Development policy affects coastal flood exposure in China more than sea-level rise

Yafei Wang[1,2,3,4*], Yuxuan Ye[1,2], Robert J. Nicholls[5,6], Lennart Olsson[3], Detlef van Vuuren[7,8], Garry Peterson[4], Yao He[1,2], Manchun Li[9,10], Jie Fan[1,2], Murray Scown[3,11*]

1 Key Laboratory of Regional Sustainable Development Modeling, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China; wangyafei@igsnrr.ac.cn (Y.W.); yeyuxuan5012@igsnrr.ac.cn (Y.Y.); heyao22@mails.ucas.ac.cn (Y.H.); fanj@igsnrr.ac.cn (J.F.)

2 College of Resources and Environment, University of Chinese Academy of Sciences, Beijing 100049, China

3 Lund University Centre for Sustainability Studies (LUCSUS), Lund University, Lund SE-22362, Sweden; lennart.olsson@LUCSUS.lu.se (L.O.); murray.scown@LUCSUS.lu.se (M.S.)

4 Stockholm Resilience Centre, Stockholm University, Stockholm SE-10691, Sweden; garry.peterson@su.se (G.P.)

5 Tyndall Centre for Climate Change Research, University of East Anglia, Norwich NR4 7TJ, UK; robert.nicholls@uea.ac.uk (R.N.)

6 School of Engineering, University of Southampton, Southampton SO17 1BJ, UK (R.N.)

7 PBL Netherlands Environmental Assessment Agency, The Hague, 2500 GH, The Netherlands; Detlef.vanVuuren@pbl.nl (D.V.V.)

8 Copernicus Institute of Sustainable Development, Utrecht University, Utrecht, 3584 CS, The Netherlands (D.V.V.)

9 School of Geography and Ocean Science, Nanjing University, Nanjing 210023, China; limanchun@nju.edu.cn (M.L.)

10 Collaborative Innovation Center for the South Sea Studies, Nanjing University, Nanjing, China (M.L.)

11 Swedish Centre for Impacts of Climate Extremes (CLIMES), Lund University, Lund, Sweden (M.S.)

Corresponding author: wangyafei@igsnrr.ac.cn (Y.W.) and murray.scown@LUCSUS.lu.se (M.S.)

Abstract

Effective coastal exposure assessments are crucial for adaptively managing threats from sea-level rise (SLR). Despite recent advances, global and regional assessments are constrained by omitting critical factors like land-use change, failing to disaggregate potential impacts by land uses and oversimplifying land subsidence. Here we address these gaps by developing context-specific scenarios to 2100 based on a comprehensive analysis of Chinese coastal development policies. We integrate high-resolution simulations of population and land system changes with inundation exposure assessments that incorporate SLR, land subsidence, tides, and storm surges, offering a more nuanced understanding of coastal risks. Across our plausible set of downscaled SSP-RCP scenarios, policy decisions have a bigger effect on what is exposed to coastal flooding in 2100 than the magnitude of SLR. Hence, coastal policy decisions largely influence coastal risk and adaptation needs to 2100, demonstrating the necessity of appropriate policy design to manage coastal risks.

Main text

Coastal zones are on the front line when it comes to facing the increasing threats associated with climate change[1–3]. Coastal scenario analysis and risk assessments are important tools for advancing knowledge and guiding policy—providing, for example, estimates of populations and assets exposed to flooding[4,5] and weighing anticipated economic losses against costs of adaptation[6]. However, coastal risk is multifaceted. Climate change affects SLR and the frequency and intensity of storms, combining to raise extreme sea levels in certain areas[7]; land subsidence driven by human activity such as groundwater extraction increases relative SLR in populated coastal lowlands often at rates much higher than that caused by climate change alone[5,8]; and coastal development and adaptation actions determine who and what are exposed and vulnerable to flooding, salinization, or erosion.

So far, limited advances have been made in global and regional coastal inundation exposure assessments and management using the scenario frameworks of the Shared Socioeconomic and Representative Concentration Pathways (SSPs and RCPs). They, for instance, mostly 1) do not disaggregate impacts on different land uses and sectors (see ref.[9] for recent advances in Europe); 2) do not consider all components driving exposure (see ref.[3]); and 3) have coarse spatial resolution (see refs.[10,11] for recent improvements to the commonly-applied Dynamic and Interactive Vulnerability Assessment [DIVA] modelling framework). Recent assessments for China have ignored the effects of land subsidence[12,13] or have failed to consider in detail how land use planning and development dynamics interact with SLR to affect coastal exposure[8,10]. Such omissions could result in underestimates of exposure and/or overemphasis on climate change and SLR as its main driver, leading to misjudgments in the urgency of adaptation and/or confusion as to which actors have agency and responsibility.

Here, we assess how Chinese coastal development plans interact with relative SLR and extreme events to determine exposure of multiple coastal zone functions across a range of scenarios. This is done by simulating land system changes for the entire coastal zone of mainland China and Hainan for five development policy scenarios and combining this with estimates of land subsidence and extreme sea levels across three SLR scenarios. For the land use and population scenarios, we use the CLUMondo model to spatially simulate future land system changes based on an analysis of 114 national and provincial coastal zone plans and policies. The scenarios capture policy elements that are oriented towards economic development (ECON), ecological protection (ECOL), or the middle road. For the ECON and ECOL scenarios, we also considered variants that differ in the intensity of the policies applied. The subsequent inundation exposure assessment advances previous attempts by including all relevant components (SLR, land subsidence, and tides and storm surges) and an improved geometric inundation model that considers spatial connectivity and attenuation (Fig. 1).

Extreme events have the greatest effect on potential inundation area, with land subsidence and SLR amplifying the effect. However, coastal development scenarios have a greater effect on which land system functions are exposed than do SLR scenarios. These findings indicate that disaster preparedness, land subsidence mitigation, and improved adaptation planning are the most important measures for coastal flood risk management in China, to be complemented by emissions reductions that will reduce the SLR effect globally, as well as along China's coastline. Our findings also suggest that the set of futures in the SSP-RCP framework used for global and regional scenario analyses does not cover the full range of possible futures that can be shaped by local and national policies. Our approach enables the integration of development policies and land system change into the analysis and could be used to explore detailed coastal adaptation scenarios in future work in China and elsewhere.

Results

China has been subject to coastal flooding due to tide/storm surge effects throughout its history and large areas are currently threatened by flooding and depend on defenses to maintain current functions[10]. Our high-resolution disaggregated analysis reveals that future exposure of different coastal zone functions depends not only upon the SLR scenario, but largely also on the policy pathways. Land system changes vary greatly across policy pathways (Supplementary Note 1; Extended Data Fig. 1) and, under all SLR scenarios, a transition in coastal policy from strictest ecological protection ("ECOL high") to most aggressive economic development ("ECON high") significantly increases the development intensity of urban and industrial land exposed to flooding (Fig. 2). The top land system types exposed shifts from sub-urban area (SU), agriculture-hinterland village (AV), high-intensity agriculture area (HA), and wetlands (WTL) in the ECOL high scenario to coastal and inland industrial areas (CTI, ILI) and low-density urban areas (LDU) in the ECON high scenario (Fig. 2). This indicates that impacts, should flooding occur, will not happen uniformly across all land systems (as aggregated GDP calculations assume) and that it is the policy scenario and not the SLR scenario that mostly determines which land system types will be exposed.

By contrast, the SLR scenario influences the total inundation area and depths in different land systems (Fig. 2; Extended Data Figs. 2–4; Supplementary Note 2). By 2100, the area potentially exposed to inundation under extreme sea levels could reach 29,290 km² (5.84% of the analysed coastal zone) in the low-end scenario; 34,400 km² (6.86%) in the mid-range; and 49,370 km² (9.85%) in the high-end scenario, assuming current flood protection standards and an interactive effect between climate change and extreme events equal to 10% of SLR ($CCEx_{10}$; please see Methods for details). The overwhelming majority of the potential inundation extent is driven by tides and storm surges (i.e., extreme events), while SLR alone and in combination with land subsidence are not high enough to exceed current protection standards anywhere along the coast (Extended Data Fig. 4). When considering no flood protection, the effect of land subsidence on inundation extent by 2100 is over 14 times that of SLR alone in the low-end scenario and about 1.5 times greater in the high-end scenario (Extended Data Fig. 4). The largest effect on inundation extent caused by increasing the magnitude of interaction between SLR and extreme events is about 17% in 2100, with current protection (Extended Data Fig. 4; Supplementary Note 2). The presence of flood protection reduces the maximum potentially inundated area in 2100 by around 18-19% compared to no protection, depending upon scenario, but the relative patterns remain very similar (Supplementary Note 3).

To gauge the potential impacts of flooding on different land system functions in China's coastal zone, we calculated five indicators within the potentially inundated areas: 1) human population, 2) monetary value of ecosystem services, 3) grain production, 4) (terrestrial) aquaculture production, and 5) GDP. The first four of these were calculated from spatial simulations using CLUMondo, while GDP was calculated based on each land system's contribution to total GDP in the coastal zone (although we did not employ discount rates, so future absolute values should be considered underestimates). Our assessment indicates a complicated interaction between development policy scenarios and their effect on land system patterns, on the one hand, and SLR scenarios and their interaction with land elevation, on the other.

Population and GDP exposure are, unsurprisingly, highest in the high-end SLR scenario and ECON high policy scenario (Fig. 3a-b, m-n; Extended Data Figs. 5 and 6). Population exposure increases in the coming decades under all scenarios. This is despite continual declines in total coastal zone population from 2020 onwards in the ECOL and MID policy scenarios (Supplementary Table S2), indicating population concentration in exposed areas near the coastline. Most scenario combinations show a slight decline in population exposure towards the end of the century due to population decline (Fig. 3a-b). By contrast, exposure of GDP continues to rise under all scenarios even at the end of the century (Fig. 3m-n). When considering the results for a 10% interaction between SLR and extreme events and assuming current flood protection standards: by 2050, 6.8% (ECOL high | Low-end) to 8.9% (ECON low | High-end) of the population, and 7.5% (ECOL low | Low-end) to 12.1% (ECON high | High-end) of GDP, within our delineated coastal zone will be exposed to inundation. By 2100, these ranges increase to between 9.5% (ECOL low | Low-end) and 19.1% (ECON high | High-end) for population and 11.9% (ECOL low | Low-end) to 22.2% (ECON high | High-end) for GDP.

In terms of food, grain production exposure is consistently higher under the ECOL and MID scenarios than the ECON scenarios (Fig. 3h; Extended Data Fig. 7). Between 4.0% (ECON high | Low-end) and 7.4% (ECOL low | High-end) of grain production in the coastal zone could be exposed by 2050; again assuming current protection and a 10% SLR interaction with extreme events. These fractions increase to 5.8% (ECON high | Low-end) and 13.5% (ECOL low | High-end), respectively, by 2100. Aquaculture is exposed to much greater inundation depths than all other land system functions we analyzed (Extended Data Fig. 8). As much as 19.2% (ECOL low | High-end) of aquaculture production in the coastal zone could be exposed to inundation depths of 2 m or more by 2050. Exposure of aquaculture production peaks around 2050 in all policy scenarios, then declines towards 2100 (Fig. 3k). However, as inundation depth and extent continue to increase under high-end SLR, as much as 11.9% of aquaculture production will be exposed to inundation depths of 3.5 m or more in the ECON low scenario (Extended Data Fig. 8). In contrast to grain, aquaculture exposure is consistently highest under the ECON high development scenario (Fig. 3k).

Exposure of absolute ESV is consistently higher in the ECOL policy scenarios, while the MID and ECON scenarios are similar (Fig. 3h). Between 5.8% (ECON high | Low-end) and 7.2% (ECOL high | High-end) of monetary ESV in the coastal zone is projected to be exposed by 2050 (with same assumptions as above). By 2100, ECON high | High-end has the highest proportional exposure (13.7%) with ECOL high | Low-end the lowest (8.2%). In our calculations, ESV is higher in natural ecosystems than in others, and these may tolerate some level of inundation—particularly wetlands, for example—so the depth (Extended Data Fig. 9) and duration of inundation of ESV may be important to consider.

Our analyses enable us to determine whether policy scenarios or SLR scenarios have a greater effect on the potential impacts on different coastal zone functions. For population and grain production exposure to flooding, the sets of SLR and policy scenarios show increasingly similar ranges by the end of the century (Fig. 3a-c, g-i), indicating relatively similar long-term influences of policy and SLR scenarios on exposure, although development uncertainty caused by different policies plays a much larger role in the coming decades (Fig. 3c, 3i). The increased role of development policy is also evident for aquaculture and GDP exposure, and this continues at least until 2100 (Fig. 3j-o). The effect is particularly large for aquaculture (Fig. 3l). By contrast, from 2090, variation in ecosystem service value exposure depends more on the SLR scenario than on the policy scenario (Fig. 3f). Regionally, in the three strategic zones in China, the Bohai Rim and Greater Bay display even greater effects of policy scenarios on exposure, whereas the Yangtze River Delta displays a much greater effect of SLR scenarios for exposure of population, GDP, grain production, and ESV by the end of the century (Extended Data Figs. 3 and 10).

Discussion

Our analysis unpacks the differential effects of the various factors contributing to coastal flood exposure. Whether changing exposure is driven mainly by land subsidence, SLR, or development in the floodplain, for example, determines what the best management strategy might be and who has agency and responsibility for that strategy. Our results reveal that inundation exposure of land in China is mostly affected by extreme sea levels associated with tides and storm surges. These are natural phenomena, although climate change and higher seas are expected to amplify them in certain areas and reduce them in others[7,14,15], Adaptation measures such as early-warning systems, floodplain zoning, and/or flood protection measures are necessary to deal with extreme events. Ecosystem-based approaches, such as seagrass meadows and mangroves, may be effective in buffering storm surges and reducing their energy[16,17], including hybrid approaches combined with dikes. In certain places along the Chinese coast, land subsidence happens much faster than mean SLR, exacerbated by groundwater extraction, dense construction, and disconnection of alluvial plains from river flooding and sedimentation. Regulating groundwater extraction is essential to mitigate and avoid worst-case-scenario land subsidence, particularly in deltas[18]. Sedimentation enhancement strategies are also promising adaptation solutions in deltas[19,20], although may be limited in highly developed areas where land is fully used and temporary flooding with sediment-laden water is not appropriate. China, being among the world's highest greenhouse-gas emitting countries, also has a great deal of agency and responsibility when it comes to mitigating climate change and associated SLR, so emissions reductions are also in the country's best interest when it comes to minimizing coastal risk up to and beyond 2100.

Beyond the physical determinants of relative SLR and extreme events, coastal development also drives flood exposure[2]. Our results reveal that for certain land functions, exposure is determined more by how the Chinese coastal zone is developed than by the magnitude of SLR. China's coastal land development tends to expand toward the shoreline, and land reclamation is common, but policies focused on economic or ecological priorities will significantly influence what is potentially exposed. For at least the next 50 years, the range across the government's existing planning policies surpasses the differences between various global climate models. Thus, policymakers have a great deal of agency in mitigating risk through land planning, particularly in strategic areas (Extended Data Figs. 3 and 10), as well as through emissions reductions. We recommend our integrated assessment findings be incorporated into China's medium- and long-term development strategies as a critical scientific basis for coastal planning at all levels. Specifically, these results should inform urban master planning, the delineation of ecological protection redlines, and the approval of land use changes. At the subnational level, coastal provinces and prefecture-level cities should develop dedicated medium- and long-term adaptation plans based on the assessment findings. These plans should specify adaptive measures including land-use transitions in high-risk zones and the implementation of managed retreat strategies to complement engineered protection.

Flood protection is currently the dominant adaptation strategy in China's coastal zone, but this comes with risks such as the "levee effect"—where risk is increased due to development behind levees that are meant to reduce risk—and can be short-sighted, obscuring long-term alternatives such as managed retreat[21]. Our results show as much as a 60% increase in potential impacts to land system functions when comparing current protection standards to no protection (Supplementary Note 3)—indicating the magnitude of the "levee effect" and the risk posed should protection fail. As of 2017, China has constructed 14,500 km of levees but their completion times, lifespans, and standards vary across regions. Shanghai is the only city with a tide protection standard as high as 1 in 500 years, depending on location, while other parts of the coastline adhere to as low as a 1 in 20-year standard. Furthermore, the construction quality compliance rate is only 42.5%[22]. Our findings reinforce the urgency of improving standards for extreme flood protection and reconsidering the reliance on protection alone for development. In particular, long-term consideration of managed retreat is necessary. The absence of retreat in any of the planning documents we reviewed is concerning, and research is required on future adaptation pathways that include alternatives to protection, such as retreat, accommodation, and ecosystem-based adaptation[23].

Scenario assessments are useful for dealing with future uncertainty and have been widely deployed in climate change contexts. Our analysis contributes to advancing regional and global scenario assessments in three ways: 1) improving existing coastal inundation exposure methodologies; 2) revealing that climate scenarios alone likely underestimate the range of possible futures in terms of coastal flood exposure; and 3) opening the door for the development of detailed adaptation scenarios for coasts (and other areas). Methodologically, DIVA[24,25] has been a leading vector-based framework for regional and global coastal flood risk assessments for over 15 years[4–6,26]. Our high-resolution raster-based framework enables much finer and disaggregated assessments that support spatial planning. Further, our methods can be coupled to other modelling frameworks, including DIVA, to extend the analysis with more detailed spatial adaptation scenarios, such as defend, advance, retreat, and accommodate[23]. By adapting the rules in CLUMondo (e.g., for spatial constraints), future work using our approach could explore such things as floodplain exclusion zoning or targeted hard protection in different adaptation scenarios.

Our analysis deals with multiple sources of uncertainty (and agency), including in SLR and its interaction with extreme events; in development policies and their potential to shape different future land systems; in the interactive effects of climate and land system changes on land subsidence; and in the presence or absence of coastal flood protection measures. Our findings support others that emphasize the importance of considering the range of uncertainty in sets of simulated futures of coastal exposure[27], as well unpacking what is really driving risk and what can be done to manage it. Our future projections span until 2100. It is imperative to recognize the longer-term risks due to climate change induced SLR. The Sixth IPCC assessment report (AR6, WG-I) finds that under the highest emissions to 2150, SLR of 2 m is possible and at the high-end 5 m cannot be ruled out. Certainly, SLR continues for centuries and high-end global SLR has been estimated at 2.5 m in 2300 under SSP1-2.6 and up to 10.4 m in 2300 under SSP5-8.5[28]—why planned retreat must be considered. Importantly, our SLR scenarios omit marine ice sheet and ice cliff instability, which could produce large SLR especially after 2100 under high emissions[29]. General policy responses to such long-term uncertainties are difficult and adaptive policy methods may provide a response framework[30], which can be supported by our analysis and approach. Ultimately, urgent emissions reductions and prudent adaptive spatial planning are required to reduce risk.

Acknowledgements

This research was funded by the National Natural Science Foundation of China (No. 42371184; 42001131; W2421009). We thank the China Scholarship Council and the CAS President's International Fellowship Initiative for their financial support. The authors wish to thank Jinfeng Liao, Zhenyu Shen, Shuwei Shen and Yi Fan for their contributions to data and policy document collection and visualizations.

Author Contributions Statement

Y.W. and M.S. conceptualized the study. Y.W., Y.Y., M.L., and J.F. developed the policy scenario and land systems methodology. Y.W., Y.Y., M.S., and R.N. developed the relative SLR and exposure methodology. Y.W. designed the scenarios. Y.W., Y.Y. and Y.H. curated the data, ran the models, and performed the data analysis. Y.W., Y.Y. and M.S. carried out the investigation. Y.W. and M.S. wrote the original draft. M.S., Y.W., Y.Y., R.N., L.O., D.V.V., G.P., M.L. and J.F. discussed the results and contributed to the review and editing of the paper. Y.W., Y.Y. and M.S. created the visualizations. Y.W. acquired the funding.

Competing Interests Statement

The authors declare no competing interests.

Figure Captions

Fig. 1. Improved coastal exposure assessment framework covering multiple components. (a) We combine land system change affected by coastal development policies alongside mean SLR, land subsidence, and tides and storm surges. (b) We combine the effects of economic- (ECON), ecological- (ECOL), and middle road-focused (MID) policy scenarios with enhanced relative SLR scenarios spanning the broad set of SSP-RCP scenarios and including land subsidence. (c) We evaluate potential impacts to multiple land system functions, as well as population and GDP, by considering potential flood exposure to different water depths over time under different scenarios. Policy scenarios have a median effect on exposure (solid lines), around which SLR scenarios create uncertainty (shaded bands). Similarly (though not illustrated), SLR scenarios have a median effect around which policy scenarios create uncertainty. The combined analysis reveals the sensitivity of exposure outcomes to both policy decisions and climatic trajectories.

Fig. 2. Inundation areas of the top five exposed land system types by water depth under different policy and SLR scenarios in 2050 and 2100, assuming current flood protection standards and an interactive effect of 10% of SLR on extreme events. Columns from left to right show the SLR scenarios of low-range (2050 and 2100), mid-range (2050 and 2100), and high-range (2050 and 2100). Rows show policy scenarios. The percentage value in each panel indicates the fraction of the total inundation area represented by the top five land systems shown. Land system abbreviations: AS = aquaculture system, AV = agricultural hinterland village, CTI = coastal industrial area, HA = high-intensity agricultural area, ILI = inland industrial area, LA = low-intensity agricultural area, LDU = low-density urban area, MA = medium-intensity agricultural area, SU = sub-urban area, TSA = towns and semi-dense areas, WTL = wetlands.

Fig. 3. Projected exposure of coastal zone functions by scenario combinations, assuming current flood protection standards. Exposed functions include (**a–c**) population, (**d–f**) ecosystem service value (ESV), (**g–i**) grain production, (**j–l**) aquaculture production, and (**m–o**) gross domestic product (GDP). Left panels (**a, d, g, j, m**): Solid lines show median exposure across three SLR scenarios, with uncertainty bands showing the effects of five policy scenarios. Middle panels (**b, e, h, k, n**): Solid lines represent median exposure across three policy scenarios, uncertainty bands showing the effects of three SLR scenarios. Right panels (**c, f, i, l, o**): Red bars show decadal variability (range) around SLR scenarios driven by policy; blue bars show decadal variability (range) around policy scenarios driven by SLR. Points represent the range around each of the three scenario combination sets; bar heights indicate the average of the three.

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Methods

We conducted our analysis over the entire coastal zone of mainland China and Hainan. The coastal zone is defined as all coastal prefecture level cities (spatial administrative areas at the level below province and above county) with 10 km buffer zones along the coastline, covering a land area of 501,300 km^2.

Policy review and scenario development

Our previous studies have demonstrated that coastal policies in China play a significant role in shaping landscape patterns and land use[31–33], emphasizing the transformative effects of "top-down" policy changes on local landscapes. Thus, here we reviewed coastal zone policies issued from national and provincial authorities that can affect local land system change[31].

First, we collected 15 national and 99 provincial coastal zone plans and policies published from 2000 to 2020 (Supplementary Data 1) through extensive searches of government websites and records, which included central and provincial agencies responsible for coastal zones and covered more than two-thirds of prefectural cities along the coastal zone. Along with other attributes, we recorded each policy's orientation as either a) development-oriented, b) (ecological) protection-oriented, or c) middle road orientation or unspecified. Development-oriented policies focus on socio-economic development, protection-oriented policies focus on ecological protection, and middle road orientation or unspecified balance both objectives and/or have no dominant priority. The classification of policy orientations was based on specific criteria such as policy titles, keyword frequency (e.g., protection, development, coordination), and stated policy priorities.

Next, we identified 54 of the 114 documents that contained explicit scenarios beyond 2030. From these, we extracted and analyzed their specified a) planning objectives, b) spatial strategies, and c) spatial constraints. Planning objectives include value constraints (e.g., target values, growth rates, minimum values) and directional semantic descriptions (e.g., steady growth, rapid growth, no less than the status quo). Spatial strategies guide the direction and focus of land development (e.g., urban expansion, industrial zones, and port layouts). Spatial constraints define protected areas such as nature reserves and heritage sites.

From the analyzed planning objectives, spatial strategies, and spatial constraints, we developed our set of five policy scenarios that are quantitatively characterized by sets of objective parameters (Supplementary Tables S1) and spatial rules. These objective parameters and spatial rules were defined by the authors' expert judgement based on the characteristics of the specific scenarios in the policies analyzed and through iterative modelling experiments (Supplementary Note 4). The policy scenarios were broadly defined as economic development-oriented ("ECON"), ecological protection-oriented ("ECOL"), and middle road ("MID"). The ECON and ECOL scenarios were divided into high and low variants to represent different intensities and stringencies of the policy pathways.

Projection of land system changes

We developed a specialized land system classification for the coastal zone of China, consisting of 21 land system types at a 1 km^2 resolution, and used the CLUMondo model to simulate future land system changes under different policy scenarios (Supplementary Note 4). Land systems denote mosaic land use and land cover patterns caused by a combination of natural and human forces[34]. In the CLUMondo model, land system changes are driven by regional demand for goods and services and influenced by local driving factors that either promote or constrain land changes[35]. Model inputs include multi-objective parameters, driving factors, and spatial rules. Our multi-objective parameters and spatial rules were derived from our policy analysis and scenario development (Supplementary Fig. S7), while the driving factors were selected based on previous research[36,37] and statistical analyses (Supplementary Note 4; Supplementary Tables S4 and S5).

We selected population, grain production, aquaculture production, and ecosystem services value (ESV) as the multi-objective parameters based on the requirements of the CLUMondo model (Supplementary Table S2; Supplementary Note 4). These values were determined by considering the quantitative policy scenarios (Supplementary Table S1), as well as the coastal zone's development expectations and its role in the national context.

Spatial constraints include conversion rules, neighborhood matrix, and area restrictions. The conversion rules encompass the difficulty of converting one land system to the others (conversion resistance), whether the conversion from one type to the other is allowed (conversion matrix), and the priority of a land system to be given when allocating for the demand (conversion order). These rules were carefully designed to reflect different policy preferences and trajectories and their details are contained within the model code provided. The matrix of neighborhood weights (Supplementary Table S3) was calibrated to capture the centripetal forces of urban expansion[35]. The area restrictions indicate areas where land changes are restricted (such as natural reserves), and the special areas allowed for conversion (e.g., coastal industry will only appear within a 10 km buffer along the coastline).

Projection of vertical land subsidence rates

We developed a 1 km^2 raster map of land subsidence in 2020 for our entire coastal zone using a machine learning model and then projected localized land subsidence under different future scenarios. In our model, future land subsidence is affected by both the policy scenario and the climate scenario. The policy scenario affects land subsidence via different rates depending on the land system in each grid cell, while the climate scenario affects land subsidence via different rates depending on climate variables in the model.

We constructed a dataset of 6,203 sample points of reported subsidence rates, georeferenced from 40 published studies, encompassing major subsidence hotspots along China's coast (Supplementary Data 2; Supplementary Note 5). Maps provided in these studies were digitized, and subsidence locations along with their respective rates were extracted. The compiled dataset, primarily covering the period 2017-2021, included 4,417 subsidence points (>0 mm/year) and 1,786 non-subsidence points (=0 mm/year), ensuring a reasonably balanced representation. The sample data represents the most recent and available land subsidence records.

We employed a Random Forest (RF) Regressor to generate maps of localized subsidence. Predictions are made as an ensemble estimate from multiple decision trees based on bootstrap samples (bagging), which helps minimize model overfitting. For model input, we selected 19 explanatory variables representing hydrological, climatic, topographic, geological, and anthropogenic factors known to influence subsidence rates[38–40] (Supplementary Table S7). These variables were originally available at different spatial and temporal resolutions, so all of them were resampled to a 1 km^2 resolution and aligned with coastal land areas. Model hyperparameters were optimized through nested cross-validation, utilizing an inner loop for tuning and an outer loop for performance evaluation. Each RF regressor is repeated 20 times using different training and validation samples to evaluate prediction variability and quantify model uncertainty.

Model validation was conducted by comparing predicted and observed subsidence rates at sample points and compared with other recent global studies (Supplementary Note 5). We evaluated the model's accuracy using Mean Absolute Error (MAE = 3.77 ± 0.268 [mean ± SD]), and Root Mean Squared Error (RMSE=7.525 ± 1.124) and coefficient of determination (R^2=0.6 ± 0.08), which are acceptable given observed subsidence rates as high as 240 mm/year.

Finally, projection of future land subsidence under the various scenario combinations was done by replacing the current land system and climate explanatory variables with their future projections in each 1 km^2 grid cell. The land system type was taken from the projected land system maps under each policy scenario. The most influential land systems on land subsidence in our best performing RF model was coastal industry, followed by urban, suburban, and inland industry (Supplementary Fig. S15). The four most influential bioclimatic variables from the best performing RF model were precipitation seasonality, precipitation in the wettest quarter, temperature diurnal range, and mean annual temperature (Supplementary Figs. S15 and S16); these were replaced with projected values from the MRI-ESM2-0 model[41]. Because these climate data are available in 20-year intervals, we used the RF model to produce maps of annual land subsidence rate (in mm) for 2030, 2050, 2070, and 2090. The annual subsidence rate (mm) for each 1 km^2 pixel was accumulated yearly using each period's initial rate: 2020's rate for 2020-2029, then adding 2030's rate for 2030-2049, 2050's rate for 2050-2069, and so on. We assumed that the relationships among features in the RF model remain constant over time.

Projections of extreme relative sea levels

Our analysis includes the important components of mean SLR, land subsidence, and transient extreme events due to high tides and storm surges corresponding to the 1 in 100 return period. This approach was selected from a maximum risk management perspective—that is, reflecting the maximum risk from extreme events with potential for extensive impacts. From a policy maker's perspective, it is often useful to adopt a cautious approach and prepare for the worst-case scenario, even if the probabilities are low[42].

To integrate long-term SLR with short-term extreme events, we express the future extreme sea level (ESL, or extreme coastal water level) in year t as a linear combination, as shown in Equation 1:

$$ESL_t = MSL + SLR_t + TS + CCEx_{int} \quad (1)$$

Where MSL is Mean Sea Level, specified by the vertical datum of the data used. SLR_t is the amount of SLR in year t, excluding relative land motion. The values of Tides and

Storm Surges (TS) are extremes obtained for a specific return period based on historical records. $CCEx_{int}$ is a factor capturing the interactive effect between climate change and extreme events.

We calculated the ESL projections in different SLR scenarios up to 2100. The SLR projections are derived from IPCC AR6 data[43], incorporating various components of future SLR, such as steric SLR, dynamic sea-level change, contributions from glaciers and ice caps, and land-water storage. To avoid double-counting land subsidence effects, we use values of the 'novlm' (no vertical land motion) version with median confidence. We took three scenarios from the AR6 data: SSP1-2.6 (5th percentile from the model ensemble; “low-end”), SSP2-4.5 (median from the model ensemble; “mid-range”), and SSP5-8.5 (95th percentile from the model ensemble; “high-end”). We chose the 5th and 95th percentiles of the low-and high-end scenarios, respectively, to cover the wide range of possible futures. While SLR differences are primarily associated with RCP (climate) differences, SSPs can, for example, alter land water storage effects. Importantly, we do not include key features of potential SLR, such as marine ice cliff instability (MICI) and marine ice sheet instability (MISI). These factors could substantially modulate the potential end-of-century SLR outcomes, but they are not well understood and are considered low confidence in AR6.

Climate change not only affects SLR, but also extreme events, and understanding these effects presents significant challenges. Previous studies[44] have revealed seemingly contradictory effects: extreme events can either amplify with SLR due to decreased bottom friction effects, or diminish due to reduced surface wind stress or deeper water columns. Such complexity underscores that the SLR-extreme-event interaction is not simply additive but involves complex hydrodynamic interactions that can produce counterintuitive outcomes, strongly modulated by local characteristics such as coastal geometry, bathymetry, tidal regime, and freshwater inputs[45]. Notably, the response of tidal constituents—such as mean high water (MHW) and tidal range—is often disproportionate to the magnitude of SLR. In many locations, MHW exhibits a super-proportional response, suggesting an amplifying effect of tidal dynamics under higher sea levels[46]. For instance, in China's Pearl River Delta, tidal amplification may exceed 0.5 meters under a projected SLR of 2.1 meters, primarily due to depth-induced reductions in bottom friction[44]. A European analysis spanning 1960 to 2018 found that trends in surge extremes closely tracked mean sea level changes, influenced by both internal climate variability and anthropogenic forcing[47]. Global analyses have found the effect of climate change on extreme sea levels is mostly driven by SLR and an interactive effect of SLR with TS[7,15]. While increased intensity storms can have a relatively large contribution to extreme events in some areas, their interactive effect with SLR can be reversed in others, leading to minimal regional contributions of storm surges (see Fig. 6 in ref.[15]). In the Yangtze River Estuary, for example, SLR could lead to a 1-meter increase in water depth, which in turn may reduce the maximum storm surge by approximately 0.15 meters[48].

Given the complexities in the climate change-extreme event interaction, we conducted multiple analyses to capture uncertainty. First, we calculated our future extreme sea levels with the $CCEx_{int}$ factor set to zero. Next, we assessed the effects of increasing this factor incrementally as 10% and 30% of SLR in each cell—more than covering the maximum 25% found in the Chinese case studies we examined[44]. The main text contains the water depth results for $CCEx_{int} = 0.1SLR$ (Fig. 2) while water depth results for $CCEx_{int} = 0$ and $CCEx_{int} = 0.3SLR$ can be found in Supplementary Note 2. All combinations of these scenarios are captured in the variability analyses in Fig. 3. Note that we do not analyze a potential overall reduction in ESL through this interaction term, which would lower the exposure caused by SLR scenarios.

The land elevation data was defined by CoastalDEM[49], whose vertical datum is the EGM96 geoid. The tidal surge (TS) data were sourced from the Coastal Dataset for the Evaluation of Climate Impact (CoDEC) dataset[7]. To convert the vertical datum of the CoDEC extremes from Mean Sea Level (MSL) to EGM96, we referred to previous studies[50] and used the Mean Dynamic Ocean Topography (MDT) CNES-CLS22 data for conversion[51]. Localized land subsidence was taken from the RF model.

Coastal flood exposure

Coastal flood exposure assessments are often conducted using a simple bathtub model, which overestimates inundated area by not accounting for hydrodynamics[52]. We used an improved geometric inundation model that considers hydrological connectivity and attenuation to project coastal flood exposure caused by SLR, land subsidence, and extreme sea levels. The modeling process begins at pixels that represent the current land-ocean border and iteratively spreads inward (Supplementary Note 6). Ocean water propagates from current oceans and inundates neighboring cells whose elevation is below a specific value subtracting the attenuation coefficient from ESL, with iterations until no cells can be inundated. It aims to minimize the overestimation of unrealistic inundation extents or depths compared to a conventional bathtub model[53].

The water depth $W_{t,i}$ of the inundated pixel i at year t is computed using Equation (2):

$$W_{t,i} = \begin{cases} (ESL_{t,i} - H_{t,i} - a_{t,i}) \cdot C_{t,i}, & ESL_{t,i} > H_{t,i} + a_{t,i} \\ 0, & ESL_{t,i} \leq H_{t,i} + a_{t,i} \end{cases} \tag{2}$$

Where:

- $ESL_{t,i}$ is the projected extreme sea level for pixel i at year t;
- $H_{t,i}$ refers to the difference between the original elevation and the projected land subsidence for pixel i at year t;
- $a_{t,i}$ denotes attenuation, accounting for the diminishing impact of water as it moves inland from the coastal starting point to pixel i at year t (see Supplementary Note 6 for sensitivity analysis);
- $C_{t,i}$ is a binary parameter, representing whether the pixel i is connected to water (=1) or not (=0) at year t, using the cardinal and diagonal connectivity rule.

To perform a localized assessment of the projected ESL values along the land-ocean border, we first extracted a high-resolution ocean mask using CoastalDEM and our land cover classification products (see Supplementary Note 6), which includes fully interconnected river mouths. The spatial resolution of the CoastalDEM was resampled from 90 m to 100 m to align with the land system's resolution of 1000 m. We used the Inverse Distance Weighting (IDW) interpolation algorithm to downscale various data sets to a 100-m resolution, thereby matching the resolution needed for localized projections. The datasets include 1°×1° IPCC SLR data and 0.25°×0.25° MDT data in raster format, as well as 100-return period CoDEC data in point format. The raster data were converted to points using 'Raster to Point' function in ArcGIS. The CoDEC points were used as control points in the IDW interpolation to create a 100-meter resolution SLR map for each component. The spatial mask and raster to be snapped were set as the derived ocean mask. Finally, we used the 'Plus' function in ArcGIS to sum the values on a cell-by-cell basis.

We compared results for all subsequent analyses using both a simple bathtub model (attenuation factor = 0) and our improved geometric inundation model (attenuation factor > 0) based on inspection of inundation maps across a range of attenuation factors (Supplementary Fig. S21). Our findings presented in the main text use an attenuation factor = 0.01 and are consistent with the rank-order results from the simple bathtub model (Supplementary Fig. S22), although absolute values differ.

We adjusted inundation exposure extents based on current coastal protection standards along the Chinese coast. These standards vary considerably by city and county, from ≥200-year return period in major cities to less than 50-year return period along most of the coastline (and as low as 20-year return period in some very vulnerable parts). We used the flood protection level map from ref.[54] to overlay protection standards (in return period) for cities and counties throughout our coastal zone. Since our water depth calculations used the 1 in 100-year extreme event, we assumed grid cells are inundated wherever protection standards are less than the 100-year return period. Wherever protection standards were ≥100-year return period, we assumed complete and successful implementation of the protection standards and, therefore, no inundation. This is likely an overestimate of real protection levels, since standards are not always met in reality, so we also conducted the full analysis assuming no protection, which gives us the best and worst cases in terms of coastal protection.

Potential impact evaluation

We analyzed the potential impacts associated with inundation assuming current coastal protection standards are met, as well as assuming no protection. The functions supported by different land systems include human habitation (population), GDP, grain production, aquaculture, and ecosystem service value (ESV). Population, grain and aquaculture production, and ESV were calculated for each pixel directly from CLUMondo. GDP was estimated from the land system map for each policy scenario each year. First, the average GDP per pixel of each land system type in 2020 was calculated from the 2020 land system map and a downscaled 2020 GDP grid. Then, for each scenario, the number of inundated pixels of each land system type was calculated and multiplied by the average per-pixel GDP for that land system type. This accounts for future changes in GDP based on our land system changes, but it does not account for future GDP growth, currency decline, nor discount rates. Thus, our absolute values of GDP and ESV exposure should be considered underestimates for the future. However, the absolute values of these metrics are not of primary concern when considering the relative effects of SLR scenarios versus policy scenarios, as we do here, since any growth and discounting functions would have the same relative effect on the metrics under both sets of scenarios.

To quantify and categorize different levels of potential SLR impacts, we classified inundation depths based on their distribution characteristics into five categories: 0-1 m, 1-2 m, 2-3.5 m, 3.5-5 m, and 5 m or more. To comprehensively assess exposure across different scenarios, we overlaid land system data with coastal flooding projections at a spatial resolution of 1 km². This analysis was conducted across the full range of policy and SLR scenario combinations over time.

To compare the magnitude of variation in exposure between policy and SLR scenarios, we calculated the exposure of different functions for each policy scenario overlaid with the inundation ranges of each SLR scenario, as well as the exposure for each SLR scenario overlaid with each policy scenario. For instance, to assess the range of variation in exposure due to SLR scenarios under the middle road policy, we overlaid the land system map of the middle road scenario with inundation maps representing low-end, mid-range, and high-end SLR scenarios for each year. We then calculated the multi-functional exposure. The range of variation was determined by the difference between the maximum and minimum values of these three observations, representing the exposure variation attributable solely to changes in SLR scenarios within the middle road policy scenario, for that year. The same approach was applied to the other four policy scenarios to obtain a complete range of variation due to SLR scenarios. Similarly, the variation attributable to policy scenarios was calculated by sequentially combining the same SLR scenario with different policy scenarios. In this way, we could identify whether SLR or policy scenarios had the largest effect on exposure for each land system function.

Data availability

The projected land system maps for five policy scenarios, together with associated validation datasets and sampling points for projecting land subsidence, are available on Figshare at https://doi.org/10.6084/m9.figshare.29263130 (ref.[55]). The input data used in CLUMondo for land system change simulations are cited throughout the paper, with full details provided in Supplementary Note 4 and Supplementary Table S4. The SLR data were obtained from the IPCC AR6 database (https://zenodo.org/records/6382554), while tide and surge data were sourced from the CoDEC dataset (https://zenodo.org/records/3660927). The CoastalDEM were acquired from Climate

Central (https://go.climatecentral.org), and MDT data were obtained from AVISO (https://doi.org/10.24400/527896/a01-2023.003). Sources for explanatory factors used in predicting land subsidence rates are listed in Supplementary Table S7. All source data supporting this study are provided with the paper.

Code availability

The CLUMondo model is publicly available on GitHub (https://github.com/VUEG/CLUMondo). Python scripts used for projecting land subsidence and generating figures can be accessed via Figshare at https://doi.org/10.6084/m9.figshare.29263130 (ref.[55]). The improved geometric inundation model, which incorporates hydrological connectivity and attenuation, is available on GitHub (https://github.com/geoye/attenuated_bathtub). Additional code supporting the findings of this study is available from the corresponding author upon reasonable request.

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