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4 **Coastal groundwater level trends reveal global susceptibility to seawater**
5 **intrusion**

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16

17 **Abstract**

18 Coastal groundwater is a vital freshwater source threatened by overabstraction and sea-level rise, yet global
19 patterns of declining groundwater levels (GWLs) and susceptibility to seawater intrusion (SWI) remain
20 poorly constrained. Here, we present the first global assessment based on in-situ observations from ~480,000
21 coastal monitoring locations. From 1990 to 2024, 21% of grid-cell aggregates had significant rising or
22 falling GWL trends with magnitudes ≥ 0.1 m yr⁻¹ and with declines becoming more frequent in the last 9
23 years. More pronounced changes are observed for deeper water tables ($\rho_s=0.63$), in arid settings ($\rho_s=0.56$),
24 and in some rural areas. SWI susceptibility is higher where seaward freshwater discharge is weak or
25 gradients reverse landward, leaving limited hydraulic resistance to SWI. Decadal trend extrapolation
26 suggests that these conditions mostly persist (93.4%), while 3.5% newly emerge and 3.1% stabilize
27 (gradients strengthen seaward). The results provide global evidence for prioritizing monitoring and
28 management of coastal groundwater at risk of salinization.

29

30 **Introduction**

31 Groundwater is a critical freshwater source in coastal regions, which are home to 2.86 billion people (Cosby
32 et al., 2024), and plays a vital role in sustaining coastal ecosystems and their services (Dyring et al., 2022;
33 Luijendijk et al., 2020) as well as marine biota (Lecher and Mackey, 2018). However, coastal aquifers face
34 pressure from growing coastal populations (Neumann et al., 2015), and are increasingly vulnerable to
35 seawater intrusion (SWI), which threatens both the quantity and quality of available water. Salinization
36 reduces water suitability for human use. It has adverse health impacts when drinking-water salinity increases
37 (Mueller et al., 2024), threatens agriculture by lowering soil fertility and crop yields when salinity of
38 irrigation water increases (Ghirardelli et al., 2024), and affects coastal ecosystems, where increased salinity
39 can stress vegetation and soil communities and lead to shifts in species composition (Venâncio et al., 2022;
40 Tully et al., 2019). Climate change and, as a consequence, sea-level rise, changes in groundwater recharge,
41 and intensifying water use increase pressure on coastal groundwater systems (IPCC, 2021; Spinoni et al.,
42 2021; Richardson et al., 2024). This makes it increasingly important to identify where coastal groundwater
43 resources are susceptible to SWI and where monitoring and management should focus to detect and respond
44 to emerging threats.

45 In coastal settings, hydraulic gradients at the land-sea boundary govern the balance between fresh submarine
46 groundwater discharge and the intrusion of seawater into the nearshore aquifer. Persistent landward or near-
47 zero seaward gradients therefore favor lateral SWI and constitute a first-order control on coastal

48 groundwater-ocean exchange (Werner et al., 2012; Werner, 2017; Kretschmer et al., 2025b). Here, we use
49 the hydraulic gradient as a scalable proxy for whether freshwater tends to discharge seaward or seawater
50 tends to intrude landward. Gradients summarize coastal head differences and thus integrate the effects of
51 multiple controls. Aquifer properties and architecture, including surface-water connectivity, modulate how
52 natural recharge, human pressures (e.g., groundwater abstraction, land drainage, land-surface changes that
53 modify recharge, sea-level rise) and sea-level rise translate into gradients (Kretschmer et al., 2025b). In
54 particular, two natural settings predispose coasts to landward or near-zero seaward gradients by constraining
55 freshwater heads: topography-limited low-relief coastal plains and recharge-limited (often arid and water-
56 limited) settings (Michael et al., 2013). In topography-limited settings, freshwater heads are already close
57 to the land surface, leaving limited capacity for further head increase under sea-level rise. In recharge-
58 limited settings, limited replenishment suppresses freshwater heads and constrains head recovery. Here,
59 long groundwater response times (hydraulic memory) can delay and buffer responses to climate variability,
60 even as water-table sensitivity to recharge or precipitation can be high and increase with aridity (Fan et al.,
61 2023; Cuthbert et al., 2019). Projected aridification and shifting precipitation regimes are expected to further
62 reduce recharge in recharge-limited coasts, increasing SWI susceptibility (Richardson et al., 2024).

63 Yet despite our general process understanding, the global spatiotemporal distribution of SWI-susceptible
64 conditions remains poorly characterized. This limits our ability to anticipate where and how salinization
65 pressures may intensify under future climatic and anthropogenic change and reflects broader limitations in
66 global groundwater assessments, which often lack the resolution, integration, and observational grounding
67 needed to capture the complexity of groundwater systems (Gleeson et al., 2020). Most assessments of
68 coastal groundwater systems are focused on local or regional case studies (e.g., Morgan and Werner, 2015;
69 Costall et al., 2020), which presents challenges of commensurability when seeking a better understanding
70 about global-scale processes (Gleeson et al., 2021). Global approaches to model SWI (Adams et al., 2024;
71 Zamrsky et al., 2024; Kretschmer et al., 2025a) continue to face high uncertainties due to assumptions
72 concerning boundary conditions and hydrogeological parameterization, and are challenging to evaluate due
73 to the coarse spatial resolution and spatially-biased availability of time-varying GWL data (Gleeson et al.,
74 2021; Reinecke et al., 2024). GRACE (Gravity Recovery and Climate Experiment) satellite observations
75 provide valuable information for major groundwater basins. However, coarse spatial resolution, land-ocean
76 leakage near coasts, and the residual-based derivation of groundwater storage changes from model-
77 partitioned water components can yield physically implausible estimates and limit applicability, particularly
78 for smaller or coastal systems (Frappart and Ramillien, 2018; Costantini et al., 2023; Arifin et al., 2025).

79 In contrast, key indicators of coastal groundwater susceptibility to SWI can be derived from in-situ GWL
80 observations, specifically hydraulic heads that favor lateral SWI and declining GWLs that lower freshwater

81 heads (Kretschmer et al., 2025a; Ferguson and Gleeson, 2012; Jasechko et al., 2020). However, GWLs
82 remain difficult to integrate at scale due to fragmented responsibilities, limited digitization, accessibility
83 issues, and non-standardized datasets (United Nations, 2022; Famiglietti and Rodell, 2013; Lall et al., 2020).
84 Despite these challenges, few efforts have leveraged large-sample in-situ GWL data. Fan et al. (2013) were
85 the first to compile GWL observations globally. This was the basis for developing modeled estimates of
86 water table depth (WTD) with global coverage (e.g., Ma et al., 2024; Fan et al., 2013), now widely used in
87 groundwater-related environmental studies (e.g., Shokri-Kuehni et al., 2020). Recent in-situ syntheses have
88 quantified GWL trends across terrestrial aquifer systems globally (Jasechko et al., 2024) and regionally in
89 southwestern Europe (Chávez García Silva et al., 2024), but without a specific coastal focus. By contrast,
90 Jasechko et al. (2020) focused on coastal areas but limited their analysis to the contiguous United States,
91 while Nolte et al. (2024) used thousands of globally distributed coastal GWL time series to identify common
92 GWL dynamics and highlight limitations of global datasets in explaining these patterns, without deriving
93 GWL trends or explicitly assessing susceptibility to SWI. Collectively, these studies underscore both the
94 value of in-situ GWL data and the persistent gap in globally integrated, observation-based assessments of
95 coastal aquifers. Here, we compile an unprecedentedly large and diverse global set of in-situ coastal GWL
96 observations to derive land-sea hydraulic gradients and recent trends summarized on a common spatial grid
97 for global mapping as observation-based indicators of SWI susceptibility, and to examine how these
98 indicators vary across aridity conditions and coastal regions worldwide.

99 **Susceptible hydroclimatic conditions**

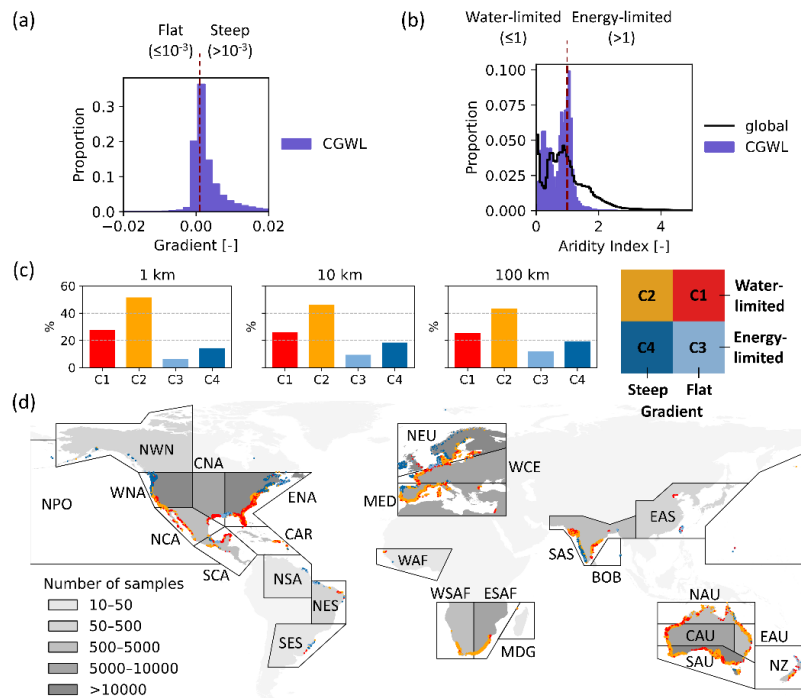
100 Hydroclimatic susceptibility to lateral SWI in our framework is defined by two variables: the land-sea
101 hydraulic gradient that we use as an observation-accessible screening diagnostic, and aridity as a practical
102 proxy for natural recharge limitation. We quantify the land-sea gradient as the change in hydraulic head
103 between inland monitoring locations and the coastline, divided by their distance to the coastline, and classify
104 it as “flat” when it is landward or weakly seaward ($\leq 10^{-3}$ m m⁻¹). This “flat-gradient” class favors lateral
105 SWI (Kretschmer et al., 2025a; Ferguson and Gleeson, 2012). All remaining gradients are grouped as steep
106 ($> 10^{-3}$), representing stronger seaward head gradients that generally oppose inland SWI. While this steep
107 class spans a wide range of seaward conditions, we use this binary split as a simple, transparent global
108 screening. Aridity is represented by the aridity index (AI; the ratio of precipitation to potential
109 evapotranspiration; Zomer et al., 2022), with water-limited climates (AI ≤ 1 ; rather dry) contrasted against
110 energy-limited climates (AI > 1 ; rather wet). The combination of flat gradients and water-limited climates
111 forms the most susceptible hydroclimatic cluster (C1) in our analysis (Fig. 1; compare Methods). Water
112 table depth (WTD) provides important context because shallow groundwater implies limited vadose storage,
113 so modest declines can more readily weaken land-sea gradients and increase salinization risk. Globally,

114 aquifers near coasts are often shallow: the median coastal WTD is 6.1 m, and nearly half of all observations
115 are shallower than 5 m (Supplementary Material A). Flat gradients, which weaken the natural flow of
116 groundwater toward the sea, are found in about one-third of all observed coastal areas. Although steeper
117 gradients dominate overall (skewed distribution in Fig. 1a), flat gradients remain common even tens of
118 kilometers inland (34-37% of all observations; Fig. 1c). Compared to the global aridity distribution of
119 coastal regions, our dataset shows a distinct clustering near the transitional AI value of approximately 1
120 (marking the boundary between water- and energy-limited climates), a zone in which groundwater recharge
121 is expected to be particularly sensitive to modest shifts in long-term aridity (Berghuijs et al., 2024). In
122 contrast, moderately arid regions ($AI \sim 0.3-0.7$) and humid regions ($AI \gg 1$) are underrepresented in our
123 dataset (Fig. 1b). Overall, 74% of observations fall within water-limited environments ($AI \leq 1$). Importantly,
124 flat-gradient, water-limited conditions (C1; most susceptible) are most frequent within 1 km of the coastline,
125 where they account for 28% of observations, but they also occur farther inland (Fig. 1c). In Fig. 1d, C1
126 forms contiguous coastal belts in regions such as the southeastern U.S. (ENA), Gulf of Mexico (CNA and
127 SCA), and northeast Australia (parts of CAU and NAU). Steep-gradient, water-limited conditions (C2)
128 dominate across all coastal distances (Fig. 1c). Near the coast, C2 accounts for 52% of observations. By
129 contrast, susceptibility conditions, where gradients are flat but recharge is not limiting (C3), are least
130 common.

131 **Prevalence of trends and sensitivity to record length**

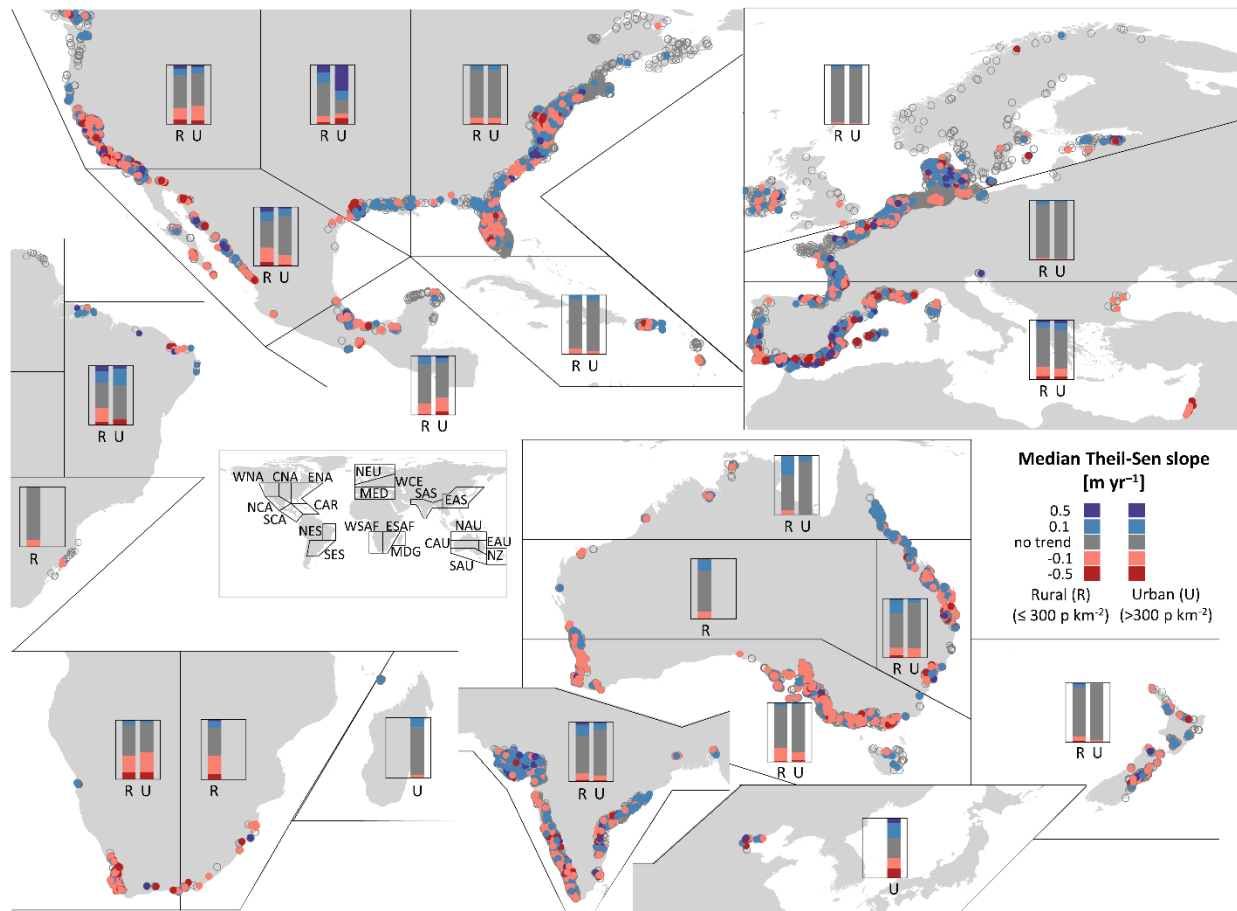
132 Changes in GWLs alter freshwater heads and, therefore, the land-sea hydraulic gradients. For the 34-year
133 period 1990–2024 studied, our trend analyses show that 28% of observations exhibit statistically significant
134 GWL changes exceeding $\pm 0.1 \text{ m yr}^{-1}$ over 9-year windows. 21% of observations exhibit such trends when
135 evaluated over 19-year windows. The frequency of upward and downward changes in GWLs is balanced
136 across both periods, with a slight bias toward declines in the shorter timeframe (42% upward compared to
137 58% downward among absolute trends). To evaluate how strongly record length affects inferred trends, we
138 compared slopes from overlapping 9- and 19-year windows for the subset of observations with both time
139 frames available (Supplementary Material B-2; B-3). These are moderately correlated across windows
140 (Spearman $\rho_s = 0.58$). Trend direction is consistent in most observations (76%), while ~19% are ambiguous.
141 Here, the 9- and 19-year slopes have opposite signs, but at least one slope is near zero ($|\text{slope}| < 0.1 \text{ m yr}^{-1}$),
142 so the apparent sign switch mainly reflects near-stable conditions in one window rather than a clear reversal.
143 Only ~5% show clearly inconsistent opposite-sign trends with $|\text{slope}| \geq 0.1 \text{ m yr}^{-1}$ in both time windows.
144 Agreement is similar at the scale of IPCC regions ($\rho_s = 0.58$; 78% consistent), although a small number of
145 regions exhibit sign changes in median trends (notably EAU, as well as NCA, SAS, and MDG in Fig. 2).
146 Large trend magnitudes (i.e., strongly upward or strongly downward trends, $|\text{slope}| > 0.5 \text{ m yr}^{-1}$) occur less

147 frequently over 19-year windows than over 9-year windows. This is consistent with longer records
 148 integrating low-frequency variability and episodic events (Baulon et al., 2022; Kuss and Gurdak, 2014).



149
 150 Fig. 1 Global patterns of hydroclimatic conditions indicating susceptibility of coastal groundwater systems
 151 to seawater intrusion. (a) Distribution of land-sea hydraulic gradients derived from the CGWL dataset, with
 152 a red dashed line marking the threshold separating “flat” ($\le 10^{-3}$; landward or near-zero seaward gradients)
 153 from “steep” seaward gradients. (b) Distribution of aridity index (AI) values (Zomer et al., 2022) for the
 154 CGWL dataset and coastal regions globally, with a red dashed line marking the climatic threshold (AI=1)
 155 used to distinguish water- and energy-limited regimes. (c) Proportions of four hydroclimatic susceptibility
 156 clusters (C1–C4) at three distances from the coastline (1 km, 10 km, 100 km). (d) Global distribution of
 157 categorized observations (plotted in grid cell centers with random overlap of clusters), shown together with
 158 the number of samples in IPCC reference regions (Iturbide et al., 2020) with ≥ 10 observations.

159 For subsequent analyses, we use a combined trend product, assigning 19-year trends where available and
 160 otherwise using 9-year trends. Globally, 24% of observations show significant GWL trends, of which 54%
 161 are downward. GWL changes are mapped with their magnitude and direction in Fig. 2. The prevalence of
 162 declining and rising GWLs varies spatially, ranging from under 10% (e.g., northern Europe – NEU) to over
 163 40% (e.g., South Africa – WSAF and ESAF; North and Central America – WNA, CAN, and NCA).
 164 Individual observations reveal strong within-region variability, with localized clusters of opposing trend
 165 directions and magnitudes.



166
 167 Fig. 2 Spatial patterns of recent groundwater level trends across global coastal zones, grouped by IPCC
 168 regions (Iturbide et al., 2020). Colored points on maps represent individual observations that are plotted in
 169 grid cell centers with random overlap of Theil-Sen slope trend categories on top of "no trend": strong decline
 170 (< -0.5 m year $^{-1}$, dark red), moderate decline (-0.5 to -0.1 m year $^{-1}$, light red), no trend (-0.1 to 0.1 m year $^{-1}$
 171 and/or non-significant, gray), moderate rise (0.1 to 0.5 m year $^{-1}$, light blue), and strong rise (> 0.5 m year $^{-1}$,
 172 dark blue). Bar charts show the proportions of trend categories per region (≥ 10 observations), stratified by
 173 rural (R; ≤ 300 people km $^{-2}$) and urban (U; > 300 people km $^{-2}$) areas (CIESIN, 2018). Supporting regional
 174 trend results are provided in Supplementary Material B-5.

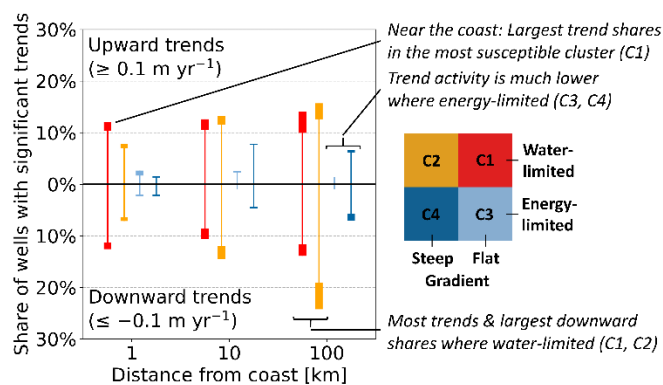
175 Trends in rural and urban coastal regions

176 Urban and rural areas often differ in land use and water management, which can influence groundwater
 177 dynamics. We therefore stratify the dataset by a rural-urban typology (Eurostat, 2021). Fig. 2 reveals rural-
 178 urban differences in GWL changes. Overall, rural areas show a slightly higher prevalence of significant
 179 GWL trends ($|\text{slope}| \geq 0.1$ m yr $^{-1}$) than urban areas, and the trend magnitude is weakly negatively correlated
 180 with population density ($\rho_s: -0.17$). This global rural-urban contrast is driven mainly by specific regions,
 181 including India (SAS), northern Central America (NCA), Australia (SAU, EAU, and NAU), and New
 182 Zealand (NZ). Urban observations show more frequent trends in fewer regions, especially southern Central
 183 America (SCA), central North America around the Gulf of Mexico (CAN), and eastern South Africa

184 (WSAF). Overall, these regional differences sum to a higher global prevalence of significant trends in rural
 185 than urban areas (26% vs 22%), with declines accounting for ~54% and ~55% of observations with trends,
 186 respectively.

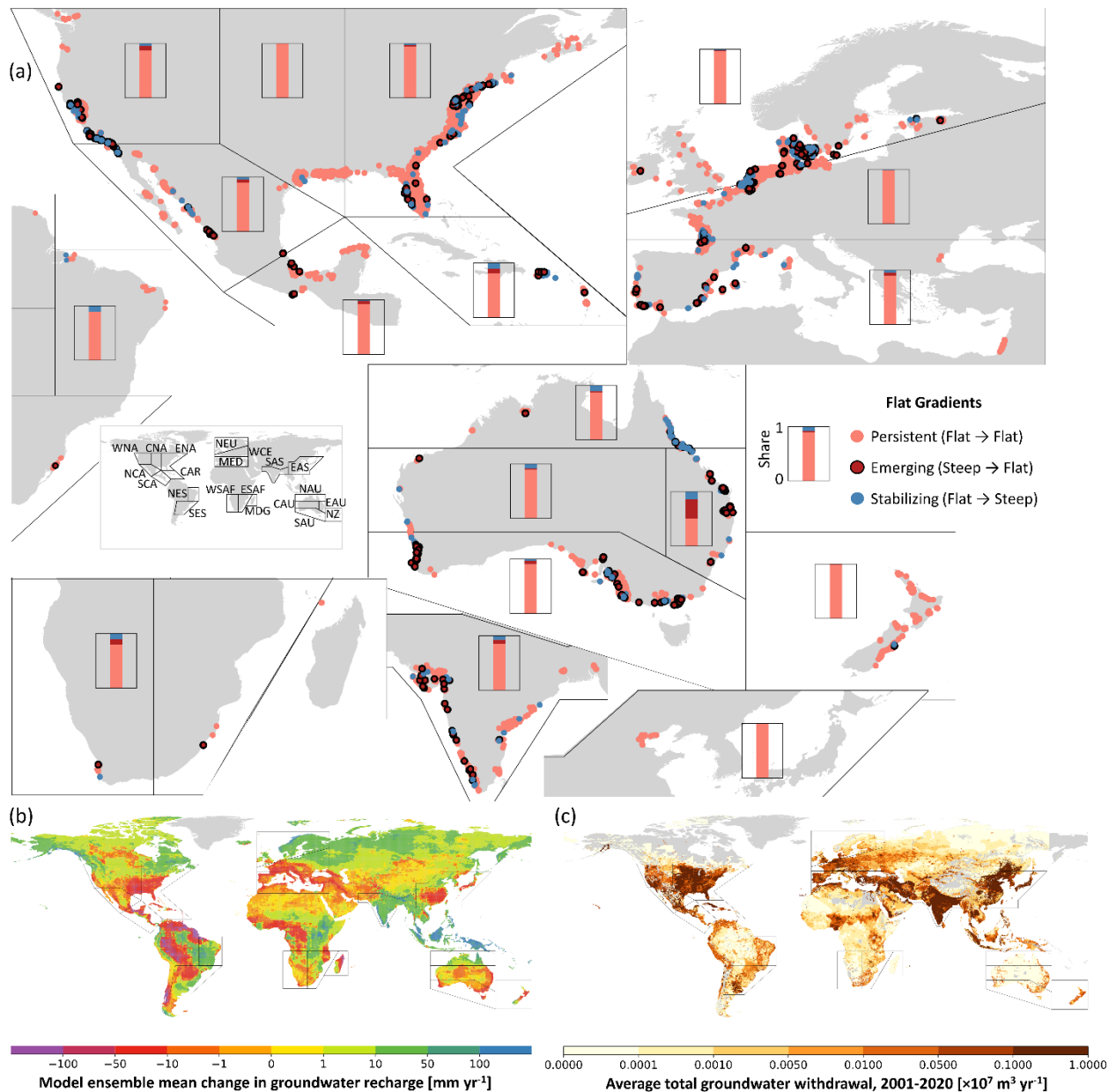
187 **Identifying hotspots of seawater intrusion susceptibility**

188 To link hydroclimatic susceptibility from aridity and land-sea hydraulic gradients (clusters C1-C4) with
 189 dynamic change, we examine how GWL trends vary across clusters and coastal distances. First, we quantify
 190 pairwise relationships using Spearman correlations between absolute trend magnitude ($|\text{slope}|$) and aridity,
 191 WTD, and hydraulic gradient. These correlations are stronger inland than near the coast. At 100 km from
 192 the coastline, the trend magnitude correlates with drier conditions ($\rho_s=0.56$), with deeper water tables
 193 ($\rho_s=0.63$), and with larger land-sea hydraulic gradients ($\rho_s=0.36$). Aridity and WTD co-vary ($\rho_s=0.50$),
 194 indicating that drier conditions tend to coincide with deeper water tables. At 1 km from the coast,
 195 associations weaken but remain detectable for aridity and WTD ($\rho_s=0.19$ and $\rho_s=0.41$), whereas the
 196 association with hydraulic gradient is negligible. Second, consistent with these pairwise patterns, trend
 197 frequencies differ across susceptibility clusters (Fig. 3). Water-limited clusters (C1 and C2), which often
 198 coincide with deeper water tables in arid regions, show the highest frequencies of both upward and
 199 downward trends across all coastal distances (absolute trends: 36% and 34%). Although less susceptible in
 200 our gradient-aridity screening due to steep gradients, C2 shows the highest prevalence of GWL declines that
 201 are most pronounced further inland. Conversely, overall trend activity is much lower in energy-limited
 202 clusters (C3 and C4; 3% and 12%). Near the coast, susceptibility and change coincide most strongly: within
 203 1 km, 28% of C1 observations show significant trends, with marginally more GWL declines than rises.



204
 205 Fig. 3 Share of wells with significant upward (top, $\geq 0.1 \text{ m yr}^{-1}$) and downward (bottom, $\leq -0.1 \text{ m yr}^{-1}$) trends
 206 as a function of distance from the coast (1, 10, 100 km). Thicker bar segments at the top and bottom indicate
 207 the shares of strongly rising ($>0.5 \text{ m yr}^{-1}$) and strongly declining ($<-0.5 \text{ m yr}^{-1}$) observations, respectively.
 208 Differently colored shares refer to the SWI susceptibility clusters (C1-C4).

209 Most trend slopes are moderate ($|\text{slope}| < 0.5 \text{ m yr}^{-1}$), yet even modest head changes can shift land-sea
 210 gradients toward or away from flat-gradient conditions. We therefore used derived GWL trends to
 211 extrapolate whether observations may enter, remain in, or exit the flat-gradient susceptibility clusters
 212 (C1/C3) over the next decade (Fig. 4a). Persistent gradient-based hotspots (93.4% of all sites) are locations
 213 already exhibiting SWI-susceptible conditions that are projected to remain within C1 or C3 over the next
 214 decade. A smaller fraction (3.1%) is projected to stabilize, meaning they may transition out of C1/C3 if
 215 recent upward trends continue, and 3.5% are emerging hotspots, i.e., locations projected to transition into
 216 flat-gradient conditions (C1/C3) over the next decade.



217

218 Fig. 4 (a) Spatial patterns of hydroclimatic, gradient-based SWI-susceptibility hotspots across IPCC regions
219 (Iturbide et al., 2020), derived from trend extrapolation. Points show individual observations (grid cell
220 centers). Hotspots are defined relative to the flat-gradient clusters C1/C3. When co-located, emerging
221 (entering C1/C3 within 10 years) and stabilizing (exiting C1/C3 within 10 years) hotspots are randomly
222 overlaid on persistent hotspots (in C1/C3 now and in 10 years). Bar charts show the relative proportions of
223 hotspot types within each region (≥ 10 observations). (b) Model-ensemble mean change in groundwater
224 recharge (mm yr^{-1}) between present-day warming ($\sim 1^\circ\text{C}$) and 3°C global warming, from the ISIMIP2b
225 multi-model ensemble (Reinecke et al., 2021). (c) Long-term mean total groundwater withdrawal (2001–
226 2020; $\times 10^7 \text{ m}^3 \text{ yr}^{-1}$), from the data-driven Global Groundwater Withdrawal (GGW) model (Nazari et al.,
227 2025).

228 Discussion

229 The results of this study are based on deriving physically motivated indicators of SWI susceptibility from
230 integrated in-situ GWL observations. Our hydroclimatic susceptibility framework links land-sea hydraulic
231 gradients with aridity conditions and incorporates recent GWL changes to assess how susceptibility states
232 may evolve, even when detailed hydrogeological information is limited. It methodologically extends
233 elevation-based screening approaches (Jasechko et al., 2020) and complements previous large-scale GWL
234 trend syntheses (e.g., Chávez García Silva et al., 2024; Jasechko et al., 2024) by focusing explicitly on
235 coastal aquifer settings. In the United States, coastal regions that we classify as hydroclimatically susceptible
236 show strong spatial concordance with areas highlighted by Jasechko et al. (2020): within 10 km of the
237 coastline, 20% of our observations have groundwater elevations below sea level (vs 27% of wells in
238 Jasechko et al. (2020)), and 37% have flat gradients ($\leq 10^{-3}$). Globally, our flat-gradient, water-limited
239 cluster (C1) captures major regions with documented SWI compiled by Cao et al. (2021) and Kretschmer
240 et al. (2025b) (Fig. 3 and Fig. 1 in the respective publications). These include the southeastern coasts of the
241 U.S., Central America, the Mediterranean, the Cape Town area, parts of India, and southeastern Australia,
242 which also show a higher prevalence of downward GWL trends in our analysis. Beyond these documented
243 hotspots, our gradient-aridity framework maps the global extent and relative frequency of comparable
244 hydroclimatic configurations, providing a quantitative screening to guide where monitoring and
245 management could be prioritized. This also helps mitigate the urban bias noted by Kretschmer et al. (2025b)
246 because our analysis draws on routine monitoring observations across both urban and rural settings, whereas
247 published SWI case studies are disproportionately from urban, economically developed regions (Kretschmer
248 et al., 2025b). At the same time, the availability of GWL observations in our analysis shows a heterogenic
249 spatial distribution globally. Coverage is strongest in temperate regions such as Europe and the United
250 States, whereas most of Africa, equatorial regions, large parts of South America and Asia, and many small
251 islands remain sparsely represented or are completely missing. Accordingly, several SWI sites reported in
252 Asia, Africa, and South America (Kretschmer et al., 2025b; Cao et al., 2021) fall outside our analyzed
253 dataset. Our SWI susceptibility patterns therefore reflect the spatial footprint of available observations, and

254 the absence of mapped hotspots in data-poor regions should not be interpreted as the absence of SWI
255 susceptibility.

256 This study further shows that continued GWL change can generate SWI-relevant gradients within a single
257 decade, and that GWLs near the coastline tend to change most strongly where flat hydraulic gradients
258 coincide with water-limited conditions (C1; most susceptible). While our observation-based indicators do
259 not quantify volumetric freshwater losses, even small deviations and variations around the gradient
260 threshold may become critical over longer timescales. Rising GWLs are as frequent as declines, both
261 globally and often regionally. Coastal aquifers are therefore not uniformly moving toward greater SWI
262 susceptibility. Instead, susceptibility can strengthen or weaken locally, and short-term variability in GWLs,
263 even without sustained declines, can temporarily shift systems toward flat-gradient, SWI-prone conditions.
264 This spatial and temporal variability highlights the value of sustained GWL observations for locally
265 grounded detection of SWI-susceptible conditions.

266 Further increases in the marine boundary head are likely to shift additional coastlines into SWI-susceptible
267 gradient states (Zamrsky et al., 2024; Adams et al., 2024): The global mean sea-level is currently rising at
268 $\sim 4.5 \text{ mm year}^{-1}$ (Hamlington et al., 2024), and is projected to rise by roughly 0.3-1.0 m by 2100 (relative to
269 1995–2014, depending on emissions scenario), with possible multi-meter rise on longer timescales as peak
270 warming increases (Kopp et al., 2023). This situation can be further exacerbated by pumping-induced
271 upconing, which can cause SWI even further inland (Jakovovic et al., 2011). This matters because our study
272 shows that deep aquifers in rural, arid regions exhibit more widespread declines. Because these systems
273 often respond slowly, management interventions may take years to decades to translate into measurable
274 head recovery, so expectations for SWI susceptibility and monitoring strategies need to account for delayed
275 results. Furthermore, the spatial distribution of significant GWL changes does not align with population
276 density. This should be read as an observed GWL signal, not a direct proxy for local groundwater use,
277 because urban demand is partly met by pumping outside cities. However, our results align with Jasechko et
278 al. (2024), who found widespread declines in dryland aquifers, particularly under croplands. Hence,
279 groundwater-dependent agricultural regions may face disproportionate SWI susceptibility where high
280 extraction pressures coincide with limited regulatory oversight. Persistent or emerging flat-gradient patterns
281 in our study frequently co-occur with regions where sectoral groundwater withdrawals are already high (Fig.
282 4c), with agriculture as the dominant groundwater user and increasing withdrawals in many regions since
283 2001 (Nazari et al., 2025). Beyond SWI, some regions with relatively low gradient-based susceptibility,
284 such as parts of South Africa, show substantial GWL declines together with projected groundwater recharge
285 reductions (Fig. 4b), indicating emerging groundwater-stress risks that are highly relevant in the context of
286 “Day Zero” drought-driven water-scarcity crises, where prolonged hydroclimatic deficits and high demand

287 can push water systems into acute supply shortfalls (Ravinandrasana and Le Franzke, 2025). In such
288 situations, groundwater can be considered a fallback supply (Nolte et al., 2021), but in coastal settings where
289 our indicators suggest SWI susceptibility and/or declining GWLs, this option may be constrained by limited
290 availability.

291 **Conclusions**

292 This study provides the first global observation-based assessment of hydroclimatic conditions associated
293 with SWI susceptibility in coastal groundwater systems that is based on in-situ GWL observations from
294 ~480,000 coastal monitoring locations. By combining land-sea hydraulic gradients, aridity, and recent GWL
295 trends in a bottom-up approach that captures spatiotemporal signals often missed by static frameworks
296 and/or coarse top-down approaches, the study delivers three main contributions. First, it translates the
297 available monitoring footprint into globally comparable quantities that can inform large-scale assessments
298 and reporting (e.g., by international frameworks). Second, the study maps where potentially susceptible
299 conditions occur and where they are changing, helping prioritize monitoring and management in coastal
300 regions where risk may be shifting in real time. Third, it provides observation-based indicators that can be
301 systematically incorporated into SWI risk assessments and used as constraints to evaluate and improve
302 large-scale models that simulate unmonitored coasts. At the same time, the hydroclimatic susceptibility
303 indicators do not by themselves resolve local vulnerability or control-response relationships. Doing so
304 requires more detailed hydrogeologic characterization, co-located salinity monitoring, and improved global
305 datasets of key controls, alongside broader efforts to expand and strengthen groundwater observations,
306 particularly in regions with large observational gaps. Avoiding or reducing SWI in susceptible settings is
307 critical because salinization of groundwater threatens safe drinking-water supplies, lowers agricultural
308 productivity, and degrades coastal and nearshore ecosystems. Looking ahead, our findings highlight that
309 stronger monitoring and data-synthesis efforts can enable scalable, observation-based tools to detect
310 emerging SWI risk early, improve system understanding, and inform timely adaptation. Such advances are
311 increasingly important as projected shifts in groundwater recharge, continued sea-level rise, and
312 anthropogenic pressures interact with existing flat-gradient settings in many coastal regions.

313 **Methods**

314 We used the Coastal Groundwater Level (CGWL) dataset, a newly compiled global resource of in-situ
315 coastal GWL observations from governmental monitoring networks and public portals (Supplementary
316 Material A). The CGWL dataset comprises ~629,000 well records (~480,000 unique locations at 3-decimal
317 coordinates) from wells within 100 km of the coastline and with WTDs shallower than 100 m
318 (Supplementary Material A-1). Raw groundwater data were quality controlled and harmonized to consistent

319 groundwater depth (WTD; ground-surface reference) and groundwater elevation, using source-provided
320 elevations where available and otherwise CoastalDEM (Kulp and Strauss, 2019) or SRTM (NASA JPL,
321 2020). We aggregated groundwater information to hexagonal grid cells with a mean cell area of 0.74 km²
322 (H3-8; Uber Technologies Inc 2024) and refer to these grid-cell aggregates as “observations”.

323 **Groundwater hydraulic gradients**

324 Land-sea hydraulic gradients were calculated at the grid level using median groundwater elevation and the
325 median Euclidean distance of wells in the cell to the coastline (dataset: Sayre et al., 2021). Using medians
326 reduces sensitivity to outliers but also smooths short-term extremes in the hydraulic head that can be relevant
327 for SWI. Because this proxy does not resolve time-varying coastal boundary heads, non-linear flow paths,
328 or within-cell hydrogeologic heterogeneity, gradients may be biased high or low at individual locations. We
329 therefore interpreted them as a first-order, observation-based screening diagnostic of prevailing coastal head
330 conditions. The sample size for gradient analysis comprised 232,419 grid cells with available groundwater
331 elevation and coastline distance data.

332 **Trend analysis**

333 To quantify recent GWL change, we filtered monthly CGWL time series and computed monotonic trends
334 over 9- and 19-year windows within 1990–2024. The record lengths used for the trend analysis were chosen
335 iteratively to balance temporal robustness against global support, consistent with prior large-scale
336 groundwater trend studies (Jasechko et al., 2024). A detailed discussion of window-length trade-offs is
337 provided in the Supplementary Material B-3. Time-series selection further allowed variable sampling while
338 limiting seasonal distortion (Supplementary Material B-1). This yielded 51,263 unique monitoring locations
339 with sufficient data to estimate a 9-year trend. Of these, 20,857 locations also met the minimum length for
340 a 19-year trend. Where both are available, the 9-year window corresponds to the final 9 years of the 19-year
341 window. Monotonic trends in GWLs were calculated using the non-parametric modified Mann-Kendall test
342 (Yue and Wang, 2004), and corresponding trend magnitudes were estimated using Sen’s slope (Sen, 1968).
343 Trends were computed at the well level and subsequently aggregated to H3-8 grid cells by taking the median
344 of slope values, regardless of individual statistical significance ($p > 0.05$); however, significance flags were
345 retained to support additional filtering. Trend slopes were classified into five trend categories: strongly
346 downward ($< -0.5 \text{ m yr}^{-1}$), moderately downward ($-0.5 \text{ to } -0.1 \text{ m yr}^{-1}$), no trend (between $-0.1 \text{ and } 0.1 \text{ m yr}^{-1}$
347 and/or non-significant), moderately upward ($0.1 \text{ to } 0.5 \text{ m yr}^{-1}$), and strongly upward ($> 0.5 \text{ m yr}^{-1}$). Only a
348 small fraction of results classified as “no trend” are non-significant solely due to statistical insignificance
349 (5.6% for 9-year trends and 1.7% for 19-year trends). After aggregation, trend results were available for

350 36,579 grid cells (9-year) and 17,703 grid cells (19-year), so that 19-year trends support ~41% of grid-level
351 trend estimates globally (Supplementary Material B-2).

352 **Hydroclimatic classification and hotspot extrapolation**

353 Hydroclimatic susceptibility was applied along two axes: aridity (as a proxy for recharge limitation) and
354 land-sea hydraulic gradient (as a proxy for the tendency toward seaward discharge versus inland salinity
355 advance). To classify gradients, we used two categories based on model-informed thresholds: flat ($\leq 10^{-3}$,
356 landward or near-zero seaward gradients) and steep seaward gradients ($> 10^{-3}$), following Ferguson and
357 Gleeson (2012) and Kretschmer et al. (2025a), who showed that gradients lower than 10^{-3} are more prone
358 to SWI or to the persistence of saline groundwater. Each H3-8 grid cell was further assigned the aridity
359 index (AI) from Zomer et al. (2022), which represents the ratio of precipitation to potential
360 evapotranspiration. Cells were categorized as either water-limited ($AI \leq 1$) or energy-limited ($AI > 1$). These
361 binary classes define clusters C1-C4 used throughout this study:

- 362 - C1 (most susceptible): Flat gradient ($\leq 10^{-3}$) & water-limited ($AI \leq 1$)
- 363 - C2: Steep gradient ($> 10^{-3}$) & water-limited ($AI \leq 1$)
- 364 - C3: Flat gradient ($\leq 10^{-3}$) & energy-limited ($AI > 1$)
- 365 - C4 (least susceptible): Steep gradient ($> 10^{-3}$) & energy-limited ($AI > 1$)

366 To analyze potential hotspot persistence/emergence under continued change, we extrapolated groundwater
367 elevation using the estimated trend slope over a 10-year horizon, recomputed the projected gradient, and
368 evaluated whether grid cells would remain in, enter, or exit flat-gradient conditions (C1/C3). This provides
369 a straightforward diagnostic that does not account for potential nonlinearities in drivers of GWL trends or
370 management responses.

371 **Preparing secondary datasets for contextual analyses**

372 The global aridity index (Zomer et al., 2022) is used directly in the SWI susceptibility classification. All
373 other secondary datasets were compiled only to contextualize and interpret gradients and GWL trends.
374 Specifically, Fig. 4b-c shows gridded sectoral groundwater withdrawals (Nazari et al., 2025) and a multi-
375 model ensemble of groundwater recharge change (Reinecke et al., 2021) for visual comparison with our
376 results. We prepared the population density of the year 2020 (CIESIN, 2018) to derive rural-urban classes
377 following Eurostat (2021). This dataset was preprocessed in ArcGIS Pro where information was derived for
378 H3-8 grid cells using zonal statistics.

379 **Limitations**

380 - **Spatial aggregation framework:** We adopted the regular, globally near-equal-area H3-8 grid (Uber
381 Technologies Inc, 2024) as a transparent, assumption-light spatial unit that provides area-representative
382 summaries while reducing the mixing of heterogeneous aquifer conditions relative to coarser aggregation
383 units. This choice reflects that, at the global scale, aquifer boundaries and vertical structure cannot be
384 delineated consistently from the available data in the CGWL dataset and existing global hydrogeologic
385 datasets (Supplementary Material A-2). We used H3-8 grid cells as the primary analysis unit, but repeated
386 all key diagnostics on coastal HydroBASINS level-12 catchments (HYBAS-12; Lehner and Grill, 2013) as
387 a sensitivity test. Aggregation error, quantified as the RMSE between well-level and unit-level median
388 WTD, is lowest for H3-8 and increases for larger aggregation units, while it decreases primarily with the
389 number of wells per unit. HYBAS-12 basins are on average ~141 km² (about four times larger than H3-6
390 hexagonal grid cells, ~36 km²), yet the share of multi-well units is similar for HYBAS-12 and H3-6, and
391 aggregation error is slightly larger for HYBAS-12, indicating no systematic reduction of aggregation error
392 relative to grid-based schemes with comparable well support (Supplementary Material A-3). We therefore
393 assume that any discrepancies between H3-8 and HYBAS-12 primarily reflect aggregation and sampling
394 effects, that is, how differently sized spatial units mix heterogeneous conditions and how unevenly well
395 density weights regional summaries. Against this background, HYBAS-12 closely reproduces the H3-8
396 patterns across IPCC coastal regions and distance-to-coast bands for flat-gradient prevalence, trend activity
397 ($|\text{slope}| \geq 0.1 \text{ m yr}^{-1}$), the fraction of downward trends among trend-active units, and the share of
398 persistent/emerging flat-gradient hotspots (Spearman $\rho_s = 0.87\text{--}0.95$). Global differences are small,
399 although a few regions deviate by >10 percentage points; for example, grids yield higher flat-gradient
400 prevalence in Western Europe (WCE), while HYBAS-12 shifts the Caribbean (CAR) toward more upward
401 and fewer downward trends, resulting in fewer persistent/emerging hotspots (Supplementary Material B-4).

402 - **Bottom-up approach and representativeness limits:** Our analysis is global in extent but bottom-up,
403 scaling local well observations to consistent spatial units, and from there to regional and global SWI
404 susceptibility indicators. The spatial representativeness of these indicators, both geographically and with
405 respect to hydrogeologic settings, is constrained by uneven data coverage globally and the limited
406 hydrogeologic characterization (notably aquifer system architecture and confinement). Our chosen fine grid-
407 based aggregation can overweight densely monitored coastal areas and may regionally yield slightly
408 different hotspot and trend-activity shares than coarser units, but it reduces the mixing of heterogeneous
409 aquifer conditions.

410 - **Simplifications with GWL-based indicators:** While this study uses GWL-based indicators to assess SWI
411 susceptibility, it necessarily simplifies the physical complexity of coastal aquifer systems, where salinization
412 can propagate through multiple interconnected pathways: over land (storm surge and tidal flooding), under
413 land via groundwater transport, and through natural and engineered surface-water networks, and via vertical

414 processes such as upconing of deeper saline water beneath pumping wells (Helton et al., 2025; Werner et
415 al., 2012). Our indicators do not explicitly represent salinity or density-driven flow, limited by salinity
416 observations being far less available than GWL time series at large scales (Panthi et al., 2022; Thorslund
417 and van Vliet, 2020) and co-located water-quality and water-quantity records being uncommon (Ebeling et
418 al., 2022). The indicators also simplify temporal dynamics relevant to SWI. In particular, gradients often
419 rely on a single or short snapshot of head data, which is insufficient to quantify variability or detect shifts,
420 while monotonic trends summarize net change over the analysis window and may miss transient or nonlinear
421 changes.

422 - **Trend robustness and record-length sensitivity:** Since trend direction at individual locations can be
423 sensitive to record length and to the timing of multiannual variability or management interventions, regions
424 with spatio-temporally inconsistent trends require particularly careful interpretation. However, our 9- vs 19-
425 year comparison indicates that, while longer records are generally more robust, 9-year time series already
426 capture the qualitative direction of GWL change for most regions, with notable exceptions such as in
427 southeastern Australia and India, where declines are stronger and more frequent in the more recent 9-year
428 window. Multi-window trend reporting can serve as a practical robustness check when long GWL records
429 are unavailable.

430 - **Limits to causal inference and attribution:** In general, this study does not establish causation. Because
431 gridded population products redistribute census counts, population-based contrasts (and any future
432 projections) carry spatially heterogeneous uncertainty. Specifically, they can systematically underrepresent
433 rural populations and misallocate density within cities (Láng-Ritter et al., 2025; Kuffer et al., 2022). Given
434 the substantial uncertainties in both global recharge projections and pumping estimates when interpreted at
435 the scale of local observations (Reinecke et al., 2021; Nazari et al., 2025), we do not directly attribute the
436 observed gradients and trends to these drivers (Fig. 4b-c). Instead, we use the aridity index as a proxy for
437 recharge limitation and, indirectly, for potential future increases in water stress and demand. However, we
438 acknowledge that its bi-categorical application (like the gradient split) is a coarse simplification that
439 facilitates transparent global screening, but can mask precipitation effects relevant to recharge and compress
440 diverse hydro-climatic (and hydro-ecological) settings into broad classes (Taylor et al., 2013; Zomer et al.,
441 2022).

442

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450 **CRedit authorship contribution statement**

451 **A. Nolte:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Writing –
452 original draft, Writing – review & editing. **S. Bender:** Funding acquisition, Supervision, Writing – review
453 & editing. **J. Hartmann:** Funding acquisition, Supervision, Writing – review & editing. **S. Baltruschat:**
454 Methodology, Writing – review & editing. **N. Moosdorf:** Methodology, Writing – review & editing. **R.**
455 **Reinecke:** Conceptualization, Formal analysis, Methodology, Writing – original draft, Writing – review &
456 editing

457 **Data availability statement**

458 The CGWL dataset is publicly available on Zenodo under a CC-BY-NC license, including all data sources
459 obtained with permission for publishing or under open licenses: [link will be provided in peer-reviewed
460 manuscript]. Code and data for conducting trend and SWI susceptibility analyses are also available on
461 Zenodo: [link will be provided in peer-reviewed manuscript]. Additional datasets used in these analyses are
462 referenced within the same repository.

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