
Seaweed farm	+0.613*	<0.001	+0.148	0.317	+0.097	0.513
Bay mouth	+0.613*	<0.001	+0.148	0.317	+0.095	0.520
Bantry Bay Buoy	+0.622*	<0.001	+0.148	0.316	+0.129	0.383
offshore 1	+0.612*	<0.001	+0.144	0.329	+0.100	0.501
offshore 2	+0.612*	<0.001	+0.144	0.329	+0.100	0.501
offshore 3	+0.611*	<0.001	+0.145	0.325	+0.117	0.429
offshore 4	+0.611*	<0.001	+0.145	0.326	+0.115	0.436

Table A.6: PRCC coefficients for Mean water level [m]. Asterisk denotes significance at $\alpha = 0.05$.

Station	ΔT		ΔS		$\Delta \eta$	
	PRCC	p	PRCC	p	PRCC	p
Castletownbere TG	-0.218	0.137	-0.069	0.641	+0.707*	<0.001
CTD 1	-0.209	0.153	-0.069	0.641	+0.708*	<0.001
CTD 2	-0.218	0.137	-0.069	0.641	+0.707*	<0.001
CTD 3	-0.222	0.130	-0.064	0.665	+0.708*	<0.001
CTD 4	-0.218	0.137	-0.069	0.641	+0.707*	<0.001
CTD 5	-0.211	0.150	-0.068	0.644	+0.708*	<0.001
CTD 6	-0.222	0.130	-0.064	0.665	+0.708*	<0.001
CTD 7	-0.218	0.137	-0.069	0.641	+0.707*	<0.001
CTD 8	-0.208	0.156	-0.070	0.639	+0.708*	<0.001
Seaweed farm	-0.220	0.133	-0.067	0.653	+0.708*	<0.001
Bay mouth	-0.218	0.136	-0.065	0.663	+0.708*	<0.001
Bantry Bay Buoy	-0.218	0.137	-0.069	0.641	+0.707*	<0.001
offshore 1	-0.210	0.151	-0.069	0.642	+0.708*	<0.001
offshore 2	-0.209	0.153	-0.069	0.641	+0.708*	<0.001
offshore 3	-0.209	0.153	-0.069	0.641	+0.708*	<0.001
offshore 4	-0.209	0.153	-0.069	0.641	+0.708*	<0.001

Table A.7: PRCC coefficients for WL std dev [m]. Asterisk denotes significance at $\alpha = 0.05$.

Station	ΔT		ΔS		$\Delta \eta$	
	PRCC	p	PRCC	p	PRCC	p
Castletownbere TG	-0.621*	<0.001	-0.124	0.401	-0.107	0.469
CTD 1	-0.391*	0.006	+0.058	0.696	+0.043	0.774
CTD 2	-0.313*	0.030	+0.228	0.119	-0.149	0.312
CTD 3	-0.609*	<0.001	-0.099	0.502	-0.038	0.796
CTD 4	-0.607*	<0.001	-0.098	0.507	-0.038	0.798
CTD 5	-0.625*	<0.001	-0.108	0.466	-0.053	0.718
CTD 6	-0.603*	<0.001	-0.136	0.357	-0.042	0.779
CTD 7	-0.599*	<0.001	-0.122	0.409	-0.052	0.724
CTD 8	-0.618*	<0.001	-0.129	0.384	-0.020	0.894
Seaweed farm	-0.603*	<0.001	-0.110	0.457	-0.038	0.797
Bay mouth	-0.614*	<0.001	-0.106	0.475	-0.041	0.782
Bantry Bay Buoy	-0.599*	<0.001	-0.105	0.478	-0.058	0.697
offshore 1	-0.617*	<0.001	-0.138	0.349	-0.014	0.926
offshore 2	-0.575*	<0.001	-0.072	0.629	+0.052	0.725
offshore 3	+0.512*	<0.001	+0.209	0.154	+0.312*	0.031
offshore 4	+0.646*	<0.001	+0.184	0.210	+0.280	0.054

A.3. Seasonal Ensemble Statistics at the Seaweed Farm

Table A.8: Annual and seasonal ensemble summary at the seaweed farm. Spread denotes the instantaneous P10–P90 band width; JFM = January–March, JA = July–August.

Variable	Quantity	Value
Surface temperature [°C]	Winter (JFM) spread, median	3.48
	Winter (JFM) spread, maximum	4.78
	Summer (JA) spread, median	2.44
	Summer (JA) spread, maximum	3.43
	Annual P10 minimum	7.76
	Annual P90 maximum	22.09
	P50 range (Jan / Apr / Dec)	10.31 / 11.73 / 10.01
	Summer (JA) P50 maximum	20.70
Surface salinity [psu]	P10–P90 spread, median	2.37
	P10–P90 spread, range	2.27–2.50
	Annual P10 minimum	31.86
	Annual P90 maximum	35.06
	P50 range (annual)	33.10–33.97
Water level [m]	P10–P90 spread, median	0.549
	P10–P90 spread, maximum	0.571
Baseline position	Temp. below ensemble P10	94% of year
	Salinity above ensemble P90	100% of year

Table A.9: Monthly box-plot statistics across the 50-member ensemble at the seaweed farm: lower quartile (Q1), median, upper quartile (Q3), interquartile range (IQR), and the relevant whisker (upper for temperature, lower for salinity).

Month	Surface temperature [$^{\circ}\text{C}$]					Surface salinity [psu]				
	Q1	Med	Q3	IQR	Whisk $_{\uparrow}$	Q1	Med	Q3	IQR	Whisk $_{\downarrow}$
Jan	9.59	10.46	11.86	2.27	15.26	32.79	33.56	34.29	1.50	31.28
Feb	9.06	9.71	10.87	1.80	13.57	32.77	33.54	34.27	1.49	31.21
Mar	8.71	9.89	11.45	2.73	15.55	32.74	33.48	34.18	1.44	31.16
Apr	10.84	11.75	12.78	1.94	15.69	32.73	33.50	34.22	1.49	31.18
May	13.59	14.32	15.28	1.70	17.83	32.57	33.38	34.13	1.56	31.01
Jun	14.79	15.54	16.37	1.58	18.75	32.69	33.54	34.31	1.62	31.04
Jul	16.57	17.49	18.48	1.91	21.34	32.86	33.67	34.43	1.57	31.21
Aug	17.58	18.33	19.35	1.77	22.01	32.97	33.84	34.60	1.62	31.29
Sep	16.91	17.58	18.47	1.56	20.81	32.74	33.58	34.33	1.60	31.05
Oct	14.73	15.46	16.26	1.53	18.56	32.61	33.47	34.22	1.62	30.78
Nov	12.03	12.92	13.60	1.56	15.95	32.47	33.23	34.01	1.54	30.82
Dec	9.41	10.44	11.17	1.77	13.82	32.56	33.31	34.04	1.49	30.82

A.4. Stress Exceedance Statistics

Table A.10: Per-run thermal exceedance at the seaweed-farm station, with the ensemble parameter triplet for cross-reference (Appendix A.1). T_{kelp} and T_{mus} are the percentage of the year above 18 and 20 $^{\circ}\text{C}$ respectively.

Run	ΔT ($^{\circ}\text{C}$)	ΔS (psu)	$\Delta \eta$ (m)	T_{kelp} (%)	T_{mus} (%)
1	-0.02	-2.69	+0.37	5.42	0.31
2	+4.70	-0.20	+0.80	28.23	13.34
3	+1.86	-0.20	+0.24	1.68	0.00
4	+4.92	-2.69	+0.61	42.74	24.54
5	-0.19	-1.04	+0.85	1.16	0.00
6	+4.92	-1.51	+0.24	27.93	12.84
7	+1.64	-2.66	+0.85	8.11	0.46
8	+2.59	-1.30	+0.58	1.59	0.00
9	-0.19	-1.18	+0.41	23.68	5.23
10	+4.91	-0.20	+0.43	7.31	0.43
11	+2.76	-2.68	+0.24	5.40	0.31
12	+4.12	-1.73	+0.85	22.89	3.29
13	+1.97	-0.20	+0.76	4.66	0.22
14	-0.03	-2.08	+0.65	22.26	2.61
15	+2.15	-1.44	+0.24	6.78	0.40
16	+2.32	-2.69	+0.56	1.34	0.00
17	-0.17	-0.21	+0.57	1.16	0.00
18	+4.92	-1.53	+0.56	12.68	0.65
19	+1.80	-1.56	+0.83	22.20	2.48
20	+4.92	-2.69	+0.31	14.36	0.75
21	+2.41	-0.31	+0.50	16.84	0.90
22	-0.15	-0.20	+0.30	22.76	3.20
23	+3.44	-1.88	+0.41	1.25	0.00
24	+1.37	-1.94	+0.45	1.17	0.00
25	+0.25	-1.85	+0.24	21.84	2.20
26	+4.78	-2.69	+0.85	3.42	0.13
27	+3.69	-0.72	+0.24	16.93	0.90
28	+0.78	-1.05	+0.65	4.49	0.21
29	+3.19	-0.89	+0.85	18.22	0.95
30	-0.19	-2.69	+0.85	4.30	0.19

Table A.10 – *continued*

Run	ΔT	ΔS	$\Delta \eta$	T_{kelp} (%)	T_{mus} (%)
31	+3.13	-2.28	+0.73	6.13	0.35
32	+0.33	-0.20	+0.85	19.57	1.09
33	+4.19	-0.72	+0.64	22.49	2.81
34	+1.65	-1.02	+0.41	19.91	1.12
35	+0.79	-0.86	+0.24	1.85	0.00
36	+4.92	-1.01	+0.83	11.41	0.60
37	+4.22	-0.95	+0.44	4.40	0.19
38	+1.63	-2.05	+0.67	3.46	0.14
39	+3.63	-2.69	+0.44	22.76	3.21
40	+0.18	-1.91	+0.85	20.81	1.35
41	+1.59	-2.69	+0.39	5.12	0.28
42	+4.92	-0.23	+0.24	6.04	0.36
43	+4.92	-2.13	+0.44	18.25	0.95
44	+0.76	-2.69	+0.56	3.12	0.10
45	+0.95	-0.31	+0.43	21.03	1.51
46	+1.32	-0.82	+0.83	1.28	0.00
47	-0.19	-1.87	+0.47	3.37	0.13
48	+3.69	-1.54	+0.68	13.07	0.67
49	+3.52	-0.20	+0.37	12.05	0.64
50	+3.26	-0.20	+0.67	2.50	0.01

Table A.11: Thermal exceedance summary at the four farm-relevant stations: ensemble median, range, and number of members exceeding the threshold for more than 5% of the year ($n = 50$).

Station	Species	Median (%)	Min (%)	Max (%)	$n_{>5\%}$
Seaweed farm	<i>S. latissima</i>	7.71	1.16	42.74	32
Castletownbere TG	<i>S. latissima</i>	1.98	0.00	39.95	19
CTD 4	<i>S. latissima</i>	7.33	1.17	40.91	31
Bay mouth	<i>S. latissima</i>	5.54	0.75	57.52	26
Seaweed farm	<i>M. edulis</i>	0.44	0.00	24.54	4
Castletownbere TG	<i>M. edulis</i>	0.00	0.00	21.56	2
CTD 4	<i>M. edulis</i>	0.34	0.00	23.76	3
Bay mouth	<i>M. edulis</i>	0.29	0.00	31.65	4

A.5. Per-Run Water-Level Skill Metrics

Table A.13 reports demeaned water-level skill at the Castletownbere Tide Gauge for all 50 ensemble members, evaluated over the full 2022 simulation period against the observed record (7,703 points, 2022-01-01 to 2023-01-01). Bias and RMSE are in metres; correlation is the Pearson coefficient; phase error is the timing offset of modelled versus observed M2 high water, in minutes.

Table A.13: Per-run water-level skill metrics (demeaned), Castletownbere Tide Gauge, 50-member ensemble.

Run ID	Bias [m]	RMSE [m]	Corr.	Phase err. [min]	Tidal range [m]
1	0.001	0.081	0.996	0.0	3.816
2	0.001	0.081	0.995	0.0	3.811
3	0.001	0.081	0.996	0.0	3.815
4	0.001	0.082	0.995	0.0	3.809
5	0.001	0.081	0.996	0.0	3.813
6	0.001	0.082	0.995	0.0	3.810

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Table A.13 – continued

Run ID	Bias [m]	RMSE [m]	Corr.	Phase err. [min]	Tidal range [m]
7	0.001	0.081	0.996	0.0	3.814
8	0.001	0.081	0.996	0.0	3.819
9	0.001	0.081	0.995	0.0	3.812
10	0.001	0.081	0.996	0.0	3.816
11	0.001	0.081	0.996	0.0	3.819
12	0.001	0.081	0.995	0.0	3.815
13	0.001	0.081	0.996	0.0	3.814
14	0.001	0.081	0.995	0.0	3.812
15	0.001	0.081	0.996	0.0	3.818
16	0.001	0.081	0.996	0.0	3.814
17	0.001	0.081	0.996	0.0	3.819
18	0.001	0.081	0.996	0.0	3.814
19	0.001	0.081	0.995	0.0	3.816
20	0.001	0.081	0.996	0.0	3.818
21	0.001	0.081	0.996	0.0	3.817
22	0.001	0.081	0.995	0.0	3.814
23	0.001	0.081	0.996	0.0	3.819
24	0.001	0.081	0.996	0.0	3.816
25	0.001	0.081	0.995	0.0	3.813
26	0.001	0.081	0.996	0.0	3.816
27	0.001	0.081	0.995	0.0	3.815
28	0.001	0.081	0.996	0.0	3.818
29	0.001	0.081	0.996	0.0	3.818
30	0.001	0.081	0.996	0.0	3.815
31	0.001	0.081	0.996	0.0	3.818
32	0.001	0.081	0.995	0.0	3.817
33	0.001	0.081	0.995	0.0	3.814
34	0.001	0.081	0.995	0.0	3.817
35	0.001	0.081	0.996	0.0	3.819
36	0.001	0.081	0.996	0.0	3.814
37	0.001	0.081	0.996	0.0	3.818
38	0.001	0.081	0.996	0.0	3.816
39	0.001	0.081	0.995	0.0	3.815
40	0.001	0.081	0.995	0.0	3.816
41	0.001	0.081	0.996	0.0	3.814
42	0.001	0.081	0.996	0.0	3.818
43	0.001	0.081	0.995	0.0	3.817
44	0.001	0.081	0.996	0.0	3.815
45	0.001	0.081	0.995	0.0	3.813
46	0.001	0.081	0.996	0.0	3.819
47	0.001	0.081	0.996	0.0	3.818
48	0.001	0.081	0.996	0.0	3.815
49	0.001	0.081	0.996	0.0	3.818
50	0.001	0.081	0.996	0.0	3.818

Table A.12: Spatial thermal-stress exceedance across all 16 observation stations: ensemble median (and P10–P90 range) of the percentage of the year above each species threshold. Salinity exceedance is zero everywhere.

Station	<i>S. latissima</i> (> 18°C)		<i>M. edulis</i> (> 20°C)	
	Median	(P10–P90)	Median	(P10–P90)
Castletownbere TG	2.0%	(0.0–23.0)	0.0%	(0.0–0.6)
CTD 1	8.6%	(1.0–30.8)	0.3%	(0.0–9.1)
CTD 2	2.8%	(0.6–25.2)	0.0%	(0.0–1.3)
CTD 3	6.5%	(1.3–23.7)	0.3%	(0.0–3.1)
CTD 4	7.3%	(1.3–22.8)	0.3%	(0.0–3.0)
CTD 5	6.0%	(0.7–26.9)	0.2%	(0.0–7.4)
CTD 6	6.6%	(1.4–24.4)	0.4%	(0.0–3.5)
CTD 7	8.1%	(1.4–22.7)	0.4%	(0.0–3.3)
CTD 8	14.8%	(1.1–34.1)	0.7%	(0.0–17.7)
Seaweed farm	7.7%	(1.3–22.8)	0.4%	(0.0–3.2)
Bay mouth	5.5%	(0.9–26.0)	0.3%	(0.0–4.7)
Bantry Bay Buoy	7.1%	(0.6–20.8)	0.2%	(0.0–2.4)
offshore 1	7.5%	(0.7–28.8)	0.3%	(0.0–9.2)
offshore 2	8.9%	(0.9–31.3)	0.4%	(0.0–9.7)
offshore 3	10.9%	(1.4–36.1)	0.7%	(0.0–11.4)
offshore 4	12.3%	(1.1–39.7)	0.6%	(0.0–13.1)

B

Supplementary Figures

B.1. Spatial Sensitivity

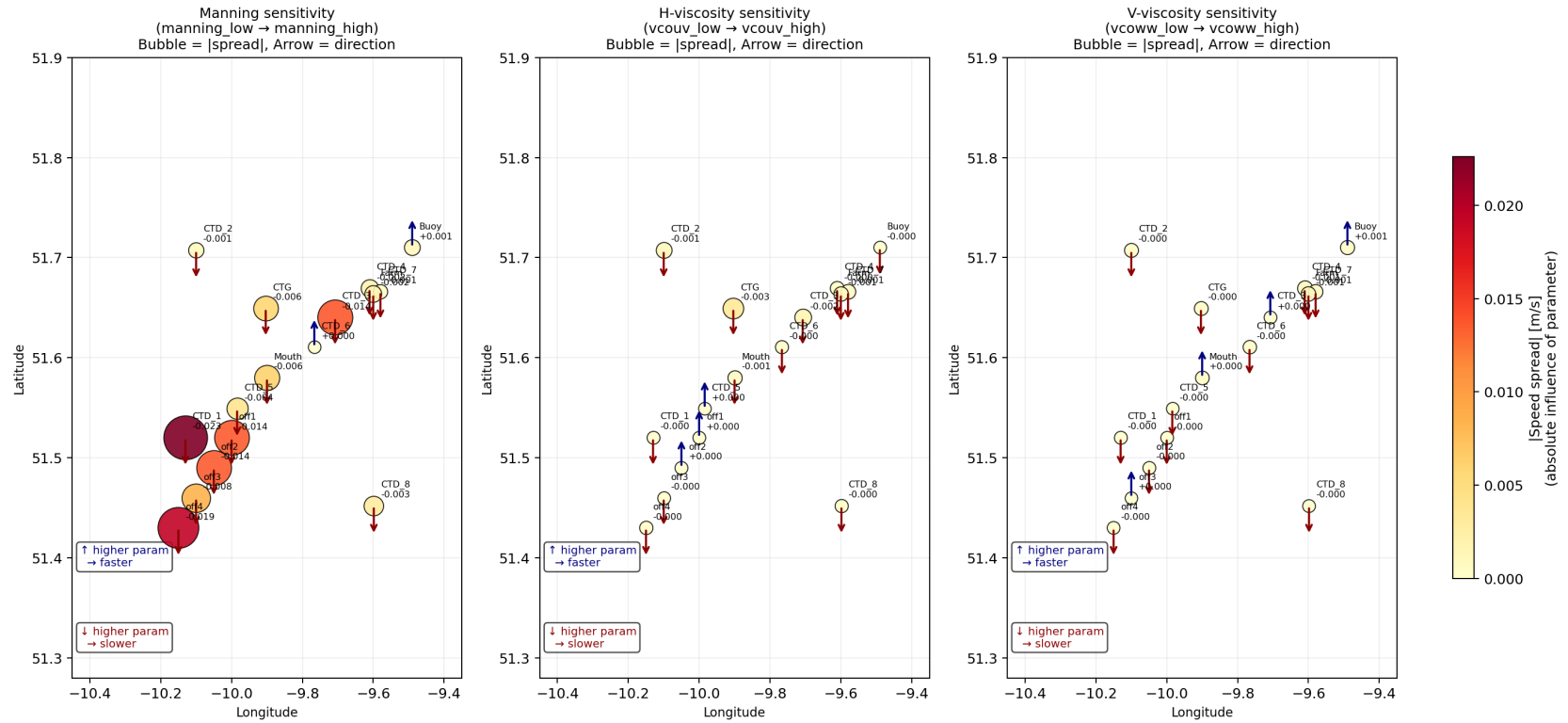


Figure B.1: Per-parameter sensitivity maps for Bantry Bay, showing the spatial variability and absolute influence of Manning's n , horizontal viscosity, and vertical viscosity on depth-averaged current speeds. Bubble sizes represent the absolute spread (magnitude of influence) and arrows indicate the direction of change when the parameter is increased.

B.2. Velocity Profiles

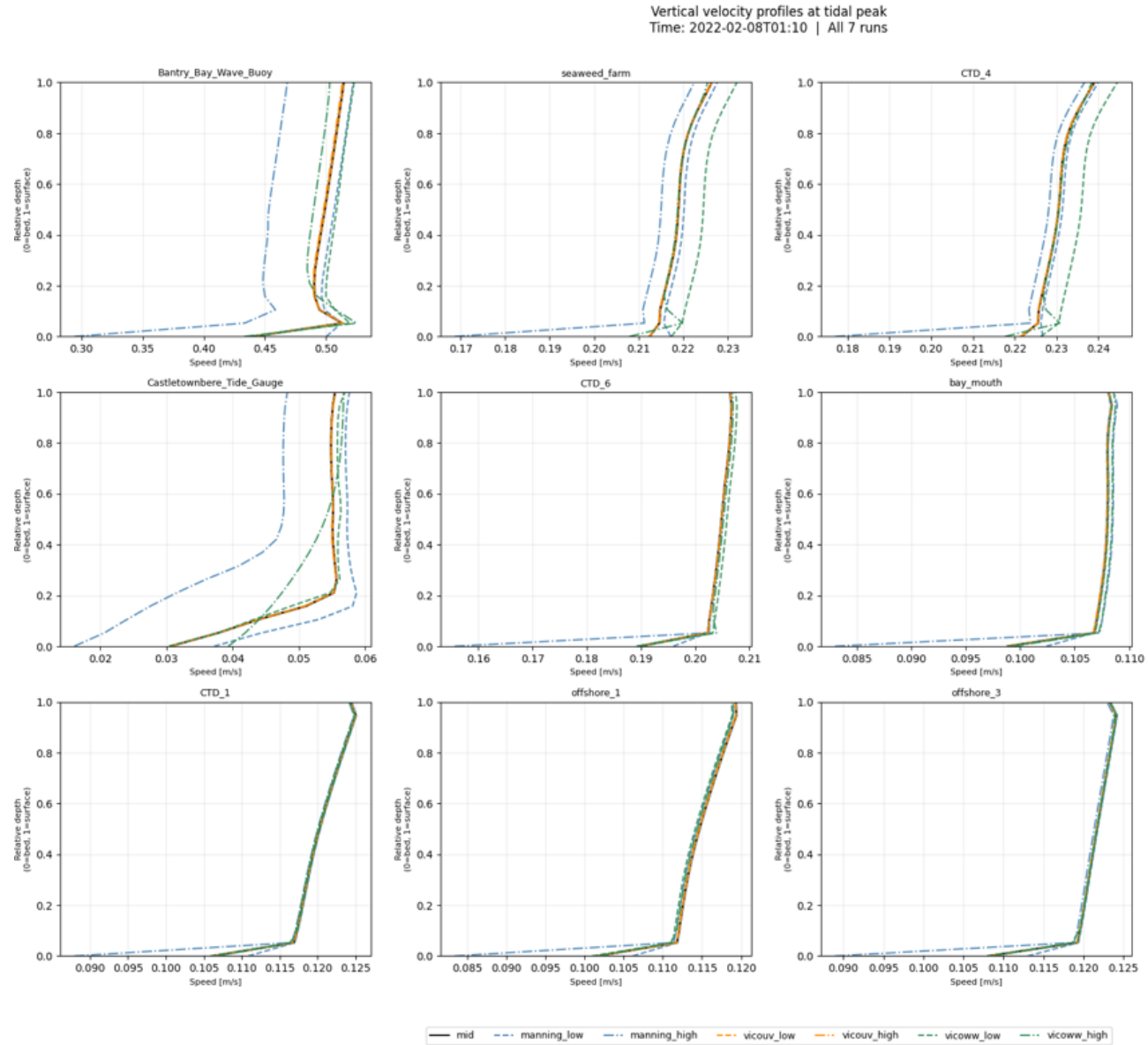


Figure B.2: Vertical velocity profiles extracted from onshore to offshore in Bantry Bay. The plot demonstrates how variations in manning, horizontal and vertical viscosity alter the vertical velocity profile.