

Supplementary Materials

Accelerating tidal marsh loss in Canada reveals the limits of static area-based protection

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1. Evaluation of consistency among tidal marsh datasets

1.1 Products

We compared the tidal marsh maps developed in this study with four global products available for Canada. For tidal marsh extent, we compared maps in 2020 derived from Worthington et al. (2024)¹, Zhang et al. (2024)², and this study. Worthington et al. mapped tidal marsh at 10 m using random-forest classification of statistical variables derived from Sentinel-1 and Sentinel-2 observations. Zhang et al. produced annual 30 m wetland maps for 2000-2022 using locally adaptive random forests applied to Landsat spectral, phenological, water-level, texture, and topographic variables, followed by spatiotemporal consistency filtering. Also, we compared tidal marsh change from Murray et al. (2022)³, Campbell et al. (2022)⁴, Zhang et al. (2024), and this study, and assessed agreement using binary change/no-change maps covering approximately comparable two-decade periods around 2000 to 2020. Murray et al. (2022) estimated global tidal wetland gain and loss (1999–2019) using a three-year interval change classification framework, while Campbell et al. (2022) detected salt marsh change based on Landsat NDVI anomalies relative to a historical baseline and reported change every five years. For Murray et al. and Campbell et al., we used the mapped change layers directly. For this study and Zhang et al., we compared marsh extent in 2000 and 2020, and classified pixels as changed where their tidal marsh status differed between these endpoints. This endpoint comparison excludes intermediate changes that had reversed by 2020.

1.2 Sample-based disagreement assessment

We assessed the products using samples drawn from areas where their classifications disagreed (Tables S1 and S2). For extent, we randomly selected 120 samples per coast and interpreted based on very high-resolution images from Google Earth. Samples were excluded when a confident reference label could not be assigned during interpretation, leaving 107 Pacific and 115 Atlantic samples. The change assessment included 150 samples. For each product, we recorded true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN) relative to the reference labels. The error magnitude index was calculated as $100 \times (FP + FN)/(TP + FP + FN + TN)$. For change, we also calculated confirmed change as $100 \times TP/(TP + FP)$, representing the percentage of mapped changes supported by reference interpretation. We estimated 95% confidence intervals using 10,000 bootstrap resamples^{5–7}. These metrics describe performance within the sampled disagreement areas and do not represent overall map accuracy.

1.3 Extent Comparison

Visual interpretation of the disagreement samples revealed two distinct patterns of commission error (Table S1). Within these samples, Zhang et al. (2024) mainly misclassified other vegetated surfaces within the intertidal zone as tidal marsh, whereas Worthington et al. (2024) tended to extend marsh classifications landward into adjacent peatlands, non-tidal marshes, and other wetlands. These errors help explain the high false-positive counts for Zhang et al. along the Pacific coast and Worthington et al. along the Atlantic coast.

The Pacific coast contains diverse intertidal and shallow subtidal habitats, including kelp forests, seagrass meadows, algae-covered rocky shores, and algae-covered tidal flats⁸ (Figure S2). Mixtures of vegetation, exposed substrate, and shallow water within 30 m pixels can produce spectral signals similar to those of tidal marsh, making these environments particularly susceptible to the intertidal confusion observed in Zhang et al. Their Pacific estimate reached 91,692 ha, compared with 16,178 ha in this study and 8,019 ha in Worthington et al.

Along the Atlantic coast, low-relief landscapes allow tidal marshes to adjoin extensive peatlands and non-tidal wetlands. Similar vegetation characteristics and small elevation differences can make their boundaries difficult to distinguish, contributing to the landward overestimation observed in Worthington et al. Their Atlantic estimate was 135,668 ha, compared with 78,351 ha in this study and 89,315 ha in Zhang et al. The steeper terrain along much of the Pacific coast may provide clearer separation between intertidal habitats and uplands, making this source of confusion less pronounced.

Dense Landsat time series may have helped our study distinguish marsh from these neighboring habitats. Temporal information supports wetland classification by capturing variation in inundation and vegetation growth^{9,10}, while studies of intertidal seagrass also demonstrate the value of tracking vegetation through time¹¹. Using these temporal patterns may therefore have reduced confusion with other intertidal vegetation along the Pacific coast and with non-tidal wetlands along the Atlantic coast.

1.4 Change monitoring

Our study provides a consistent annual record of tidal marsh extent and change from 1988 to 2023, supporting analyses that require both frequent observations and comparable maps through time (Figure S1e&f). Murray et al. (2022) and Campbell et al. (2022) reported change at three- and five-year intervals, respectively, which limits their ability to resolve annual variation. Zhang et al. (2024) provided annual

maps, but year-to-year classification inconsistencies can propagate into post-classification change estimates, producing apparent fluctuations and reversals that may obscure the underlying marsh trends^{6,7}. By providing consistent annual maps, our record allows us to estimate change rates, assess whether those rates accelerated or slowed, and compare marsh change before and after the establishment of protected and conserved areas (PCAs).

Within the sampled disagreement areas, this study's change maps agreed more closely with the reference interpretations than the three global products (Table S2). Dense Landsat time-series modelling may have contributed to this agreement by distinguishing persistent marsh changes from short-term spectral variation. This interpretation is supported by comparative wetland studies showing that continuous time-series modelling can improve change-detection accuracy and reduce false detections^{10,12}.

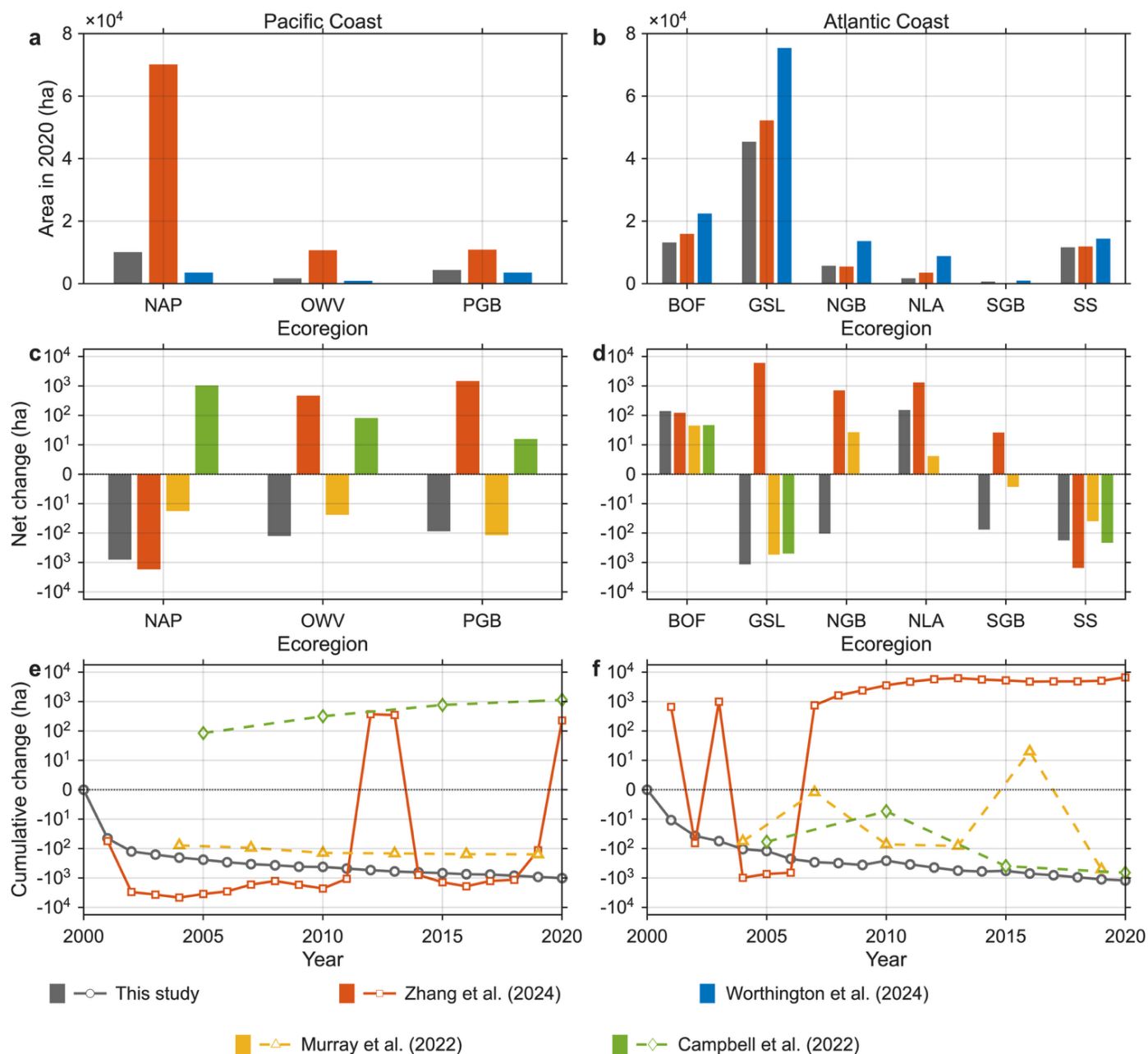


Figure S1 | Comparison of tidal marsh extent and net change across independent products. **a,b**, Mapped tidal marsh extent in 2020 across Canadian marine ecoregions for the Pacific (**a**) and Atlantic (**b**) coasts. **c,d**, Net tidal marsh change over 2000-2020 for individual ecoregions along the Pacific (**c**) and Atlantic (**d**) coasts. **e,f**, Cumulative tidal marsh change relative to the year 2000 baseline for the Pacific (**e**) and Atlantic (**f**) coasts. Solid lines indicate annual mapping products, whereas dashed lines indicate interval-based change products. Net-change panels are shown using a signed logarithmic scale to preserve gain and loss direction while improving comparison across ecoregions and products.

Abbreviations: BOF, Gulf of Maine/Bay of Fundy; GSL, Gulf of St. Lawrence–Eastern Scotian Shelf; NAP, North American Pacific Fjordland; NGB, Northern Grand Banks–Southern Labrador; NLA, Northern Labrador; OWV, Oregon–Washington–Vancouver Coast and Shelf; PGB, Puget Trough–Georgia Basin; SGB, Southern Grand Banks–South Newfoundland; SS, Scotian Shelf.

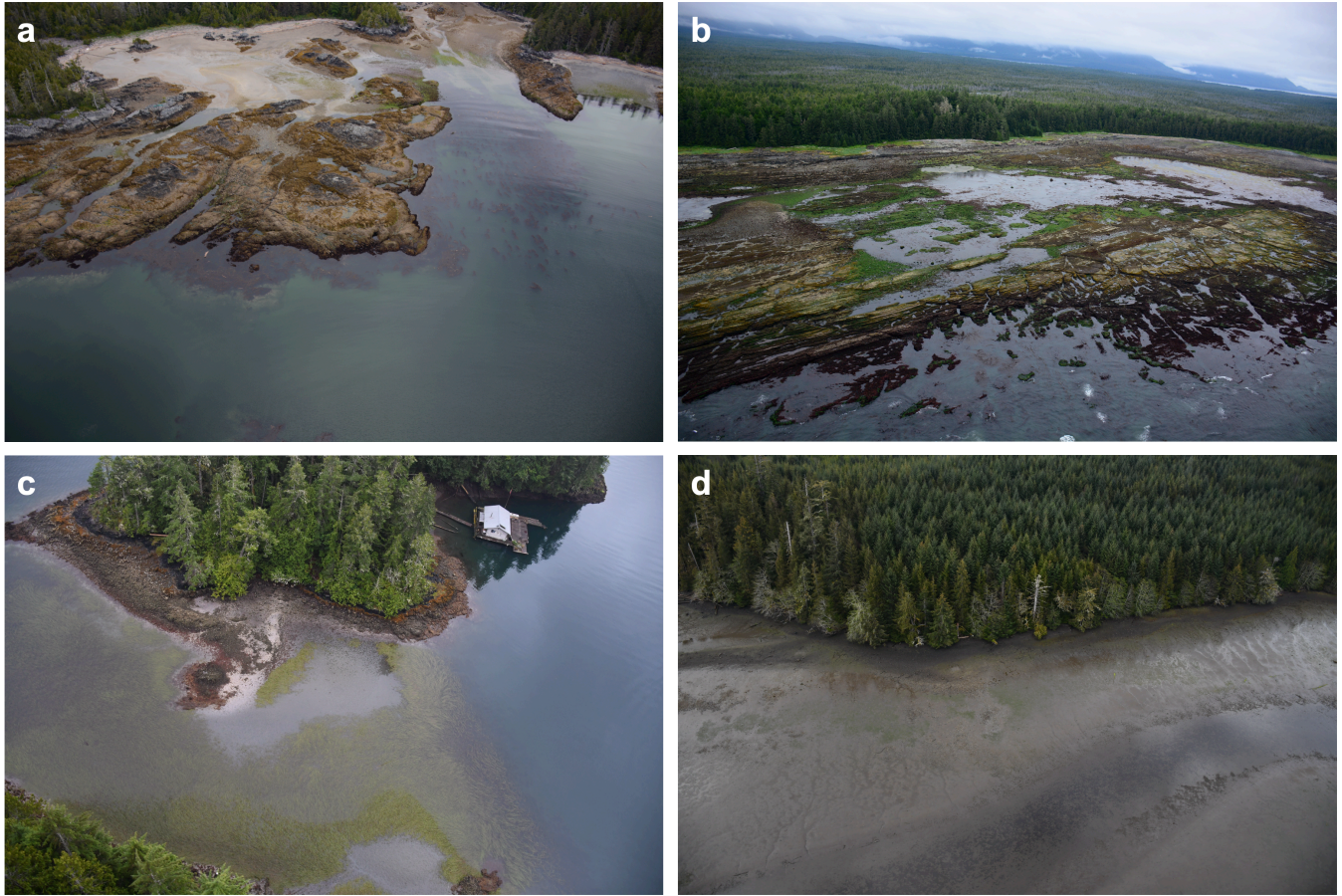


Figure S2 | Examples of heterogeneous intertidal ecosystems along Canada's Pacific coast. a, Kelp forests (54.38°N, 130.82°W). b, Algae-covered rocky intertidal habitat (49.40°N, 126.56°W). c, Seagrass meadow (48.98°N, 124.97°W). d, Algae-covered tidal flat (53.98°N, 132.69°W). These spectrally complex coastal environments may contribute to disagreement among tidal marsh products. Image credit: ShoreZone airborne oblique imagery.

Table S1. Product comparison for disagreement areas for tidal marsh classification map in 2020 for Canada Pacific and Atlantic coasts. TP, FP, FN and TN denote true positives, false positives, false negatives and true negatives, respectively; bracketed values are 95% bootstrap confidence intervals (10,000 resamples). Because sampling is restricted to disagreement areas, metrics reflect classification performance within contested pixels and do not represent overall map accuracy.

Product	Coast	Area (ha)	TP	FP	FN	TN	Error Magnitude (%)
Worthington et al. 2024¹	Pacific	8019	3 [0, 7]	5 [1, 10]	2 [0, 5]	97 [91, 103]	6.5 [1.9, 11.2]
	Atlantic	135668	8 [3, 14]	68 [58, 78]	4 [1, 8]	35 [26, 45]	62.6 [53.9, 71.3]
Zhang et al., 2024²	Pacific	91692	3 [0, 7]	96 [90, 102]	2 [0, 5]	6 [2, 11]	91.6 [86.0, 96.3]
	Atlantic	89315	5 [1, 10]	36 [26, 46]	7 [3, 12]	67 [57, 77]	37.4 [28.7, 46.1]
This Study	Pacific	16178	4 [1, 8]	6 [2, 11]	1 [0, 3]	96 [89, 102]	6.5 [1.9, 11.2]
	Atlantic	78351	8 [3, 14]	14 [7, 21]	4 [1, 8]	89 [80, 98]	15.7 [9.6, 22.6]

Table S2. Comparison of gross tidal marsh change (2000–2020) and change detection performance across products among disagreement areas. TP, FP, FN and TN denote true positives, false positives, false negatives and true negatives, respectively; bracketed values are 95% bootstrap confidence intervals (10,000 resamples). Because validation samples were drawn exclusively from disagreement areas rather than the full mapped extent, these statistics characterize classification behaviour in contested change regions and do not represent overall map-wide change accuracy for any product.

Product	Gross Change (ha)	TP	FP	FN	TN	Confirmed change (%)	Error Magnitude (%)
This Study	9941	28 [19, 38]	20 [12, 29]	32 [22, 42]	70 [58, 82]	58.3 [44.2, 72.0]	34.7 [27.3, 42.7]
Murray et al. 2022 ³	2689	12 [6, 19]	21 [13, 30]	48 [37, 59]	69 [58, 81]	36.4 [20.0, 53.3]	46.0 [38.0, 54.0]
Campbell et al. 2022 ⁴	4753	8 [3, 14]	26 [17, 35]	52 [41, 64]	64 [52, 76]	23.5 [10.0, 38.7]	52.0 [44.0, 60.0]
Zhang et al. 2024 ²	35945	15 [8, 22]	25 [16, 34]	45 [34, 56]	65 [54, 77]	37.5 [23.1, 52.8]	46.7 [38.7, 54.7]

2. Environmental variable analysis

We examined basin-scale associations of tidal marsh loss and reorganization with four environmental and human-pressure variables: marsh elevation, suspended particulate matter, historical sea-level conditions, and human pressure (Figs. S3 and S4). The multivariable analysis included 117 basins containing at least 1 ha of tidal marsh in 1988 and valid data for all four variables. Loss and reorganization were expressed relative to the 1988 marsh area, with reorganization representing the sum of gross loss and gross gain rather than their net balance.

2.1 Data sources

Marsh elevation was obtained from DeltaDTM v1.1, a global coastal terrain model with approximately 30 m resolution and elevations referenced to the EGM2008 geoid¹³. We calculated the median elevation within each basin's maximum observed tidal marsh footprint during 1988–2023. Suspended particulate matter was estimated from Landsat 8 and 9 surface reflectance using the algorithm of Teng et al. (2025)¹⁴. We selected scenes with cloud cover below 5% from May, June, September and October 2023 and applied pixel-level quality screening. Temporal medians were calculated for each pixel and summarized using the spatial median across valid permanent marine-water pixels within each basin and its surrounding 2 km buffer. This variable characterized contemporary suspended-particle concentrations rather than historical sediment supply or marsh accretion. Historical sea-level conditions were represented by the combined gridded barystatic relative sea-level and steric components provided by Frederikse et al. (2020)¹⁵. Each basin was assigned a nearby valid ocean grid cell, and the combined change during 1988–2018 was divided by 30 years to obtain an average rate. This estimate did not include glacial isostatic adjustment or other local vertical land-motion contributions and therefore represented only part of local relative sea-level change. Human pressure was calculated as the basin-level mean of pixel-level human-modification indices¹⁶ averaged across the available 1990–2020 observations.

2.2 Statistical Analysis

We used Pearson correlations to examine how tidal marsh loss and reorganization varied with each explanatory variable¹⁷. We then fitted separate multiple linear regression models for loss and reorganization to examine the four variables together. Before fitting, we standardized all predictors and outcomes to zero mean and unit standard deviation to facilitate comparison of the regression coefficients¹⁸.

For each basin, we calculated each variable's contribution to the model prediction by multiplying its standardized basin value by its regression coefficient. We averaged the absolute contributions across basins and expressed each variable's average as a percentage of the combined total across the four variables (Fig. S3). These percentages summarize contributions to model predictions, not percentages of explained variance. We also mapped the absolute contributions to predicted loss to examine their spatial patterns (Fig. S4).

2.3 Results and Interpretation

The four-variable model had an R^2 of 0.356 for basin-scale tidal marsh loss. Marsh elevation showed the largest relative contribution to model predictions for both loss and reorganization (Fig. S3). Local contributions also varied spatially (Fig. S4). For example, human-pressure contributions were more pronounced around Vancouver and parts of the Bay of Fundy, despite their relatively small contribution in the national summary (Fig. S4).

However, tidal marsh change is associated with a broader range of climatic, environmental, biological and human influences than these four variables can represent. A comprehensive understanding requires considering the coastal environmental setting and its changes over time, including climate, relative sea-level change and vertical land motion, tidal and freshwater regimes, sediment supply and accretion, shoreline erosion, wave exposure, storms and ice disturbance¹⁹. These processes interact with vegetation productivity, species composition, soil organic-matter dynamics and herbivory, including grazing and grubbing by geese²⁰. Coastal development, land conversion, river regulation, nutrient enrichment, diking, drainage and management actions can further modify these interactions, tidal connectivity and opportunities for landward migration^{21,22}.

Understanding their combined influence requires explicit consideration of spatial variation across Canada's coastal settings. Future regional studies are therefore needed to examine how environmental processes, ecological conditions, land-use history and management actions interact to shape tidal marsh change.

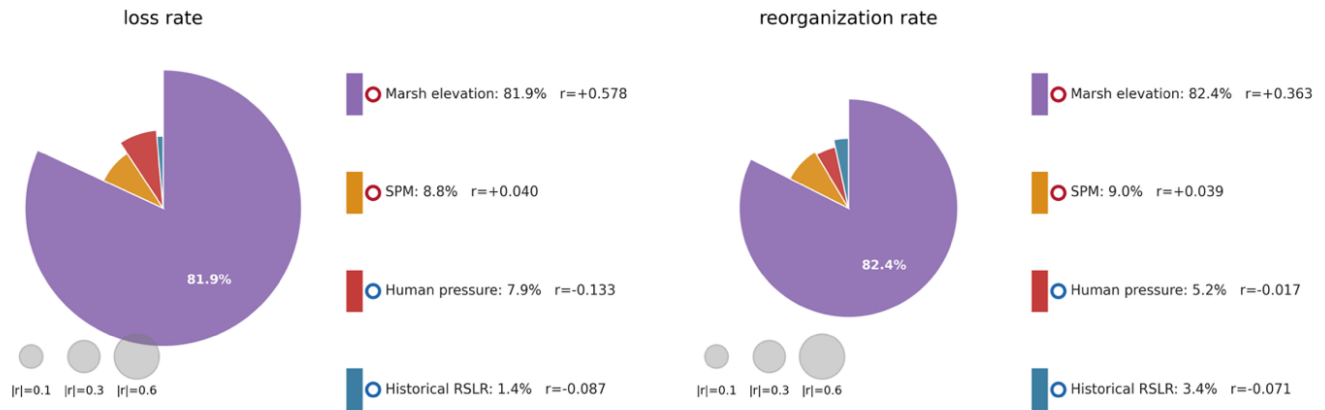


Figure S3 | Relative contribution of environmental and human pressure variables to basin-scale tidal marsh change. Four variables were assessed across 117 basins containing at least 1 ha of tidal marsh in 1988: marsh elevation, suspended particulate matter (SPM), human pressure and historical relative sea-level rise (RSLR). Slice radius represents the absolute Pearson correlation coefficient ($|r|$) with tidal-marsh loss or reorganization, with labels showing its signed value. Slice angle represents each variable's percentage contribution estimated from the standardized regression analysis, with contributions summing to 100%.

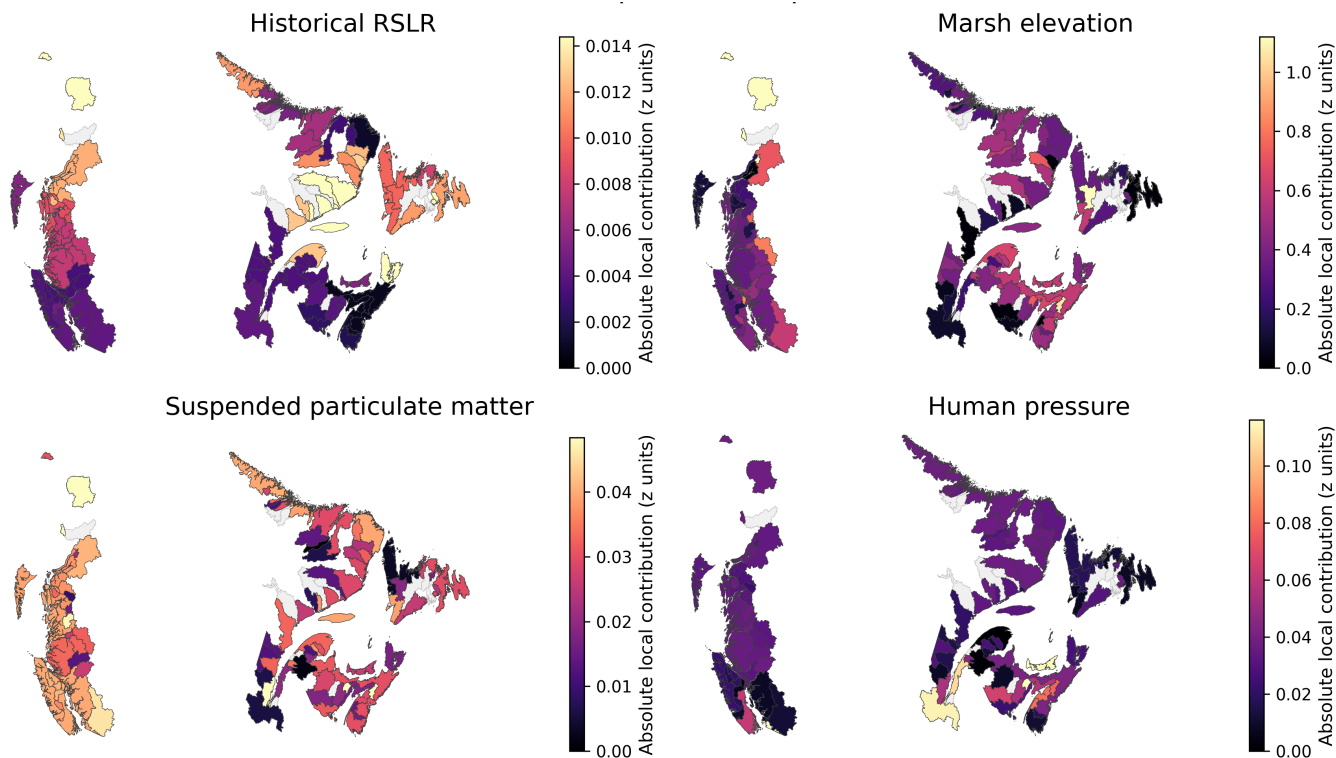


Figure S4 | Spatial variation in local contributions to basin-scale tidal marsh loss rate. Maps show the contributions of historical relative sea-level rise (RSLR), marsh elevation, suspended particulate matter (SPM) and human pressure across 117 basins containing at least 1 ha of tidal marsh in 1988. Contributions were calculated from a single regression fitted across all basins. Values are expressed in standardized units and show the size of each contribution, without distinguishing positive from negative values. Each panel uses a separate color scale, with values above the 95th percentile shown in the highest color.

3. Tidal marsh map validation

Following good-practice recommendations²³ for land-cover accuracy assessment and area estimation, we selected 900 validation samples using stratified random sampling across five mapped land-cover classes. The allocation included 150 samples each for tidal marsh, tidal flat, land–water interface and low-elevation upland, and 300 samples for open water. These samples covered the study domain along Canada’s Pacific and Atlantic coasts, with each sample defined by its location and reference year (Figure S5).

We also examined how close the validation samples were to the training data in space and time (Figure S6). For each validation sample, we identified the nearest training sample based on geographic distance alone, then calculated the absolute difference between their observation years. Of the 900 validation samples, 244 (27.1%) were more than 3,000 m from their nearest training sample, while 597 (66.3%) differed from that sample by more than 10 years. Together, 682 samples (75.8%) exceeded at least one of these thresholds.

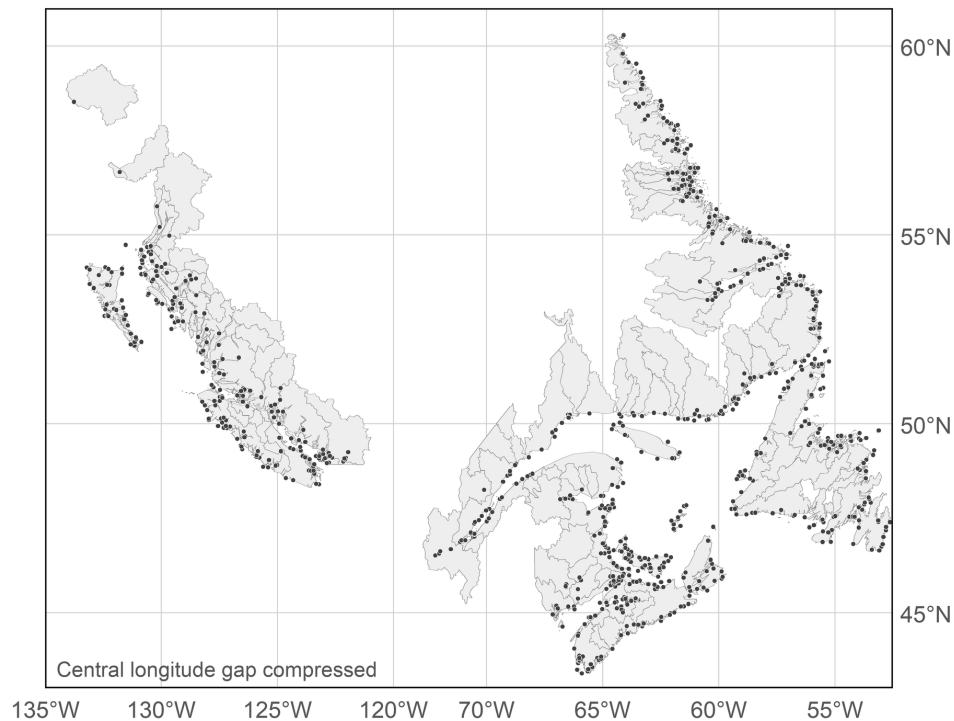


Figure S5 | Spatial distribution of validation samples along Canada’s Pacific and Atlantic coasts. Black points show the 900 reference samples selected by stratified random sampling across five mapped land-cover classes. The central longitude gap is compressed to display both coasts in a single panel.

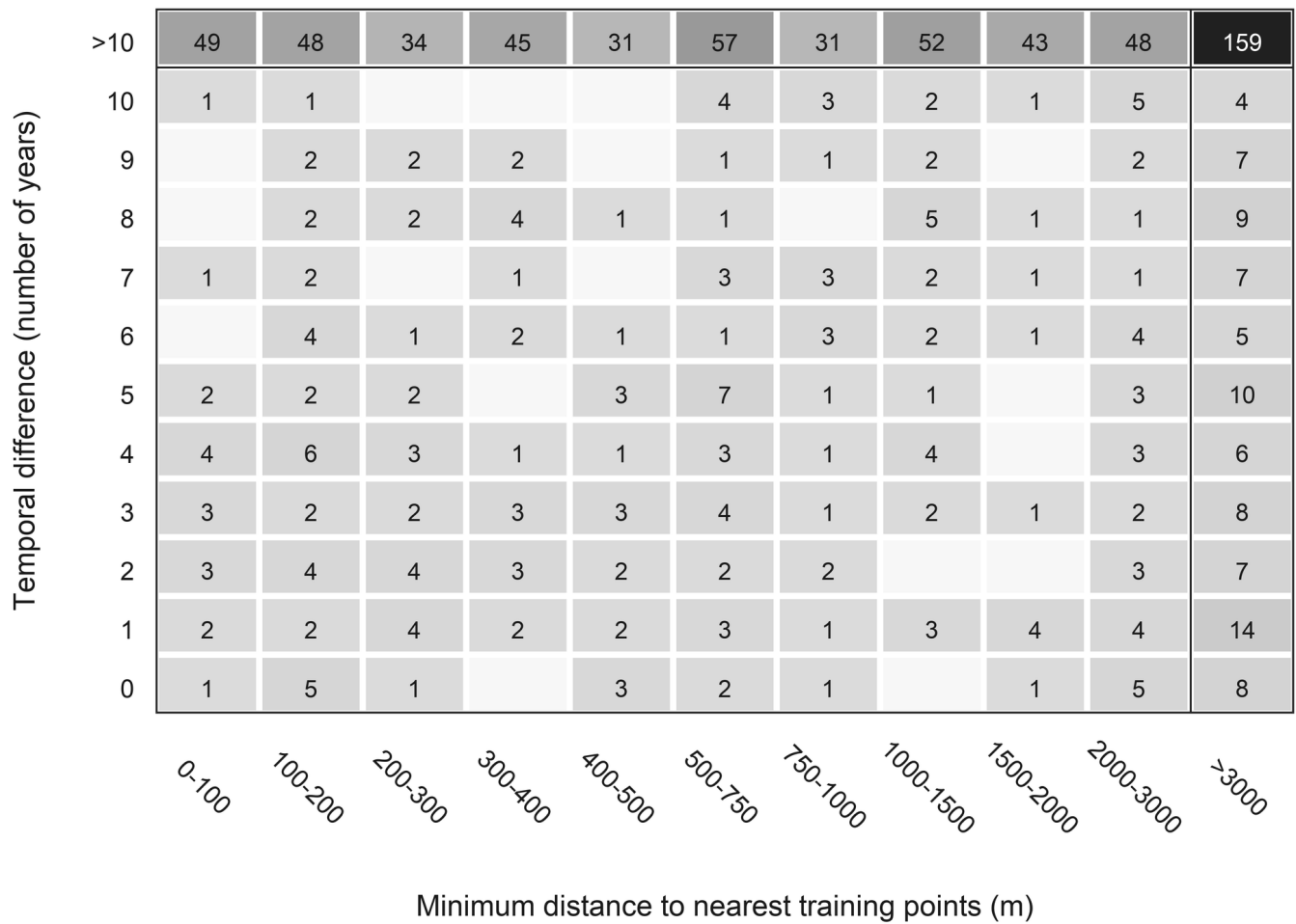


Figure S6 | Spatial and temporal separation between validation and training samples. The heatmap shows the geographic distance from each validation sample to its spatially nearest training sample and the absolute difference between their observation years. The nearest training sample was identified without restricting its year. Numbers in cells indicate the number of validation samples in each distance–time bin. Distances greater than 3,000 m and temporal differences greater than 10 years are grouped into the >3,000 m and >10-year bins, respectively.

Table S3 | Accuracy assessment of tidal marsh extents. Error matrices are from the stratified random sample for the entire study period (1988-2023) expressed as area proportions and sample counts in addition to accuracy and area estimates from the stratified estimator. Columns represent reference labels and rows represent map strata. Uncertainties are reported at 95% confidence intervals.

Reference data					
Map class	Tidal marsh	Tidal flats	Open water	Land-water interface	Low-elevation uplands
Confusion matrix, sample counts					
Tidal marsh	126	4	1	9	10
Tidal flats	3	119	20	8	0
Open water	0	0	299	1	0
Land-water interface	0	1	9	135	5
Low-elevation uplands	0	1	0	7	142
Confusion matrix, area proportions					
Tidal marsh	0.0033	0.0001	0	0.0002	0.0003
Tidal flats	0.0003	0.0113	0.0019	0.0008	0
Open water	0	0	0.8747	0.0029	0
Land-water interface	0	0.0002	0.0016	0.0236	0.0009
Low-elevation uplands	0	0.0005	0	0.0036	0.0738
Accuracy Assessment					
F1 score [%]	87.85	85.78	99.63	82.35	96.49
User's acc. [%]	84.00 ± 5.89	79.33 ± 6.50	99.67 ± 0.65	90.00 ± 4.82	94.67 ± 3.61
Producer's acc. [%]	92.08 ± 8.21	93.37 ± 8.37	99.60 ± 0.14	75.78 ± 15.42	98.48 ± 1.02
Overall acc. [%]	98.67 ± 0.66				

References

1. Worthington, T. A. *et al.* The distribution of global tidal marshes from Earth observation data. *Global Ecology and Biogeography* **33**, e13852 (2024).
2. Zhang, X. *et al.* Global annual wetland dataset at 30 m with a fine classification system from 2000 to 2022. *Sci. Data* **11**, (2024).
3. Murray, N. J. *et al.* High-resolution mapping of losses and gains of Earth's tidal wetlands. *Science* (1979). **376**, 744–749 (2022).
4. Campbell, A. D., Fatoyinbo, L., Goldberg, L. & Lagomasino, D. Global hotspots of salt marsh change and carbon emissions. *Nature* **612**, 701–706 (2022).
5. Kulesa, A., Krzywinski, M., Blainey, P. & Altman, N. Sampling distributions and the bootstrap. *Nat. Methods* **12**, 477–478 (2015).
6. Jamaludin, J., Lambin, E. F. & Webb, E. L. Pixel time series-based quantification and validation to improve spatiotemporal analysis of land cover data. *International Journal of Applied Earth Observation and Geoinformation* **149**, (2026).
7. Pontius, R. G. & Lippitt, C. D. Can error explain map differences over time? *Cartogr. Geogr. Inf. Sci.* **33**, 159–171 (2006).
8. Cook, S., Daley, S., Morrow, K. & Ward, S. *ShoreZone Coastal Imaging & Habitat Mapping Protocol*. (2017).
9. Di Vittorio, C. A. *et al.* Mapping coastal wetland changes from 1985 to 2022 in the US Atlantic and Gulf Coasts using Landsat time series and national wetland inventories. *Remote Sens. Appl.* **37**, (2025).
10. Yang, X. *et al.* From Extent to Change: AlphaEarth and Time Series Analysis for Tidal Marsh Monitoring. Available at SSRN <https://ssrn.com/abstract=7317755> (2026).
11. Davies, B. F. R. *et al.* Intertidal seagrass extent from Sentinel-2 time-series show distinct trajectories in Western Europe. *Remote Sens. Environ.* **312**, (2024).

12. Demarquet, Q., Rapinel, S., Gore, O., Dufour, S. & Hubert-Moy, L. Continuous change detection outperforms traditional post-classification change detection for long-term monitoring of wetlands. *International Journal of Applied Earth Observation and Geoinformation* **133**, (2024).
13. Pronk, M. *et al.* DeltaDTM: A global coastal digital terrain model. *Sci. Data* **11**, (2024).
14. Teng, W. *et al.* High spatial-resolution satellite mapping of suspended particulate matter in global coastal waters using particle composition-adaptive algorithms. *Remote Sens. Environ.* **323**, (2025).
15. Frederikse, T. *et al.* The causes of sea-level rise since 1900. *Nature* **584**, 393–397 (2020).
16. Theobald, D. M. *et al.* Global extent and change in human modification of terrestrial ecosystems from 1990 to 2022. *Scientific Data* **12**, (2025).
17. Schober, P. & Schwarte, L. A. Correlation coefficients: Appropriate use and interpretation. *Anesth. Analg.* **126**, 1763–1768 (2018).
18. Schielzeth, H. Simple means to improve the interpretability of regression coefficients. *Methods Ecol. Evol.* **1**, 103–113 (2010).
19. Fitzgerald, D. M. & Hughes, Z. Marsh Processes and Their Response to Climate Change and Sea-Level Rise. *Annual Review of Earth and Planetary Sciences* **47**, 481–517 (2019).
20. Lane, S. L., Shackelford, N. & Martin, T. G. Passive Recovery Risks Non-native Vegetation Invasion Following Intensive Herbivory by Canada Geese in Two Salish Sea Estuaries. *Estuaries and Coasts* **47**, 2160–2173 (2024).
21. Kirwan, M. L. & Megonigal, J. P. Tidal wetland stability in the face of human impacts and sea-level rise. *Nature* **504**, 53–60 (2013).
22. Chmura, G. L. Protected areas are not enough to protect blue carbon ecosystems and their services. *Front. Mar. Sci.* **12**, (2025).
23. Olofsson, P. *et al.* Good practices for estimating area and assessing accuracy of land change. *Remote Sens. Environ.* **148**, 42–57 (2014).