

The future fate of groundwater-dependent wetlands globally driven by groundwater dynamics and land cover change

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Abstract

Groundwater-dependent wetlands (GDWs) sustain biodiversity, regulate freshwater systems and store carbon, yet their vulnerability to changing groundwater and land use is poorly understood. Using a high-resolution global groundwater model, five global climate models (GCMs) and land use scenarios, we simulate global GDW extent from 1979 to 2050 under three Shared Socioeconomic Pathway-Representative Concentration Pathway (SSP-RCP) scenarios. We estimate a global extent of 3.43 million km² (3.39–3.47 across GCMs) for the 2005–2014 baseline. Ensemble-mean GDW extent is projected to decline by mid-century under all scenarios, including the most sustainable pathway, largest under SSP3-RCP7.0 (–173 [–337.1 to –11.7] thousand km²). The relative contribution of groundwater dynamics and land conversion differs among the three scenarios: land-use change accounts for the largest share of losses under SSP3-RCP7.0, whereas groundwater dynamics dominate under the lowest and highest emission pathways. Protecting GDWs will require integrating groundwater management, land use planning and wetland conservation.

Introduction

Groundwater dependent wetlands (GDWs) are expected to undergo substantial changes as climate change, groundwater abstraction and land use changes reshape shallow aquifer systems worldwide ¹⁻⁴. Because GDWs persist through prolonged access to shallow water tables, even modest declines in groundwater recharge or increases in abstraction can push groundwater levels beyond ecological thresholds critical for their persistence ⁵⁻⁷. Under high emission scenarios and high agricultural and industrial development pathways, intensification of evapotranspiration, altered precipitation regimes and increasing water demands are expected to contribute to groundwater level declines across many semi-arid and agricultural regions ⁸. Future climate projections indicate increasing recharge variability and intensification of hydrological droughts in subtropical drylands and monsoon-dependent basins ^{9,10}. These hydro-climatic changes raise the risk that GDWs, among other hydrologically sensitive terrestrial ecosystems, may experience accelerated deterioration or changes in their ecological functioning by 2050 ¹.

Groundwater recharge is not projected to decline uniformly. Global multi-model assessments indicate increasing recharge and groundwater storage across parts of the high latitudes under climate warming ¹¹, and permafrost thaw is expected to deepen active layers, enhance infiltration and increase groundwater discharge in these regions ¹². Together, these changes may increase groundwater availability and create conditions that support groundwater-dependent wetlands where natural vegetation exists. On the other hand, large-scale groundwater modelling results suggest that aquifer resilience may decline under warming scenarios, particularly in regions where groundwater withdrawals are projected to increase with population growth and irrigation expansion trajectories ^{13,14}. These changes particularly affect wetlands reliant on shallow groundwater and can result in rapid wetland loss or altered ecosystem functioning ^{7,15}.

Although global wetland losses over recent decades are well documented ^{1,16,17}, consistent spatio-temporal mapping of historical and potential future changes in wetland extent are lacking. Recently, developments in remote sensing have improved global wetland inventories and surface water monitoring ¹⁸⁻²⁰, providing high-resolution snapshots of wetland extent over time. However, these time series only cover recent time periods and are difficult to extrapolate into the future. In addition, most global wetland maps rely on surface inundation detection and may therefore underestimate potential declines in wetland extent, as declining groundwater tables may first manifest as reduced soil saturation duration before complete surface wetland loss ^{7,21}.

Recent advances in groundwater-dependent ecosystem mapping have highlighted approaches that relate groundwater depth directly to ecosystem function as a promising alternative ^{5,22}. At the same time, the recent development of high-resolution transient global groundwater models allows for dynamic simulation of water table depth and groundwater-surface water interactions based on recharge variability and groundwater pumping ^{23,24}. Combined with climate projections and land use scenarios, transient global groundwater models allow consistent projections of groundwater regime changes into the future ²⁵. These emerging modelling efforts have demonstrated strong skill in capturing groundwater-dependent wetland distributions and show high agreement with independent inventories ^{26,27}, providing a basis for consistent past-to-future simulations of GDWs globally.

Here, we use a high-resolution global groundwater model and a GDW-mapping framework (see Methods) to project GDW extent from 1979 to 2050, with emphasis on mid-century under three potential future development scenarios under the Shared Socioeconomic Pathway-Representative Concentration Pathway (SSP-RCP) framework (SSP1-RCP2.6, SSP3-RCP7.0 and SSP5- RCP8.5). Building on advances in large-scale transient groundwater modelling ²³⁻²⁵ and groundwater-based GDW delineation ²⁶, we derive monthly GDW extent by identifying grid cells where water table depth and soil saturation jointly meet the conditions required to sustain groundwater-dependent wetlands ²⁶.

We additionally incorporate land use trajectories consistent with SSP1-RCP2.6, SSP3-RCP7.0 and SSP5-RCP8.5 socioeconomic development scenarios to account for possible GDW losses due to conversions into agricultural and urban land. Our study offers the first globally consistent, process-based assessment of GDW extent under various potential future development pathways.

Results

Global declines in GDW area under future changes

Global groundwater-dependent wetland (GDW) area over the 2005–2014 baseline period is estimated at 3.43 (3.39 to 3.47 range across the five GCMs) million km², distributed across all major biogeographic realms. Under all three future scenarios, the ensemble-mean global GDW area is projected to decline by mid-century, with net changes of −173 (−337.1 to −11.7), −34 (−176.0 to +116.2) and −32 (−237.1 to +147.4) thousand km² under SSP3-RCP7.0, SSP1-RCP2.6 and SSP5-RCP8.5 respectively, where ranges span the five GCMs (Fig. 1b). All five GCMs agree on a decline under SSP3-RCP7.0, whereas under SSP1-RCP2.6 and SSP5-RCP8.5 three of the five GCMs project a net loss and two project net gain. Agreement among the five GCMs in the simulated GDW area is further illustrated in Supplementary Note S1. Gross losses are largest under SSP3-RCP7.0 (218 [115–338] thousand km²) and smallest under SSP1-RCP2.6 (104 [25–191] thousand km²), while gross gains are largest under SSP5-RCP8.5 (120 [64–203] thousand km²) and smallest under SSP3-RCP7.0 (45[0.4–104] thousand km²). The ensemble-mean net change is negative under all three scenarios (Fig. 1b) indicating that net GDW losses are not directly related to emissions level. Although SSP5-RCP8.5 represents the highest warming pathway, its ensemble mean decline is smaller than SSP3-RCP7.0.

Projected changes are spatially heterogeneous (Fig. 1a). Losses are concentrated in tropical South America, South and Southeast Asia and parts of sub-Saharan Africa, whereas gains occur in the Sahel transition zone, northern high latitudes and interior Australia. Although the direction of change is consistent among scenarios, the magnitude of both losses and gains varies among pathways.

Contrasting contributions of groundwater dynamics and land conversion to projected wetland change

Groundwater dynamics and land conversion contribute differently to projected GDW losses across scenarios (Fig. 1d). Under SSP3-RCP7.0, land conversion accounts for the largest share of declining GDW area (39% of the affected historical GDW area, 36–41% across GCMs), exceeding the 33% (26–43%) attributable to groundwater dynamics and consistent with the extensive agricultural expansion projected under this pathway. Under SSP1-RCP2.6 and SSP5-RCP8.5 the ordering reverses: groundwater-driven loss accounts for 34 % (23–40%) and 40 % (34–48%) of the affected area respectively, against 23% (22–24%) and 25% (23–27%) for land conversion (Fig. 1d). Groundwater dynamics therefore dominate wetland decline under both the lowest and the highest emission pathway, and land conversion dominates only under the pathway with the most extensive agricultural expansion. GCM ranges for all shares are shown as whiskers in Fig. 1d.

Groundwater dynamics account for the largest share of GDW gains across all scenarios, contributing 25%, 31% and 31% of the affected area under SSP3-RCP7.0, SSP1-RCP2.6 and SSP5-RCP8.5 respectively, against 3%, 12% and 3% for land conversion. Decomposing the global net change into its two components gives −74 thousand km² from groundwater dynamics and −97 thousand km² from land conversion under SSP3-RCP7.0, −28 and −5 thousand km² under SSP1-RCP2.6, and −93 and +63 thousand km² under SSP5-RCP8.5. Land conversion is therefore the dominant driver of net loss

only under SSP3-RCP7.0; under SSP1-RCP2.6 groundwater dynamics account for almost the entire net decline, and under SSP5-RCP8.5 the contraction of cropland projected under that pathway returns wetland area and partially offsets a substantially larger groundwater-driven loss. Across all scenarios, groundwater dynamics drive the largest changes in both directions and determine where wetland gains are possible.

Regional and biome-realm patterns

While projected GDW responses show ensemble-mean global net declines under all three scenarios, strongest under SSP3-RCP7.0, there is a strong variability in projected changes among biogeographic realms (Fig. 2 and Fig. 4). The Neotropical realm shows the largest absolute decline across all scenarios, with losses of 54-110 thousand km² across scenarios by mid-century (Fig. 3; GCM ranges per scenario are shown as whiskers). The substantial difference between the total net GDW area change and net GDW area change without land conversion (Fig. 3) indicates that agricultural and urban expansion reduce GDW extent beyond the variation caused by groundwater change alone.

The Indo-Malayan realm shows the sharpest scenario divergence, with losses of 20 thousand km² under SSP3-RCP7.0 contrasting with gains of 43 thousand km² under SSP5-RCP8.5 (GCM ranges in Fig. 3). The Palearctic and Nearctic realms show moderate gains or near-neutral responses under SSP1-RCP2.6 and SSP5-RCP8.5, but substantial inter-model uncertainty across the five GCMs (Fig. 2).

At the biome-realm level, combined losses from both drivers under SSP3-RCP7.0 produce the steepest declines in Neotropics, while contrary driver effects in the Afrotropical and Indo-Malayan realms under SSP5-RCP8.5 result in near-neutral combined changes where groundwater-driven gains offset losses from land conversion (Fig. 4). Analysis of persistence classes indicates that most projected GDW areas remain perennial, highlighting the buffering role of groundwater in sustaining GDW persistence (Supplementary Fig. S2). Seasonal and episodic GDWs are concentrated in hydroclimatic transition zones including the Sahel, southern Africa, the northern high latitudes and interior Australia, where groundwater dynamics are highly correlated with climatic variability ^{12,15}.

Evaluation of simulated GDW distribution in drylands

Comparison of the simulated GDW distribution against an independent validation dataset for 2014–2019, constructed by intersecting GLWD v2 ²⁸ with the groundwater-dependent ecosystem map of Rohde et al. (2024) and restricted to dryland regions, shows that the model identifies GDW locations accurately (Fig. 5). Precision is high on every continent (Fig. 5a) and reaches 0.88 overall for the thresholds adopted here (Supplementary Fig. S3).

Simulated areas closely match the validation dataset globally and, in most continents, with some underestimation in Asia. The thresholds adopted here give the highest F1 of the combinations tested, and grid cells meeting the criterion have a median sub-grid water table depth of approximately 1.7 m on average (Supplementary Note S.1, Fig. S3 and Fig. S4). As the validation dataset is restricted to GDWs in drylands, model performance in humid tropical and boreal systems cannot be directly assessed.

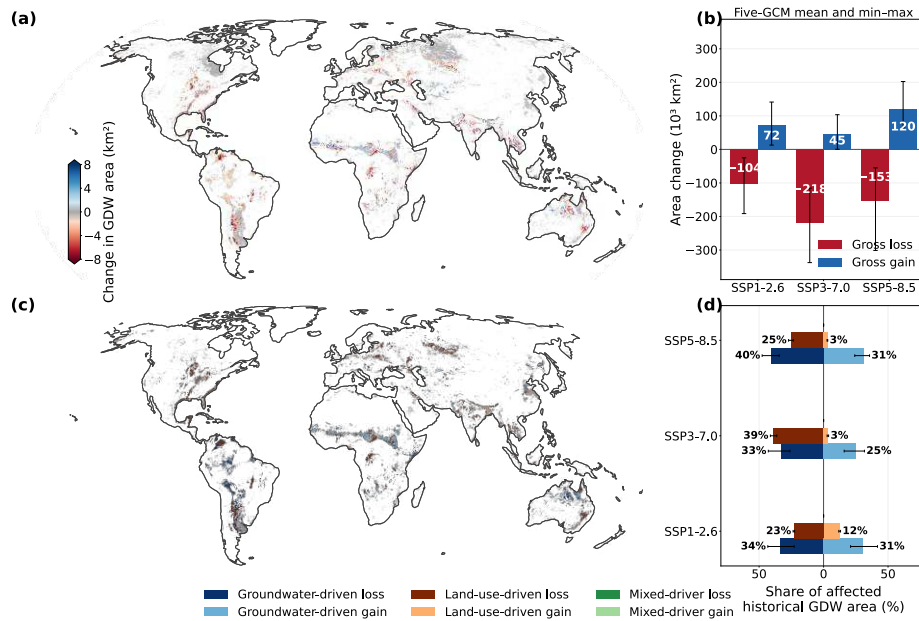


Figure 1 | Projected changes in GDW extent and dominant drivers of change under future scenarios. a, Change in GDW area per grid cell (km²) between the 2005–2014 historical baseline and 2041–2050 projection period under SSP3-RCP7.0. b, Global total GDW area lost and gained between the 2005–2014 baseline and 2041–2050 projection period under the three socio-economic development scenarios. Gross losses and gains were obtained by summing, respectively, the negative and positive net area changes across the six biogeographic realms, per GCM. c, Dominant driver of GDW change at the grid-cell level under SSP3-RCP7.0. For each grid cell the change in GDW fraction attributable to groundwater dynamics alone and change to attributable to land use conversion alone were computed by comparing the fraction GDW area with and without land use conversion; the driver with the larger magnitude was assigned as dominant and cells in which the two were of comparable magnitude were classified as mixed. d, Fraction of total affected GDW area classified by driver for each scenario, expressed relative to the historical GDW area. The loss side shows the relative decline in GDW area attributed to groundwater dynamics (dark blue), land use changes (dark red). Mixed drivers are excluded from this figure because of their small fractions. Panels a and c are based on five GCM ensembles while panels b and d were computed per GCM showing the mean across the 5 GCMs with the whiskers indicating the minimum and maximum across GCMs (and Figure S1).

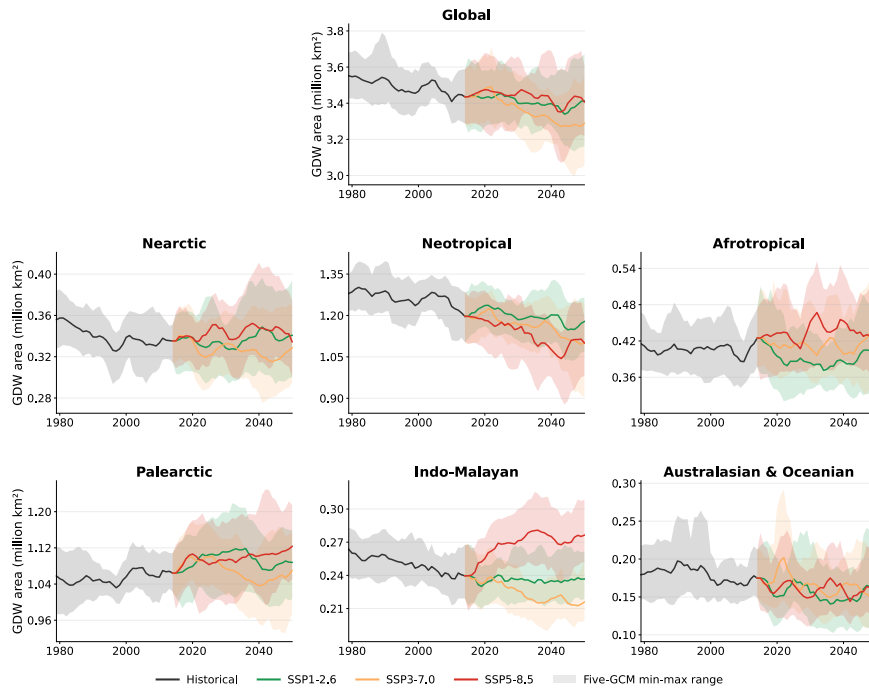


Figure 2| Annual GDW area globally and by biogeographic realm, 1979-2050. Annual GDW-area (million km²) under historical atmospheric forcing (1979-2014) and three future socio-economic development scenarios: SSP1-RCP2.6 (Sustainability; low emission) SSP3-RCP7.0 (Fragmented world and moderate emissions) and SSP5-RCP8.5 (Economic growth and fossil energy intensive; high emissions), shown globally (upper panel) and for each of the six biogeographic realms (lower panels). Lines show the five-GCM ensemble mean GDW area and shading shows the full GCM range (minimum to maximum).

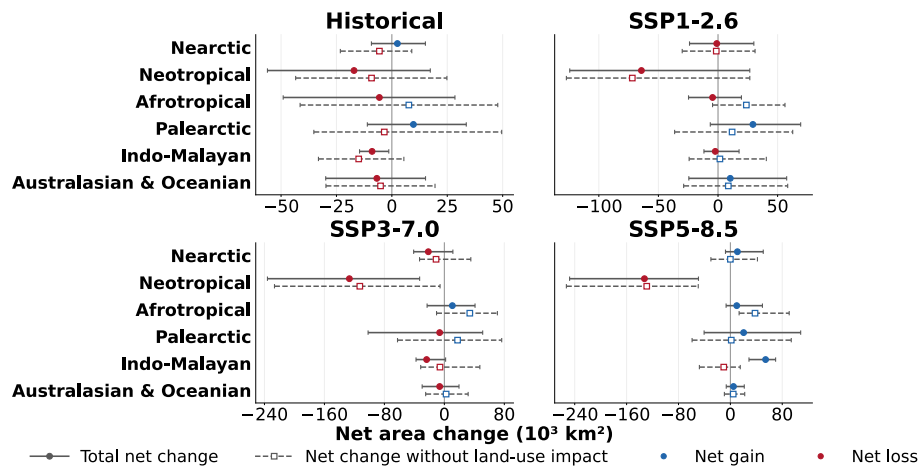


Figure 3 | Decadal net GDW area changes by biogeographic realm and scenario. Net change in mean GDW-area (10^3 km^2) between two decadal periods, globally (top row, shaded) and for each biogeographic realm and scenario. For the historical panel, the baseline period is 1995–2004 and the comparison period is 2005–2014. For future scenarios, the baseline is 2005–2014 and the comparison period is 2041–2050. Filled circles represent total changes in GDW area and open squares are the changes in GDW area without considering land-use impact. Blue denotes gain and red denotes loss. Markers show the mean across the five GCMs and horizontal whiskers the minimum-to-maximum range across GCMs. The gap between the two lines for each realm indicates the degree to which land conversion suppresses or enhances changes in GDW extent beyond what groundwater dynamics alone would produce.

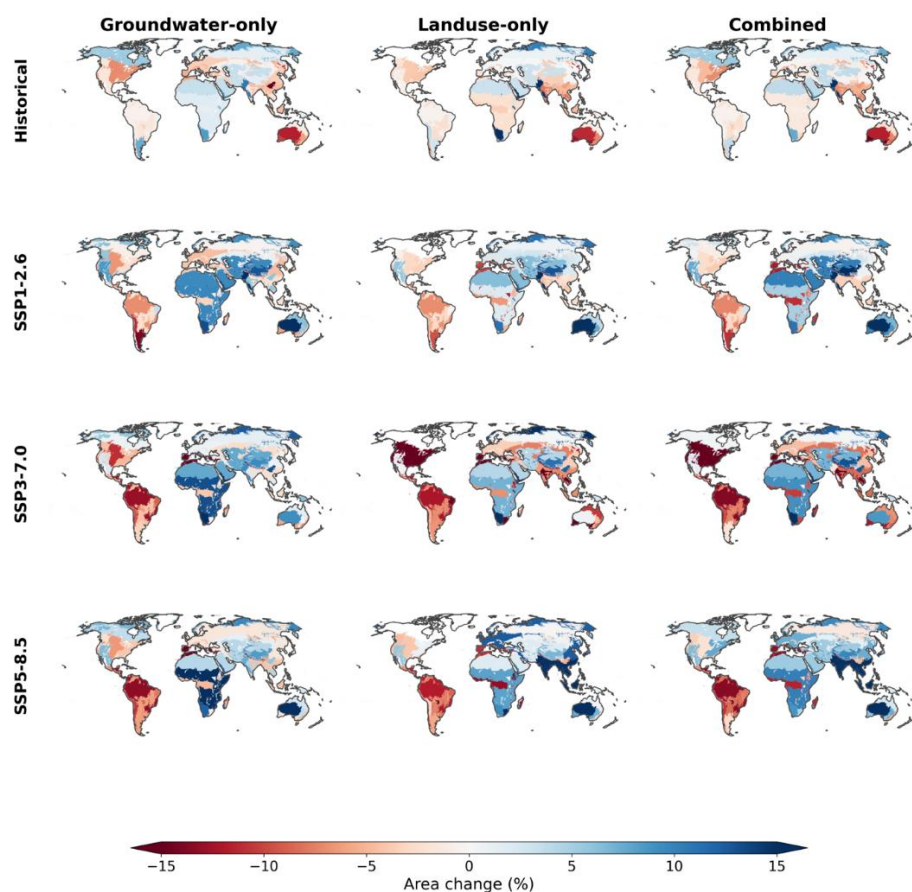


Figure 4 | Biome-realm GDW-area change attributed to groundwater dynamics and land conversion. Percentage change in GDW area relative to baseline, aggregated to WWF biome-realm units ²⁹, attributed to changes in groundwater dynamics (left), land conversion (center) and the two drivers combined (right), for historical period and three future scenarios. The groundwater-only results represent the GDW response to groundwater dynamics alone, without considering land conversion. The land-use-only results reflect the change in GDW area due to land cover change, based on water table depth and saturated area fraction fixed at the 2005–2014 climatology. For the historical period (top row), changes are computed between 1995–2004 and 2005–2014. For future scenarios, changes are computed between the 2005–2014 baseline and 2041–2050. All results are based on the five- GCMs.

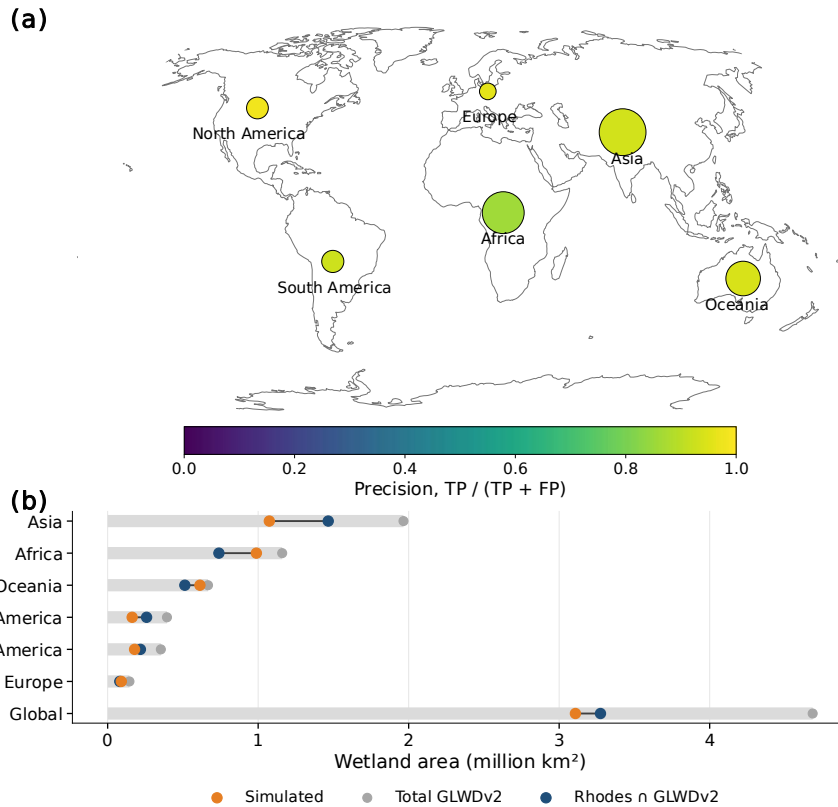


Figure 5 | Evaluation of the simulated GDW distribution against an independent reference dataset for the period of 2014-2019. The reference dataset was created by intersecting the groundwater-dependent ecosystem map by Rohde, et al. ⁵ with the Global Lakes and Wetlands Database (GLWD) v2 by Lehner, et al. ²⁸. a, Spatial distribution of validation precision ($TP/TP+FP$) where TP is true positives and FP is false positives by continent, bubble size is proportional to the GDW area of the reference dataset, and colours indicate precision on a scale from 0 to 1. Precision is defined as the fraction of simulated GDW-cells that coincide with reference wetland cells. b, Comparison of simulated GDW area and the reference dataset by continent. The total wetland area according to the GLWD v2 is also provided. As the reference dataset classifies cells as GDW presence or absence rather than providing a continuous area estimate, simulated GDW-area within each cell is compared against a binary presence, implicitly if a classified reference cell represents the full 5 arcminute cell area. Validation is restricted to dryland regions where Rohde, et al. ⁵ reference is defined.

Discussion and conclusions

The ensemble mean global area of groundwater-dependent wetland (GDW) is projected to decline under all three SSP scenarios examined, albeit with considerable uncertainty for SSP1-RCP2.6 and SSP5-RCP8.5, extending the historical trajectory of wetland loss, estimated at roughly 35% of global wetland area since 1970 as previously reported Davidson ¹⁶ and Fluet-Chouinard, et al. ¹ The two drivers act in contrasting ways, while groundwater dynamics produce both large losses and large gains, land conversion produces losses almost exclusively. Land conversion accounts for most of the projected net decline under SSP3-RCP7.0, but groundwater dynamics account for most of it under SSP1-RCP2.6 and SSP5-RCP8.5. Under SSP3-RCP7.0, land-use conversion accounts for the largest share of declining GDW area, consistent with the extensive agricultural expansion projected under this pathway ^{30,31}, related to a larger self-sufficiency under regional rivalry, which disproportionately affects large tropical wetland systems that would otherwise be sustained by shallow groundwater tables. Under SSP5-RCP8.5, groundwater dynamics emerge as the leading driver of loss, which appears to reflect the sensitivity of large GDW systems, including Amazonian floodplains and high-latitude wetlands, to water table decline under intensified evapotranspiration at high warming levels ³². Under SSP1-RCP2.6, contributions from land use and groundwater are more evenly balanced and the near-balance between projected losses and gains suggests that ambitious climate mitigation combined with lower agricultural expansion and urban development may limit net GDW decline.

Groundwater dynamics account for the largest share of projected GDW gains across all scenarios, indicating that rising water tables in some regions partially offset losses elsewhere. Under SSP1-RCP2.6, these gains occur alongside relatively limited land conversion, contributing to the near balance between gains and losses. Under SSP5-RCP8.5, substantially larger groundwater-driven gains are accompanied by substantially larger groundwater-driven losses, producing a smaller net decline than under SSP3-RCP7.0 despite the higher level of climate forcing. These projected gains should, however, be regarded as potential rather than realised, because wetland expansion ultimately depends on local land management which is not fully represented in our simulations. Consequently, the smaller net decline projected under SSP5-RCP8.5 should not be interpreted as evidence that higher-emission futures pose a lower risk to GDWs. Instead, it reflects the combination of greater spatial heterogeneity in groundwater responses and the more limited agricultural expansion projected under SSP5-RCP8.5 relative to SSP3-RCP7.0 ^{30,31}.

The projected spatial patterns are broadly consistent with previous global wetland projections based on surface inundation and soil moisture, which likewise indicated losses across tropical South America and gains in Central Africa and northern Asia under moderate-to-high emissions ³². Projected reductions in Amazonian inundations ³³ and in North American inland wetland area under SSP5-RCP8.5 ³⁴ are likewise consistent with the regional trajectories identified here. Unlike these previous studies, however, our analysis explicitly partitions the future GDW change into groundwater-and-land-use driven components, revealing that the dominant driver differs among regions and SSP-RCP scenarios.

At the regional scale, two contrasting patterns of GDW response are apparent. In the Neotropical realm, losses are consistent across scenarios and large in absolute terms. The gap between the combined and groundwater only experiment suggests that structural wetland loss through agricultural and urban expansion reduces GDW extent in this region beyond what groundwater change alone could produce, with the two drivers appearing to complement one another. The Palearctic realm shows the opposite pattern, with moderate gains under lower-emission scenarios and a small gap between the combined and groundwater-only experiments, suggesting that groundwater dynamics rather than land use are the primary control of GDW trends in this region.

A particularly strong regional contrast is evident in the Indo-Malayan realm, where the sign of GDW change reverses between SSP3-RCP7.0 and SSP5-RCP8.5. Under SSP5-RCP8.5, agricultural productivity is projected to increase through intensification rather than area expansion³⁵⁻³⁷, reducing the proportion of land under cultivation in parts of this realm and contributing to new GDW gains. Under SSP3-RCP7.0, continued extensive agricultural expansion suppresses groundwater-driven stabilization that would otherwise occur, producing losses from the same hydrological starting point. This suggests that the socioeconomic pathway may, in some regions, be a stronger influence of GDW distribution than the emission level.

Our projections remain subject to several sources of uncertainty. Validation against an independent dataset indicates consistent high precision for dryland GDWs, but the validation dataset is restricted to drylands and therefore does not assess model performance in humid tropical and boreal regions, which comprise much of the simulated global GDW extent. Additional uncertainty arises from the five-member climate model ensemble, which is intended to encompass the full range of CMIP6 climate responses but may not be representative at a regional level and from the use of single integrated assessment model to represent land use trajectories within each SSP.

Our results suggest that conserving groundwater-dependent wetlands will require integrated management of groundwater resources and land use. In regions where groundwater dynamics account for a substantial proportion of projected wetland change, maintaining groundwater availability may be as important as limiting direct wetland conversion^{15,38,39}. Conversely, in regions where land use change dominates projected losses, limiting further wetland conversion will remain essential. Integrating GDWs into groundwater allocation, land use planning and wetland conservation strategies will therefore become increasingly important under future climate and socioeconomic change. Despite its uncertainties, this study provides the first globally consistent assessment of future groundwater-dependent wetland trajectories that explicitly separate the influences of groundwater dynamics and land use change, demonstrating that groundwater will play a central role in shaping future wetland distributions and highlighting the importance of integrating groundwater management and land use planning to sustain groundwater-dependent wetlands.

Methods

Global groundwater model simulations

Groundwater dynamics were simulated with GLOBGM^{23,24}, a global MODFLOW-based groundwater model with two aquifer layers operating at 30 arc-second (~1 km) spatial resolution and monthly time step. The model is forced by output of the global hydrological model PCR-GLOBWB 2 (Sutanudjaja et al., 2018), which simulates daily soil moisture, evapotranspiration, runoff, groundwater recharge and groundwater abstraction at 5 arcminute resolution.

PCR-GLOBWB 2 was first used to generate daily runoff, groundwater recharge and abstraction fields. Groundwater recharge and groundwater abstraction were downscaled from 5 arcminutes (~10 km) to 30 arcseconds (~1 km) by subsampling and bilinear interpolation. Local runoff from PCR-GLOBWB 2 was converted to surface water discharge and associated surface water levels by routing it through the 30-arcsecond HYDROSHEDS river drainage network⁴⁰. The 30-arcsecond recharge, surface

water levels and groundwater abstractions were aggregated from daily to monthly time step by averaging daily values within each month. The resulting monthly recharge, surface water levels and abstraction fields were used to force GLOBGM. The model implementation incorporates a recently developed recharge bias correction described by van Jaarsveld, et al.²⁵. Monthly saturated area fractions, additionally needed for the wetland delineation (see below), were derived from upper-soil moisture using the enhanced ARNO scheme from PCR-GLOBWB 2^{41,42}. Drainage elevation in GLOBGM was dynamically updated to improve the representation of shallow groundwater–surface water interactions²⁷. All input datasets to run the model for historical and future projections can be found in Supplementary Table S1

Climate forcing and scenario simulations

Historical simulations (1979–2014) followed the ISIMIP3a protocol⁴³ based on the CHELSA-W5E5 dataset⁴³, while future simulations (2015–2050) followed ISIMIP3b⁴⁴. Bias-adjusted climate data from five Global Climate Models (GCMs) within CMIP6 climate projections (Lange and Büchner, 2021) for SSP1-RCP2.6, SSP3-RCP7.0 and SSP5-RCP8.5 were used as forcing to PCR-GLOBWB 2⁴⁵. The five GCM experiments for each of the three global change scenarios (i.e. total of 15 climate model experiments), were selected to span warm-cold and wet-dry climate responses: GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0 and UKESM1-0-LL⁴⁵.

Groundwater-dependent wetland identification

GDWs were identified at a 5-arcminutes resolution based on a dual criterion: water table depth ≤ 5 m and saturated area fraction (f_{sat}) ≥ 0.5 . Water table depth was assessed at a 30-arcsecond resolution from GLOBGM; a 5-arcminute cell was considered to meet the water table criterion if at least 50 % of its constituent 30 arcsecond cells had a water table depth ≤ 5 m. The water table threshold captures both core groundwater-fed wetlands and peripheral systems influenced by shallow groundwater, while accounting for unresolved sub-grid variability. The saturated area fraction was taken directly from PCR-GLOBWB 2 at 5 arcminute resolution and where the water table criterion was met, retained as a continuous measure of GDW extent within each cell rather than applying a binary classification as in Otoo, et al.²⁶. All open water bodies were excluded based on the GLWD v2²⁸. Antarctica, mountainous regions, permafrost areas and regions affected by groundwater model spin-up artefacts were excluded throughout the analysis⁴⁶.

GDW identification was performed independently for each of the five GCMs. All reported GDW areas and area changes are the mean across the five GCMs, with the ensemble spread reported as the minimum and maximum across GCMs, changes were computed per GCM and then averaged. GDWs were also categorised in persistence classes according to the average number of months per year that the groundwater table depth criterion is met, namely, episodic (1-3 months), seasonal (4-6 months) and perennial (7-12 months) per year. Both thresholds were tested across a range of values and the sub-grid distribution of average water table depth within qualifying grid cells was examined to establish what the 5 m threshold implies at ecologically relevant scales (Supplementary Note S4.1, Fig. S3 and Fig. S4).

Model validation

The global evaluation of simulated against observed heads resulted in a distribution of KGE scores (Fig. S5, top panel). Each point represents the location of one of the 15,846 wells used in this

evaluation. Based on the available observation locations, GLOBGM performs best in Central and Western Europe (notably Germany, France and the Netherlands) and the Eastern United States compared to Sub-Saharan Africa, interior Australia and Southeast Asia. Performance is classified in four categories, including Poor ($KGE \leq -0.41$, indicating that the simulation results are less accurate than using the mean of observed values; Knoben, et al. ⁴⁷, Reasonable ($-0.41 < KGE \leq 0.5$), Good ($0.5 < KGE \leq 0.75$), Very good ($KGE > 0.75$). Overall, model predictions have a $KGE \geq -0.41$ for 73.5% of wells (Table S2), indicating that the model's predictive power exceeds the mean of the observations of most monitoring locations.

The cumulative distribution functions (CDFs) indicate that the model performance is highest for shallow groundwater depths (0-5 m; Fig. S5a). In this range, 75.4 % of wells outperform the mean benchmark ($KGE \geq -0.41$) meaning model outperforms the mean benchmark at most locations. While variability is generally underestimated (20% within acceptable range), bias is well represented (85.9% within $0.5 \leq \beta \leq 2$). Correlation is also strongest near surface, with 36.7% of wells showing good agreement ($r \geq 0.5$). See Table S2 for full performance summary for shallow wells, 0-5 m.

The simulated GDW distribution was evaluated against a reference dataset constructed by intersecting GLWD v2 originally produced at 15 arc-seconds ²⁸ and the global map of groundwater-dependent ecosystems (GDE) in drylands by Rohde, et al. ⁵, retaining only wetlands in drylands likely identified as groundwater-dependent. The Rohde, et al. ⁵ dataset, originally produced at 30 m resolution, was aggregated to the 5 arc-minute model grid for comparison. Model performance was evaluated for the period 2014-2019 with climatic forcing from the CHELSA-W5E5 ⁴³ using precision, recall and F1 score, with a spatial tolerance of 1 km applied to account for positional uncertainty (Fig. 5a). Continental-scale comparisons were also made by comparing total wetland area from GLWD v2, reference GDW area and simulated GDW area (Fig. 5b).

Representation of land-use impacts

Land use fractions following the SSP-RCP scenario framework were derived from the PCR-GLOBWB 2 forcing datasets ⁴⁸ and originate from the IMAGE integrated assessment model ³⁷. Within PCR-GLOBWB 2, only irrigated cropland (paddy and non-paddy) is dynamically coupled with hydrological processes and therefore affects groundwater recharge, evapotranspiration and abstraction. Other land use classes are not explicitly linked to groundwater dynamics. To account for additional wetland loss (or gain) by land use change, the simulated GDW area per cell was reduced proportionally to the fraction of land converted for human use. The adjusted wetland area was calculated as:

$$A_{gdw,i} = f_{gdw,i} \times (1 - f_{conv,i}) \times A_i \quad (1)$$

where $A_{gdw,i}$ is the GDW area in cell i , $f_{gdw,i}$ is the saturated fraction in the cell, thus the fraction GDW (0-1), $f_{conv,i}$ is the fraction of the cell converted from natural to either agricultural lands or urban area (0-1) and A_i is the total cell area of a cell i (km^2). This adjustment accounts for structural wetland loss due to land conversion while retaining hydrological responses represented within the model.

Attribution experiments

To disentangle the contributions of groundwater and land-use change to projected GDW trends, three experiments were performed. In the groundwater only experiment, we mapped GDWs using the dynamic water table depths and saturation criterion, while land use was kept at its mean 2005–2014 level. In the land-use only experiment, land-use evolved dynamically while groundwater depth and

saturated area fraction were held constant at 2005–2014 levels. In the combined experiment, which corresponds to the default simulation set up, both land use and the hydrological conditions evolved dynamically. The 2005–2014 reference period represents the final two decades of the historical simulation, prior to scenario divergence in 2015

Change in GDW extent and attribution to groundwater dynamics and land-use drivers

Change in GDW extent at the cell level was determined by comparing the simulated GDW area between the historical baseline (2005–2014) and the late projection period (2041–2050) under the different SSP-RCPs. To attribute GDW area change at each cell to either groundwater or land-use change, the contribution of each driver was quantified. The groundwater-driven signal was defined as the change in GDW fraction between periods in absence of land-use change:

$$|d_{GW,i}| = |f_{gdw,i,fut} - f_{gdw,i,hist}| \quad (2)$$

where $f_{gdw,i}$ is the GDW fraction of cell i .

The land-use driven signal was defined as the change in the fraction of each cell converted from GDW due to land-use change between periods:

$$|d_{LU,i}| = |f_{conv,i,fut} - f_{conv,i,hist}| \quad (3)$$

where f_{conv} is the fraction of total land use is converted within the cell.

The dominant driver at each cell was assigned by directly comparing the two signals. Cells for which $0.5 < |d_{GW,i}| / |d_{LU,i}| < 1.5$ were classified as mixed. Where this ratio was ≥ 1.5 or ≤ 0.5 , cells were classified according to the largest signal as either groundwater-driven or land use driven. The direction of change (loss or gain) was assigned from the sign of the total change in GDW fraction between the two periods.

Spatial aggregation

The GDW area was aggregated to WWF biome–realm combinations (Olson et al., 2001). The monthly GDW area was calculated as the sum of 5 arcminute cell areas classified as GDW within each biome or biome–realm unit and averaged annually.

GDW area change quantification

Time series of annual GDW area, globally and per realm and realm-biome combination, were calculated by including the area of 5 arcminute cells classified as GDW for at least one month during that year. Scenario time series were aligned to the 2010–2014 historical mean to ensure continuity between historical and projection simulations.

Changes in GDW area were quantified as the difference in decadal means between two consecutive periods. For the historical period, the early decade (1995–2004) and the late historical decade (2005–2014) were compared. For future scenarios, the 2005–2014 historical baseline was compared against the 2041–2050 projection. Gross losses and gains were computed independently by summing area reductions and increases across cells between the two periods.

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