Evaluating the Economic Cost of Coastal Flooding[†]

By Klaus Desmet, Robert E. Kopp, Scott A. Kulp, Dávid Krisztián Nagy,
Michael Oppenheimer, Esteban Rossi-Hansberg,
and Benjamin H. Strauss*

Sea level rise will cause spatial shifts in economic activity over the next 200 years. Using a spatially disaggregated, dynamic model of the world economy, this paper estimates the consequences of probabilistic projections of local sea level changes. Under an intermediate scenario of greenhouse gas emissions, permanent flooding is projected to reduce global real GDP by 0.19 percent in present value terms. By the year 2200, a projected 1.46 percent of the population will be displaced. Losses in coastal localities are much larger. When ignoring the dynamic response of investment and migration, the loss in real GDP in 2200 increases from 0.11 percent to 4.5 percent. (JEL E23, F01, Q54, Q56)

Many effects of climate change develop gradually over prolonged periods of time. For example, global mean sea level is currently increasing at a rate of about 3 millimeters per year (Hay et al. 2015). Under intermediate scenarios of greenhouse gas emissions, the International Panel on Climate Change projects that by the year 2100 the global mean sea level is likely to increase by 0.4 to 0.7 meters compared to the period 1986–2005 (Church et al. 2013). In addition to being gradual and prolonged, many effects of climate change are heterogeneous across space. Rising oceans bode ill for many large coastal cities, such as Amsterdam, Bangkok, and Ho Chi Minh City, whereas inland cities, such as Mexico City, Dallas, or Kinshasa, will be untouched by the direct effects of sea level rise.

Understanding these spatial and temporal dimensions is essential to any economic evaluation of climate change. In particular, permanent coastal flooding will shift the spatial distribution of economic activity to more inland regions.[1] Moving the centers of economic production to the interior is certainly possible, since land is still a relatively abundant resource, as reflected by 90 percent of world GDP being produced on 10 percent of land (Desmet and Rossi-Hansberg 2015). However, the feasibility of relocation does not necessarily make it easy or costless. Natural, economic, and institutional barriers to moving people and goods abound. While relocating to higher ground should be relatively straightforward in the United States, it is harder in the Netherlands and close to impossible for small Pacific islands.

Of course, the cost of changing the spatial distribution of economic activity is likely to be somewhat mitigated as long as sea level rise occurs gradually over time. Faced with a slow-moving process of rising oceans, the required geographic relocation of people and economic activity over any short horizon is limited. The gradual nature of this process also implies that any substantial rise in sea level takes longer to materialize than the standard time it takes for capital and infrastructure to depreciate. As a result, the cost of capital destruction due to the permanent rise in sea level is likely to be relatively small. Much more important than the loss in structures per se may be the loss of local agglomeration economies that come with density. Intuitively, flooding Manhattan is costly because of the technology and agglomeration economies lost. Manhattan's buildings are valuable primarily because of where they are, not because of the cost of rebuilding them.

In addition to the static cost of relocating people and the static impact on agglomeration economies, there are also important dynamic growth effects associated with changing the spatial distribution of economic activity. Depending on whether the partial abandonment of Ho Chi Minh City due to permanent inundation leads to the spatial dispersion of economic activity or to the emergence of new clusters, productivity and innovation will be affected differently. To assess the growth effects of coastal flooding, we therefore need to account for the entire economic geography of the world, as some clusters may disappear while others come into being. These growth effects play out both at the local and the aggregate level. Ultimately, if sea level rise destroys coastal high-density clusters, without new ones appearing in other places, global growth may suffer.

The above discussion suggests that a comprehensive economic evaluation of climate change in general, and coastal flooding in particular, should focus on (i) quantifying the costs associated with changing the spatial distribution of economic activity, (ii) analyzing the dynamic spatial response at a high spatial resolution, (iii) embedding this high-resolution analysis in a global general equilibrium framework, and (iv) incorporating static and dynamic agglomeration economies when estimating the effects of the destruction of existing economic clusters and the emergence of new ones.

Incorporating these considerations into an evaluation of the effects of sea level rise requires a change in focus, from computing the value of destroyed land and structures to evaluating the dynamic changes in the location of economic activity. To do so, we

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[1] Throughout the paper, we use the term "flooding" to indicate permanent inundation and not episodic, temporary, flooding.

need a high-resolution global dynamic equilibrium framework that is able to analyze the effects of permanent inundation on both the places that suffer directly from the rise in sea level and the rest of the world economy. In such a model, dynamics are crucial if we want to evaluate how different localities are likely to evolve. Assessing how the economy reacts to flooding also requires realistically modeling the economic links between locations, in particular the trade of goods and the migration of people.

Desmet, Nagy, and Rossi-Hansberg (2018) propose and quantify a model of the world economy at a 1° by 1° resolution that incorporates these elements, except for the impact of sea level rise. Rather than focusing on investment in capital, the model emphasizes investment in local technology. In doing so, it explicitly models the effect of static and dynamic agglomeration economies on productivity and growth. Our paper uses the benchmark economic scenario in Desmet, Nagy and Rossi-Hansberg (2018) and incorporates probabilistic sea level rise projections for different greenhouse gas emissions scenarios constructed by Kopp et al. (2014) and Kopp et al. (2017) for the period 2000 to 2200. Using many realizations of sea level paths, we analyze which areas become permanently submerged over time and compute economic scenarios in which people cannot live or produce in flooded areas. This exercise yields average predicted costs of flooding in all areas of the world over time, as well as confidence bands for these costs, which depend on the severity of the realized flooding paths. We measure these costs in terms of an individual's real income and in terms of her welfare; the latter measure also takes into account local amenities and an individual's idiosyncratic preferences for a location.

Our evaluation of the effects of permanent coastal inundation emphasizes *economic* adaptation. Hence, in our analysis we take sea level rise projections to be exogenous to the evolution of the economy and ignore other adaptation efforts aimed directly at reducing flooding.[2] The novelty of our approach lies in incorporating endogenous economic adaptation to flooding through migration, trade, and local investments in technology. Our assessment quantifies the costs of flooding relative to a counterfactual scenario in which sea levels remain constant; these costs can then be combined with cost estimates of flood mitigation and other forms of physical adaptation to properly evaluate different policy options.

Under an intermediate scenario of greenhouse gas emissions, we project that sea level rise will lead to a drop in global real GDP of 0.19 percent in present discounted value terms (with a 95 percent credible interval of 0.07–0.37 percent) and a displacement of 1.46 percent of world population in 2200 (with a 95 percent credible interval of 0.15–3.54 percent). The spatial variation in these effects is large: some countries, such as Vietnam, lose more than 7 percent of real GDP, and some coastal cities, such as Bangkok and Shanghai, lose an important share of their population. These magnitudes would be significantly larger if we ignored the dynamic spatial adjustment of the economy to sea level rise. If people were immobile when faced with rising oceans (or unable to move far from inundated areas), the real GDP loss

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[2] Impact-specific optimization models have been used to look in greater detail at the trade-off between adaptation costs and residual damages (Vafeidis et al. 2008, Hinkel et al. 2014, Diaz 2016). An alternative approach forgoes optimization, focusing instead on comparing costs under different adaptation scenarios (Neumann et al. 2015; Nicholls et al. 2011; Yohe, Knee, and Kirshen 2011).

in the year 2200 would be 4.5 percent, compared to 0.11 percent in our benchmark model. When not taking into account the spatial dynamic reaction of the economy, our quantitative findings are in the same ballpark as those of Nicholls and Tol (2006) and Hinkel et al. (2014). We quantitatively show that these insights are unchanged in an extension that includes the losses in physical residential capital for the particular case of the United States. Although damage to physical structures adds to the overall cost of flooding, its impact is minimal compared to the mitigating effects from the dynamic spatial adjustment of the economy. This confirms our intuition that, in relative terms, the cost of lost capital is minor since inundation evolves slowly, capital depreciates, and individuals discount the future.

Existing evaluations of sea level rise mostly fail to account for the geographic evolution of the world economy, and in particular for its spatial dynamic reaction to flooding. In its simplest form, assessing the costs of sea level rise is often done on the basis of today's economy (Dasgupta et al. 2009). This overlooks that the spatial distribution of the world economy will change over the coming centuries. It also ignores that people will move when their land becomes inundated, and that their migration will affect existing and future clusters of population, economic activity, and innovation. Some researchers incorporate static projections of the changing future distribution of population and economic activity into their analysis by using different socioeconomic scenarios, such as those of the IPCC's Special Report on Emissions Scenarios (Nakićenović et al. 2000; Nicholls 2004; Hinkel and Klein 2009; Anthoff, Nicholls, and Tol 2010). However, these scenarios only make projections for large regions, and they are not general equilibrium in nature. As an example, one such scenario simply assumes rapid future convergence in GDP per capita and fertility across the different regions of the globe. More importantly, the existing literature does not incorporate economic adaptation in the form of migration or new innovation in emerging clusters (Hsiang et al. 2017).

In addition to the issue of dynamic adaptation, it is key to choose the appropriate geographic level of analysis when evaluating the impact of permanent flooding. Damages from a rise in sea level have been assessed at the local level (Neumann et al. 2011, Hallegatte et al. 2011), the regional level (Bosello, Roson, and Tol 2007; Houser et al. 2015), and the global level (Nicholls and Tol 2006, Diaz 2016). Local studies ignore the economic linkages to the rest of the world, such as the possibility of people moving to other areas, while regional or global studies often are not conducted at a spatially disaggregated level and thus ignore that many of the effects of flooding are local in nature. By analyzing the global economy at a high resolution, we are able to assess the heterogeneity in local effects, without losing sight of the linkages between different locations.

The rest of the paper is organized as follows. Section I summarizes the dynamic spatial model of Desmet, Nagy and Rossi-Hansberg (2018), with the difference that the amount of land is time-dependent due to flooding. Section II explains how to calibrate and simulate the model, and then discusses the different flooding scenarios. Sections III and IV present the quantitative results at the global and the local level, respectively. Section V extends the quantitative assessment by including the flooding-induced damage to physical capital for the United States, and Section VI concludes. An Appendix conducts extensive robustness and sensitivity

analysis, both in terms of the model's parameter values and in terms of alternative datasets on sea level rise projections and elevation.

I. A Dynamic Spatial Model

Our dynamic spatial model of the economy follows that of Desmet, Nagy, and Rossi-Hansberg (2018), with two differences. First, because of future flooding, the amount of available land in each location will be time-dependent. Second, there is uncertainty about the future global and local sea level rise. When presenting the model, we do so for one particular path of sea level rise. In the simulations, we will solve the model for many different paths, so we can analyze the uncertainty faced by the world economy as it moves forward. As we will make clear below, individual and firm decisions are directly affected by the realized path, but not by the uncertainty around the severity of the realized flooding scenario.

A. *Endowments and Preferences*

The world economy occupies a two-dimensional surface S, where a location is defined as a point $r \in S$. The surface S is partitioned into C countries. Location r has land density $H_t(r)$ which is time-dependent because of sea level rise. There are $\bar{L}$ agents in the world economy, each supplying one unit of labor.[3] An agent derives utility from local amenities and from the consumption of a set of differentiated products. Utility is further affected by an agent's idiosyncratic locational preferences and by the moving costs from having resided in different places in the past. More precisely, the period utility of agent i who resides in r in period t and who lived in locations $\bar{r}_- = (r_0, \ldots, r_{t-1})$ in the previous periods is

$$(1) \qquad u_t^i(\bar{r}_-, r) = a_t(r) \left[\int_0^1 c_t^\omega(r)^\rho \, d\omega \right]^{\frac{1}{\rho}} \varepsilon_t^i(r) \prod_{s=1}^t m(r_{s-1}, r_s)^{-1},$$

where $a_t(r)$ are the local amenities, $c_t^\omega(r)$ is the consumption of variety ω, $1/(1-\rho)$ is the elasticity of substitution between different varieties, $\varepsilon_t^i(r)$ is a location preference shock drawn from a Fréchet distribution with shape parameter $1/\Omega$, and $m(r_{s-1}, r_s)$ is the cost of moving from r_{s-1} in period $s-1$ to r_s in period s. Local amenities take the form $a_t(r) = \bar{a}(r) \bar{L}_t(r)^{-\lambda}$, where $\bar{a}(r)$ can be thought of as a location's exogenous amenity, and $\bar{L}_t(r)^{-\lambda}$ represents the negative effect of population per land, $\bar{L}_t(r)$, on amenities. A higher value of λ means more congestion from amenities; this acts as a geographic dispersion force. A greater value of Ω implies more dispersion in agents' tastes across locations; this acts as a second geographic dispersion force. An agent earns income from work, $w_t(r)$, and from the local ownership of land, $R_t(r)/\bar{L}_t(r)$. Agents discount the future at rate β.

We assume that the mobility cost of moving from r to s is the product of an origin-specific cost, $m_1(r)$, and a destination-specific cost, $m_2(s)$. In addition, we

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[3] We keep total world population fixed throughout. Hence, our model has implications about population shares rather than population counts.

also assume that staying in the same location is costless. Taken together, this means that $m(r,s) = m_1(r) m_2(s)$ and $m(r,r) = 1$ for all $r, s \in S$. Because $m(r,r) = 1$ implies that $m_2(r) = m_1(r)^{-1}$, the permanent utility flow cost of entering a location is compensated by a permanent utility flow benefit when leaving that location. As a result, agents only pay the flow cost of having entered s while residing in s. For example, if an agent migrates from Mexico to the United States and later returns to Mexico or moves to a third country, she only pays the utility flow cost of having entered the United States while living in the United States. As shown by Desmet, Nagy, and Rossi-Hansberg (2018), this implies that an agent's dynamic location decision simplifies to a sequence of static decisions. This formulation is what ultimately makes the model computationally tractable.[4]

B. *Technology*

Production per unit of land of a firm producing good ω depends on the amount of labor per unit of land hired, $L_t^\omega(r)$, and the level of total factor productivity (TFP),

$$(2) \qquad q_t^\omega(r) = \phi_t^\omega(r)^{\gamma_1} z_t^\omega(r) L_t^\omega(r)^\mu,$$

where $\phi_t^\omega(r)$ denotes how much a firm innovates and $z_t^\omega(r)$ is a random productivity draw. Because land is a fixed factor, it causes congestion. A higher value of $1 - \mu$ implies more congestion; this constitutes a third geographic dispersion force. Innovating an amount $\phi_t^\omega(r)$ requires a fixed labor cost $\nu \phi_t^\omega(r)^\xi$. Because innovation is local, it creates a local advantage to scale; this constitutes an agglomeration force. The strength of this force is increasing in the returns to innovation, as captured by γ_1/ξ. In addition to how much it innovates, a firm's TFP also depends on the realization of a random variable, $z_t^\omega(r)$, drawn from a Fréchet distribution

$$F(z,r) = e^{-T_t(r)z^{-\theta}},$$

where $T_t(r) = \tau_t(r) \bar{L}_t(r)^\alpha$ and

$$(3) \qquad \tau_t(r) = \phi_{t-1}(r)^{\theta \gamma_1} \left[\int_S \eta(r,s) \tau_{t-1}(s)\, ds \right]^{1-\gamma_2} \tau_{t-1}(r)^{\gamma_2},$$

where $\eta(r,s)$ is such that $\int_S \eta(r,s)\, dr = 1$.[5] This specification implies that the average draw is increasing in population density, past innovation, and past productivity in the own location and in the rest of the economy. The positive effect of population density on the average draw introduces a second agglomeration force. Given that there is more scope for this effect when there is greater dispersion in draws across locations, this agglomeration force is increasing in α/θ. The importance of past innovation introduces intertemporal spillovers and guarantees that the economy

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[4]For other recent work on labor mobility decisions in a spatial framework, see Caliendo, Dvorkin, and Parro (2019). One key difference is that in our model the dynamic evolution of technology depends itself on the evolving distribution of population across space.

[5]In the numerical calibration, we will take η to be a constant, though we will consider spatial decay in technology diffusion in Appendix B.

does not stagnate in the long run. In addition to the two static agglomeration forces mentioned before, these intertemporal spillovers introduce an additional dynamic agglomeration force. High-density locations that have innovated in the past continue to be productive today. This attracts more people, increases market size, and so makes them good places to continue innovating today. The role of past productivity in the rest of the economy in determining a location's average draw ensures that this dynamic agglomeration force does not lead the economy to concentrate over time in one place. As such, the dynamic agglomeration force will be increasing in $\gamma_1/(\xi(1 - \gamma_2))$.

Productivity draws are correlated across space, with that correlation going to one when the distance goes to zero. This, together with the fact that the cost of innovation is per unit of land, implies that in any small interval there is a continuum of firms that compete in prices. These firms bid for land to the point of making zero profits net of the fixed innovation cost. To the extent that innovating allows firms to offer a higher bid for land in a particular location, firms will innovate. Our specification of technology in equation (3) implies that any innovation in location r in period t becomes available to all potential entrants in location r in period $t + 1$. As in Desmet and Rossi-Hansberg (2014), the firm's dynamic innovation decision therefore simplifies to a sequence of static decisions. Hence, after learning their common local productivity draw, a potential firm in r maximizes current profits,

$$\max_{L_t^\omega(r),\phi_t^\omega(r)} p_t^\omega(r,r)\phi_t^\omega(r)^{\gamma_1} z_t^\omega(r) L_t^\omega(r)^\mu - w_t(r) L_t^\omega(r) - w_t(r)\nu\phi_t^\omega(r)^\xi - R_t(r),$$

where $p_t^\omega(r,r)$ is the price charged by the firm of a good sold at r. If we denote the iceberg cost of transporting a good from r to s by $\varsigma(s,r) \geq 1$, then the price of a good ω, produced in r and sold in s can be written as $p_t^\omega(s,r) = p_t^\omega(r,r)\varsigma(s,r)$.

C. Prices, Export Shares, and Trade Balance

Because firms are subject to perfect competition, it is easy to see that in any $r \in S$, we have $L_t^\omega(r)$ and $\phi_t^\omega(r)$ being identical across goods ω. That is, if one of the goods gets a better productivity draw, $z_t^\omega(r)$, it will simply sell at a proportionately lower price $p_t^\omega(r,r)$, leaving the maximization problem above unchanged. This allows us to write the price of a good produced at r and sold at s as

$$(4) \quad p_t^\omega(r,s) = \left[\frac{1}{\mu}\right]^\mu \left[\frac{\nu\xi}{\gamma_1}\right]^{1-\mu} \left[\frac{\gamma_1 R_t(r)}{w_t(r)\nu(\xi(1-\mu) - \gamma_1)}\right]^{(1-\mu)-\frac{\gamma_1}{\xi}} \frac{w_t(r)\varsigma(s,r)}{z_t^\omega(r)}$$

$$= \frac{mc_t(r)\varsigma(s,r)}{z_t^\omega(r)},$$

where the second equality defines $mc_t(r)$ implicitly. The expression (4) is similar to the one in Eaton and Kortum (2002): the price is inversely proportional to $z_t^\omega(r)$ and proportional to a term that captures the marginal input cost. Importantly, that marginal input cost term is exogenous from the point of view of the individual firm, so that productivity draws affect prices without changing the input cost.

This result allows us to apply many of the results of Eaton and Kortum (2002). In particular, the probability density that a good produced in r is bought in s is given by

$$\pi_t(s, r) = \frac{T_t(r)\left[mc_t(r)\varsigma(r, s)\right]^{-\theta}}{\int_S T_t(u)\left[mc_t(u)\varsigma(u, s)\right]^{-\theta} du} \quad \text{all } r, s \in S,$$

and the price index of a location s is

$$(5) \qquad P_t(s) = \Gamma\left(\frac{-\rho}{(1-\rho)\theta} + 1\right)^{-\frac{1-\rho}{\rho}} \left[\int_S T_t(u)\left[mc_t(u)\varsigma(s, u)\right]^{-\theta} du\right]^{\frac{-1}{\theta}}.$$

We assume that trade balance holds location by location, so that

$$w_t(r) H_t(r) \bar{L}_t(r) = \int_S \pi_t(s, r) w_t(s) H_t(s) \bar{L}_t(s) \, ds \quad \text{all } r \in S.$$

D. *Equilibrium: Existence and Uniqueness*

The conditions above define a dynamic competitive equilibrium of this economy that can be reduced to a system of equations that determines wages, employment levels, and utility in all locations. In particular, for any t and for all $r \in S$, given $\bar{a}(\cdot), \tau_t(\cdot), \bar{L}_{t-1}(\cdot), \varsigma(\cdot, \cdot), m(\cdot, \cdot)$, and $H_t(\cdot)$, the model determines the equilibrium wage, $w_t(\cdot)$, population density, $\bar{L}_t(\cdot)$, and utility, $u_t(\cdot)$. Desmet, Nagy, and Rossi-Hansberg (2018) show that a dynamic competitive equilibrium exists and is unique if

$$(6) \qquad \frac{\alpha}{\theta} + \frac{\gamma_1}{\xi} < \lambda + 1 - \mu + \Omega.$$

This condition essentially states that the static agglomeration forces must be less strong than congestion forces. The left-hand side consists of agglomeration forces from getting better draws in more dense places (α/θ), and from spreading the innovation cost over more units in more dense places (γ_1/ξ). The right-hand side consists of congestion from amenities (λ), land ($1 - \mu$), and taste heterogeneity (Ω). The intuition for this condition is that if congestion is stronger than agglomeration, we get rid of possible multiplicities common to many economic geography models.

E. *Balanced Growth Path*

In a balanced growth path (BGP) the spatial distribution of employment is constant and all locations grow at the same rate. Desmet, Nagy, and Rossi-Hansberg (2018) show that a unique balanced growth path exists if

$$(7) \qquad \frac{\alpha}{\theta} + \frac{\gamma_1}{\xi} + \frac{\gamma_1}{[1 - \gamma_2]\xi} \leq \lambda + 1 - \mu + \Omega.$$

This condition is similar, but stronger, than the condition for uniqueness. In particular, the left-hand side now includes an extra term reflecting the dynamic part of agglomeration economies. If dynamic agglomeration forces are too strong, it leads

the economy to eventually concentrate in one location. For example, if $1 - \gamma_2 = 0$, the above condition (7) no longer holds. Innovations cease to diffuse to the rest of the economy, and the economy would increasingly concentrate in the most productive location. In the balanced growth path, aggregate real consumption can be shown to grow according to

$$(8) \qquad \left[\frac{\int_0^1 c_{t+1}^\omega(r)^\rho d\omega}{\int_0^1 c_t^\omega(r)^\rho d\omega}\right]^{\frac{1}{\rho}} = \eta^{\frac{1-\gamma_2}{\theta}} \left[\frac{\gamma_1/\nu}{\gamma_1 + \mu\xi}\right]^{\frac{\gamma_1}{\xi}} \left[\int_S \bar{L}(s)^{\frac{\theta\gamma_1}{[1-\gamma_2]\xi}} ds\right]^{\frac{1-\gamma_2}{\theta}}.$$

As a result, the BGP growth rate depends on the spatial distribution of population.

In all simulations presented below, conditions (6) and (7) are always satisfied. Because the current calibrated world economy is not at the balanced growth path, its spatial distribution changes over time, even in the absence of flooding. During this transition to the balanced growth path, the world growth rate also varies over time. Of course, once we add flooding, the dynamics of the world economy also vary due to the progressive inundation of some of the available land.

II. Quantification, Calibration, and Flooding Scenarios

A. *Data and Calibration*

The quantification of the model follows closely Desmet, Nagy, and Rossi-Hansberg (2018). Here, we describe briefly its main features but refer to that paper for a more thorough description. We discretize the world into 64,800 1° by 1° cells. Parameter values are partly taken from the literature and partly estimated from data as described below. Our quantification identifies initial productivity and amenities by cell, as well as bilateral cell-to-cell transport and migration costs.

Main Parameter Values.—The parameter values, reported in Table 1, come from the baseline simulation in Desmet, Nagy, and Rossi-Hansberg (2018). Many of the values are standard in the literature. For the few that are not, we offer a brief explanation. The parameter Ω determines the dispersion in preferences for different locations, and it is the inverse of the elasticity of migration flows with respect to real income. Based on Monte, Redding, and Rossi-Hansberg (2018), a reasonable value for that elasticity is 2, so we set $\Omega = 0.5$. The parameter λ represents the elasticity of local amenities to local population. We estimate this parameter using data from Desmet and Rossi-Hansberg (2013) on amenities and population for 192 metropolitan areas in the United States, and we use an instrumental variable strategy (with local productivity) to deal with the possibility of reverse causality.

The technology parameters require some more discussion. To get values for γ_1 and γ_2, we rely on cell-level data from the G-Econ 4.0 database developed by Nordhaus et al. (2006) to estimate the country-level relation between growth and the spatial distribution of population in (8).[6] In particular, after

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[6]This implicitly assumes that the relative distribution of population within countries has converged to its balanced-growth path, although the distribution of population across countries may continue to change.

TABLE 1—PARAMETER VALUES

Parameter	Target/Comment
Panel A. Preferences	
$\beta = 0.96$	Annual discount factor
$\rho = 0.75$	Elasticity of substitution of 4 (Bernard et al. 2003)
$\lambda = 0.32$	Relation between amenities and population
$\Omega = 0.5$	Elasticity of migration flows with respect to income
	(Monte, Redding, and Rossi-Hansberg 2018)
$\psi = 1.8$	Deaton and Stone (2013)
Panel B. Technology	
$\alpha = 0.06$	Static elasticity of productivity to density (Carlino, Chatterjee, and Hunt 2007)
$\theta = 6.5$	Trade elasticity (Eaton and Kortum 2002, Simonovska and Waugh 2014)
$\mu = 0.8$	Labor or nonland share in production
	(Greenwood, Hercowitz, and Krusell 1997; Desmet and Rappaport 2017)
$\gamma_1 = 0.319$	Relation between population distribution and growth
Panel C. Evolution of productivity	
$\gamma_2 = 0.993$	Relation between population distribution and growth
$\xi = 125$	Desmet and Rossi-Hansberg (2015)
$\nu = 0.15$	Initial world growth rate of real GDP of 2 percent
Panel D. Trade costs	
$\varsigma_{rail} = 0.1434$	
$\varsigma_{no\_rail} = 0.4302$	
$\varsigma_{major\_road} = 0.5636$	
$\varsigma_{other\_road} = 1.1272$	Allen and Arkolakis (2014)
$\varsigma_{no\_road} = 1.9726$	
$\varsigma_{water} = 0.0779$	
$\varsigma_{no\_water} = 0.779$	
$\Upsilon = 0.393$	Elasticity of trade flows with respect to distance of -0.93 (Head and Mayer 2014)

taking logs and discretizing space, we can rewrite (8) for country c as $\log y_{t+1}(c) - \log y_t(c) = \alpha_1 + \alpha_2 \log \sum_{S_c} L_c(s)^{\alpha_3}$, where S_c is the two-dimensional surface occupied by country c. By estimating this equation, we can recover γ_1 and γ_2 because they are functions of α_2 and α_3. As for the innovation cost parameter ν, we set it at a level that matches a 2 percent growth rate of real GDP in the initial period.

Trade Costs.—We assume that the cost of passing through a cell is given by

$$\log \varsigma(r) = \log \varsigma_{rail}\, rail(r) + \log \varsigma_{no\_rail}\big[1 - rail(r)\big] + \log \varsigma_{major\_road}\, major\_road(r)$$

$$+ \log \varsigma_{other\_road}\, other\_road(r)$$

$$+ \log \varsigma_{no\_road}\big[1 - major\_road(r) - other\_road(r)\big]$$

$$+ \log \varsigma_{water}\, water(r) + \log \varsigma_{no\_water}\big[1 - water(r)\big],$$

where $rail(r)$ equals one if there is a railroad passing through r and zero otherwise; $major\_road(r)$ equals one if there is a major road passing through r and zero otherwise; $other\_road(r)$ equals one if there is some other road passing through r and zero otherwise; and $water(r)$ equals one if there is a major water route at r and zero otherwise. The values of the cost parameters $\varsigma_{rail}, \varsigma_{no\_rail}, \varsigma_{major\_road}, \varsigma_{other\_road}, \varsigma_{no\_road},$

ς_{water}, and ς_{no_water} come from Allen and Arkolakis (2014), and the data on the presence of roads, water routes, and railroads in each grid cell come from Natural Earth Data (http://www.naturalearthdata.com/). With $\varsigma(r)$ in hand for each cell, we use Gabriel Peyre's Fast Marching Toolbox for Matlab to compute the lowest cost to go from r to s, $\varsigma(r,s) = \left[\inf_{g(r,s)} \int_{g(r,s)} \varsigma(u)\, du\right]^{\Upsilon}$, where $\int_{g(r,s)} \varsigma(u)\, du$ denotes the line integral of $\varsigma(\cdot)$ along the path $g(r,s)$. To calibrate Υ, we run a gravity equation regression on trade data simulated by the model for the initial period, and we search for the value of Υ that matches the elasticity of bilateral trade flows to distance as measured by Head and Mayer (2014).

Local Amenities and Initial Productivity.—To simulate the model, we need measures of the spatial distribution of amenities, $\bar{a}(r)$, and initial productivity, $\tau_0(r)$. Using data on land $H_0(r)$ from the National Oceanic and Atmospheric Administration, as well as population $\bar{L}_0(r)$ and wages $w_0(r)$ as measured by GDP per capita in 2000 (period 0) from the G-Econ 4.0 database, we can uniquely recover the distributions of $\tau_0(r)$ and $\bar{a}(r)/u_0(r)$. To disentangle a location's amenity, $\bar{a}(r)$, from its initial utility, $u_0(r)$, we use data on subjective well-being from the Gallup World Poll (Gallup 2012). Subjective well-being, denoted by $\check{u}_0(r)$, is measured on a ten-step scale, going from the worst possible life and to the best possible life. Deaton and Stone (2013) show that this measure depends linearly on the *log* of real income, whereas in our model utility depends linearly on the *level* of real income. Hence, the relation between utility as defined in our model, $u_0(r)$, and utility as defined by subjective well-being, $\check{u}_0(r)$, can be written as $u_0(r) = e^{\psi \check{u}_0(r)}$. Based on estimates from Deaton and Stone (2013), we set $\psi = 1.8$ and use data on subjective well-being to get estimates of $u_0(r)$. Since we already have measures for $\bar{a}(r)/u_0(r)$, this allows us to obtain estimates for $\bar{a}(r)$.

Migration Costs.—We estimate the cost of migrating in and out of each location so that the model matches the evolution of population between 2000 and 2005 exactly. The intuition is simple: if a location experiences a large relative increase in productivity but its relative population level does not change much, it must have high barriers to immigration. To be more precise, from the technology in period 0 (year 2000), $\tau_0(\cdot)$, and the population in period 0, $\bar{L}_0(\cdot)$, we can use the model to obtain technology in period 1 (year 2005), $\tau_1(\cdot)$. Using the technology in period 1, we solve for the migration costs $m_2(\cdot)$ consistent with the observed population in period 1 (year 2005), $\bar{L}_1(\cdot)$, where the data for population in 2005 come from G-Econ 4.0. Once we have measures for $m_2(\cdot)$, we also have measures for $m_1(\cdot)$, since the latter is the inverse of the former.

Robustness and Sensitivity.—Desmet, Nagy, and Rossi-Hansberg (2018) show that the model and its calibration perform well when running the model backwards for 130 years and comparing the model-implied distribution of population to empirical observations. Nevertheless, it is important to understand how sensitive our results are to the different parameter values and to our way of estimating mobility frictions. To that end, Appendix B conducts extensive robustness and sensitivity analyses of our results.

B. *Simulation*

Once we have estimates for all the parameters, the migration and trade costs, and the initial distributions of technology, amenities, and land, we can simulate the model forward for the years 2000 to 2200. Every period we update the spatial distribution of technology given local innovations, we account for the amount of land lost to flooding, and then solve for the distribution of population and welfare. As shown by Desmet, Nagy, and Rossi-Hansberg (2018), the model can be solved by a simple iterative procedure.

C. *Flooding Scenarios*

To incorporate the flooding of land in every period, we rely on probabilistic sea level rise (SLR) projections by Kopp et al. (2014) for the global mean and for local relative SLR at 1,091 tide-gauge sites around the world from 2000 to 2200. Note that sea level does not change uniformly across space, due to differences in ocean dynamics and tectonics, among others. For example, because of high subsidence, Galveston, Texas is predicted to experience SLR close to double the average rate, whereas because of solid earth responses to regional glacial mass loss, Juneau, Alaska is predicted to experience a drop in sea level.[7]

These projections are conditional upon three alternative pathways of future greenhouse gas concentrations, known as Representative Concentration Pathways (RCPs) 8.5, 4.5, and 2.6 (Van Vuuren et al. 2011). RCP 8.5 is a high-emissions pathway, consistent with fossil-fuel-intensive economic growth, leading to CO_2 concentrations of 540 ppm in 2050, 936 ppm in 2100, and 1,830 ppm in 2200 (compared to 278 ppm in 1750 and 400 ppm in 2015). RCP 4.5 is a moderate-emissions pathway, leading to CO_2 concentrations of 487 ppm in 2050, rising to 538 ppm in 2100, and then stabilizing at 543 ppm. RCP 2.6 is a low-emissions pathway, consistent with the aspirational goals laid out in the Paris Agreement, in which atmospheric CO_2 concentrations peak at 443 ppm in 2050 and decline to 421 ppm in 2100 and 384 ppm in 2200.

For each RCP, Kopp et al. (2014) generate 10,000 Monte Carlo samples to calculate a joint probability distribution of global and local relative SLR at 1,091 tide-gauge sites around the globe. For our analysis, we take the 10,000 paths in the year 2100, divide them into 40 equally sized 2.5 percentile bins based on the global sea level rise implied by them, and then take a random path from each one of the 40 bins.

To compute how much land gets flooded, for each grid cell we combine the estimated SLR with topographic data. To that end, we primarily employ Climate

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[7]These projections are fairly consistent with those of the Intergovernmental Panel on Climate Change's Fifth Assessment Report (Church et al. 2013). They do not include recent scientific findings regarding modes of Antarctic ice sheet instability, which are likely to revise upward estimates of GMSL rise after 2050, particularly under high-emissions scenarios (e.g., DeConto and Pollard 2016). Thus, the resulting numerical estimates are most likely biased low. Appendix C considers an alternative set of projections (DP16 projections of Kopp et al. 2017) that incorporate a physical model allowing for a relatively unstable Antarctic ice sheet. This particular model is at the high end of literature projections; thus, the two sets of projections taken together can be viewed as roughly bounding the space of plausible sea level PDFs.

Central's CoastalDEM (Kulp and Strauss 2018), a near-global elevation model based on NASA's SRTM (NASA 2015). CoastalDEM uses an artificial neural network to substantially reduce the vertical error present in SRTM, caused by factors such as vegetation density, population density, and random noise. This dataset has coverage between latitudes 60N and 56S and has a horizontal resolution of 1 arcsecond. At higher latitudes, we employ JAXA's ALOS World 3D 30m mesh (AW3D30) (Tadono et al. 2016), which has full global coverage and equivalent horizontal resolution, but contains vertical error comparable to SRTM (Hu et al. 2017, Santillan and Makinano-Santillan 2016). In Appendix C, we assess the sensitivity of our results to only using AW3D30.

We convert elevations to reference local mean higher high water levels (MHHW), corresponding roughly to local high tide lines, to be used as the baseline for adding sea level projections and then estimating inundated land. We begin with the global mean sea level (GMSL) model MSS CNES-CLS15 (Aviso 2015), based on TOPEX/Poseidon satellite measurements from 1993 to 2012, vertically referenced to the GLAS ellipsoid (MSL_{GLAS}). Using the tidal model TPX08 (Egbert, Bennett, and Foreman 1994), Mark Merrifield (University of Hawaii) developed and provided us MHHW deviations from GMSL, which we add to MSL_{GLAS} to compute a global MHHW surface relative to the ellipsoid. We convert MHHW, CoastalDEM, and AW3D30 to a common vertical datum using NOAA's VDatum tool (Parker et al. 2003) version 3.7, so that we may compute our final elevation map, expressing elevation as height above local MHHW.

For each time period t and each 1° by 1° grid cell r, we take the corresponding water height from each of the 40 stratified GSML paths to determine $H_t(r)$, the proportion of land in the grid cell that is not inundated. Low-lying regions isolated from the ocean by high ridges are removed using connected components analysis and are not included in these calculations.

III. Global Effects

In this section, we examine the global effects of sea level rise, focusing on real GDP and welfare losses, as well as on the displacement of population. We start by showing time paths of these effects, and then estimate the present discounted value of future losses. Given the uncertainty about sea level rise, all our estimates come accompanied by credible intervals. The key contribution of our model is to incorporate the spatial dynamic reaction of the world economy to future flooding. To quantify how this form of economic adaptation matters for our results, we compare our findings with more naive models that do not account for this type of adjustment.

A. *Time Paths of Global Losses and Population Displacement*

Figure 1, panel A shows 40 stratified, random paths of GMSL rise over the next 200 years under the moderate-emissions Representative Concentration Pathway (RCP) 4.5. It also depicts the mean, the median, and the 20–80 percent band of the RCP 4.5 probability distribution of Kopp et al. (2014). The median shows GMSL rise of ~1.3 meters between 2000 and 2200, with a 20–80 percent band going
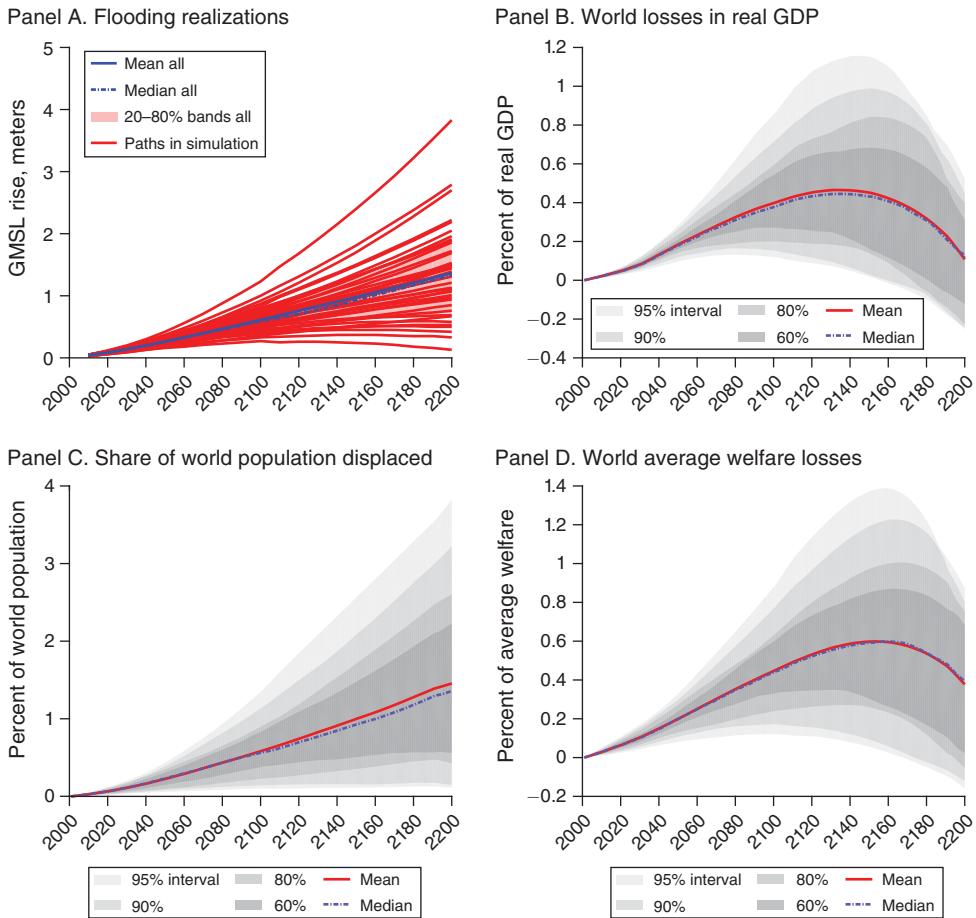
FIGURE 1

Note: All results shown are for RCP 4.5.

from 0.7 to 1.8 meters. Figure 1, panel B displays the percentage of real GDP per capita that is lost due to flooding. The mean loss peaks at 0.47 percent of real GDP in the year 2133, and then declines, reaching a loss of ∼0.11 percent by 2200. This nonmonotonicity is due to the dynamics of how the world adjusts to coastal flooding. As people are forced to move out of flooded areas, some economic clusters get destroyed, but others are reinforced and new ones emerge. Over time, the greater geographic concentration of people increases the dynamic incentives to innovate, thus partly compensating the direct negative impact of flooding. Uncertainty in SLR implies uncertainty in its economic effects. Taking a 95 percent credible interval,[8] the effect on real GDP/capita in the year 2200 ranges from ∼−0.24 percent

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[8] Given that we use 40 paths, we take the interval between the second-largest outcome and the second-smallest outcome. We refer to this as a credible interval, since the procedure used to generate the SLR probability distribution in Kopp et al. (2014) is Bayesian.

TABLE 2—SHARE OF WORLD POPULATION DISPLACED BY FLOODING IN 2050, 2100, AND 2200
UNDER EACH OF 3 RCPS

Scenario	2050		2100		2200	
Panel A. Extreme (*RCP 8.5*)						
Mean (percent)	0.25		0.79		2.25	
95 percent credible interval (percent)	0.07	0.41	0.22	1.60	0.70	4.43
Panel B. Medium (*RCP 4.5*)						
Mean (percent)	0.22		0.58		1.46	
95 percent credible interval (percent)	0.07	0.41	0.13	1.30	0.15	3.54
Panel C. Mild (*RCP 2.6*)						
Mean (percent)	0.22		0.49		1.16	
95 percent credible interval (percent)	0.06	0.36	0.11	1.16	0.13	2.93

Note: Percentage of population displaced refers to the sum of differences in absolute value of cell population under no flooding scenario and cell population under the mean flooding scenario divided by twice the total population.

to ∼+0.49 percent. Both Table 2 and Figure 1, panel C show the share of the world population displaced by flooding. The mean share displaced increases monotonically over time and reaches 0.58 percent in 2100 and 1.46 percent in 2200 under RCP 4.5 (Table 2). In the more extreme emissions scenario RCP 8.5, the mean share of population displaced rises to 2.25 percent in 2200.

Figure 1, panel D depicts average welfare losses across individuals in the world over the next 200 years for the different sea level paths. Losses peak at ∼0.6 percent in the second half of the twenty-second century and then decline to ∼0.4 percent in 2200, with a 95 percent credible interval between −0.2 percent and 0.9 percent. The welfare losses are slightly larger than the real GDP losses. Coastal flooding makes people move to areas with less attractive amenities, either because they relocate to inland places with worse inherent amenities or because they relocate to more crowded places where amenities suffer from greater congestion.

B. *Present Discounted Value of Future Losses*

In addition to examining the time series of losses, we also compute the expected present discounted value of future losses. All present-value calculations reflect the period 2000 to 2200 for the three different emissions pathways. Using a 4 percent annual discount rate, Table 3 reports how much higher the present discounted value of real GDP is under no flooding relative to the mean under flooding (see Appendix Table B1 for alternative discount rates).[9] For the moderate-emissions RCP 4.5, the expected present-value loss of world real GDP per capita due to flooding is 0.19 percent (95 percent credible interval of 0.07–0.37 percent). Across scenarios, the expected present-value losses range from 0.16 percent (95 percent credible interval of 0.07–0.33 percent) under RCP 2.6 to 0.25 percent (0.12–0.44 percent) under RCP 8.5. Turning to welfare, Table 3 also reports that the present discounted mean loss

[9] Note that our choice of discount rates is restricted to be above the growth rate of the economy since otherwise present discounted values are not bounded.

TABLE 3—PRESENT DISCOUNTED VALUE AGGREGATE WORLD LOSSES IN REAL GDP AND WELFARE

Scenario	Real GDP PDV		Welfare PDV		Real GDP Maximum		Year
Panel A. Extreme (RCP 8.5)							
Mean (percent)		0.25		0.31		0.71	2151
95 percent credible interval (percent)	0.12	0.44	0.14	0.55	0.26	1.36	
Panel B. Medium (RCP 4.5)							
Mean (percent)		0.19		0.24		0.47	2133
95 percent credible interval (percent)	0.07	0.37	0.08	0.45	0.16	1.08	
Panel C. Mild (RCP 2.6)							
Mean (percent)		0.16		0.21		0.35	2131
95 percent credible interval (percent)	0.07	0.33	0.08	0.41	0.14	0.81	

Notes: Calculations based on 4 percent annual discount rate. Percentage change in PDV refers to (PDV of nonflooding scenario/mean of PDV of flooding scenarios) − 1, using a simulation over 200 years. "Maximum" refers to maximum effect of flooding for mean, 97.5th percentile and 2.5th percentile paths. "Year" denotes the year of the maximum effect of flooding for mean path.

in the moderate-emissions pathway RCP 4.5 amounts to 0.24 percent (95 percent credible interval of 0.08–0.45 percent) over the period 2000 to 2200, slightly higher than the loss in real GDP. Under the more extreme RCP 8.5, mean losses increase to 0.31 percent (0.14–0.55 percent). Appendix B explores the sensitivity of these results to changes in the model's main parameter values, as well as in the degree of both migration and trade frictions.

C. *Heterogeneity in GMSL Rise*

To further analyze the impact of flooding, panel A of Figure 2 plots the relationship between GMSL rise in 2100 and the present discounted value of world real GDP per capita for each of the 40 stratified random paths and three RCPs. The slope is around 0.4: the present-value of real world GDP per capita between 2000 and 2200 drops by about 0.4 percent per 1-meter GMSL rise in 2100. This relation appears to be similar under RCP 2.6, 4.5, and 8.5. Figure 2, panel B plots a similar graph for the share of the world population in 2100 that is displaced by flooding. The slope is around 1.2, indicating that a 1-meter GMSL rise in 2100 implies a displacement of around 1.2 percent of the world population in 2100.

Figure 2 also shows that GMSL rise in 2100 is not a full description of the entire dynamics of an SLR path, nor of its local variation. Outcomes with a similar GMSL rise in 2100 can generate different losses. For example, for a GMSL rise of 0.8m, variation in the geography and timing of flooding can generate GDP losses of between 0.2 percent and 0.3 percent. That is, depending on the spatial and temporal characteristics of the path, we can have effects that are 50 percent larger. The variation of the fraction of displaced population for a given GMSL rise is even larger. An increase of 0.8m in GMSL can yield displaced populations that go from 0.5 percent to 1.0 percent; the displaced population estimates for a given GMSL can differ by 100 percent due to the dynamics and local variation of the paths.

Panel A. PDV world losses in real GDP

Panel B. Displaced world population in 2100
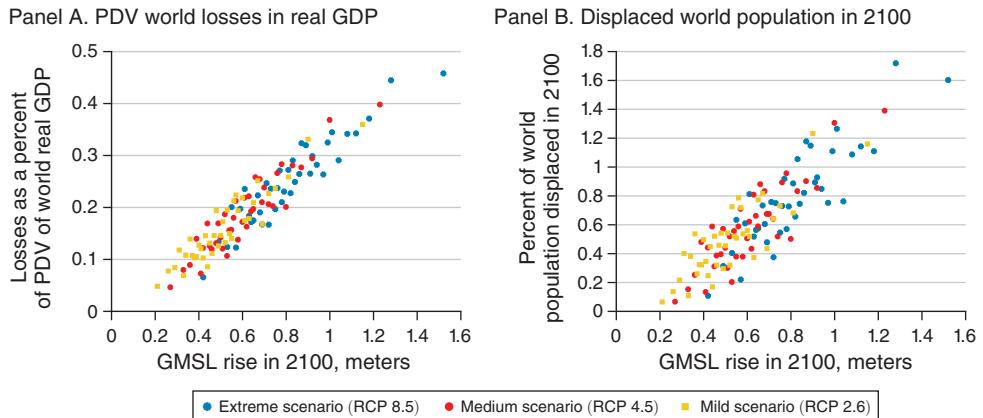
FIGURE 2

Note: Panel A displays present discounted value of world losses in real GDP, and panel B shows displaced world population in 2100, both as a function of GMSL rise in 2100.

D. *The Importance of Economic Adaptation*

Compared to the existing literature, an essential contribution of our model is that it takes into account economic adaptation: the dynamic and spatial reaction of the economy to flooding. For example, if rising sea level leads to Ho Chi Minh City becoming inundated, its population will move elsewhere. This will change the geographic distribution of population, thus affecting the incentives for innovation in different locations. As a result, it will put the economy on a different dynamic spatial path.

To assess the importance of incorporating the dynamic spatial reaction of the economy, we compare the quantitative predictions of our model to the predictions of alternative evaluations that abstract partially or completely from economic adaptation. To that end, we consider a number of simplified assessments of sea level rise. A first assessment estimates the losses of flooding, without taking into account the possibility of moving. That is, for each year *t*, we take our model's predictions in the absence of flooding, and compute which fraction of world population, GDP, and world welfare gets flooded using the median GMSL rise projection under RCP 4.5 for that year. We refer to the population that lives in these regions as "flooded" and compare it to the population displaced in our baseline evaluation. Because this approach does not allow people to move when faced with flooding, in Figure 3 we refer to it as the "no adaptation (naive)" model.

As can be seen in panel B of Figure 3, the percentage of population that gets "flooded" in 2200 increases to ∼1.65 percent from a fraction of displaced population in our baseline case of ∼1.45 percent.[10] The effect on real GDP losses for the year 2200 is substantially larger, increasing from 0.11 percent in the benchmark model

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[10]These figures are of the same order of magnitude as others estimated in the literature. For example, Nicholls and Tol (2006) report estimates of between 0.7 percent and 1.5 percent of additional world population suffering from flooding by 2080.

Panel A. World losses in real GDP

Panel B. Share displaced or flooded population

Panel C. World losses in welfare

Baseline
No adaptation (naive)
No adaptation (fixed population)
No adaptation (static equilibrium)
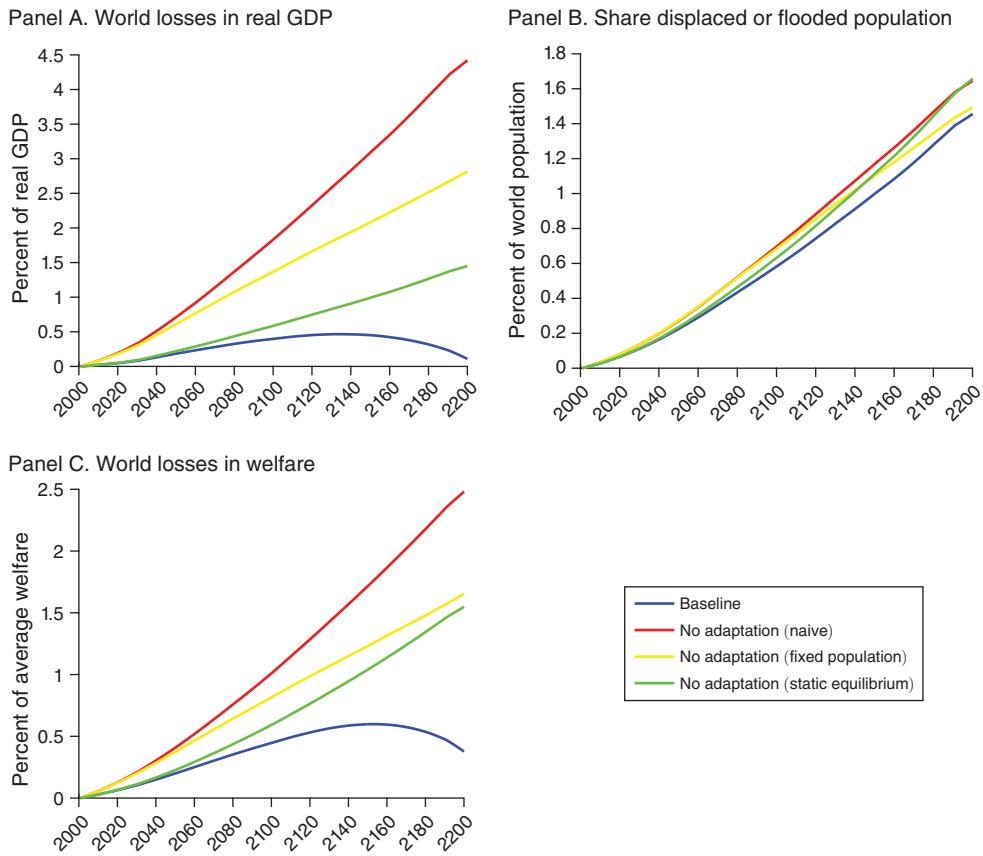
FIGURE 3

Note: This figure displays, for versions of the model with alternative economic adaptation mechanisms, the effect of flooding on: world losses in real GDP (panel A), share of world population displaced (panel B), and world losses in welfare (panel C).

to ~4.5 percent in the no adaptation naive model (Figure 3, panel A). This much larger loss is due to two effects that are ignored in the naive model. First, when locations become permanently inundated, people can generally move, albeit at a cost. As a result, the loss in real GDP in flooded coastal regions is (partly) compensated by the gain in real GDP in other nonflooded inland regions. To be clear, in our model we are not assuming people can freely move when flooding occurs. (Recall that we are using migration costs between locations as estimated from observed changes in population between 2000 and 2005.) The difference with the naive model is simply that we are not assuming such migration costs are always and everywhere infinite. Second, when people move to other places, this leads to growing spatial concentration in these places, and hence to greater incentives to innovate in these newly emerging clusters. Both effects help to mitigate the negative effect of sea level rise. Hence, ignoring these effects leads to much greater estimated losses from flooding.

To understand the differential impact of both effects, we consider a second alternative evaluation where we allow people to move when faced with permanent inundation, but we do not allow this to affect firms' incentives to innovate. That is, location-specific productivity is not affected by people moving due to flooding, but we do take into account that people who move away from flooded areas add to real GDP in the places where they settle. In Figure 3, we refer to this case as the "no adaptation (static equilibrium)." In this alternative setup, the loss in real GDP in 2200 is around 1.5 percent. As expected, this loss is greater than in the full-blown model that incorporates changes in the incentives to innovate, but less than in the naive model that does not allow people to move.

To complete our comparison, we contrast our findings to a third alternative evaluation where we take today's geographic distribution of economic activity and keep it unchanged over time. This is the simplest possible form of evaluation; it is akin to the accounting exercise in Dasgupta et al. (2009). We simply use the GMSL rise projection for each year t, and then estimate which part of real GDP is lost and which part of the population is flooded based on today's data. In Figure 3, we refer to this case as the "no adaptation (fixed population)" model. Compared to the naive model, where losses are also calculated without taking into account people's reallocation as a result of flooding but the economy evolves spatially over time, we find smaller losses in real GDP and population "flooded." This is consistent with the spatial dynamic model predicting coastal areas becoming relatively more productive over time and harboring an ever greater share of world population.

From these comparisons, we conclude that incorporating the spatial dynamic adjustment of the economy is key to quantitatively assessing the economic impact of sea level rise. In spite of migration being costly, the possibility of moving and the dynamic effects of the spatial reallocation of economic activity lead to a significant decrease in the real GDP loss from flooding. We see a similar, though somewhat smaller, mitigating effect on welfare losses (Figure 3, panel C). However, even for welfare, the effect of flooding is more than five times larger in the naive evaluation than in our baseline. These results also imply that the cost of coastal flooding depends crucially on the size of migration costs. Higher costs due to, for example, more restrictive migration laws would increase the cost of coastal flooding significantly.

IV. Local, Country, and City Effects

The global economic effects of SLR mask heterogeneous local effects. Some regions suffer dramatically from inundation, while others experience economic gains. When presenting real output and welfare outcomes at the local level, we face the decision whether to focus on total local real GDP and welfare, which are directly affected by the number of people in a given region, or on per capita outcomes, which are not. The former is helpful to illustrate that some areas not only experience a decline in the average well-being of their residents, but also become relatively empty by losing population. In what follows, we will discuss both total and per capita outcomes. We analyze these effects at the cell level, the country level, and the city level.
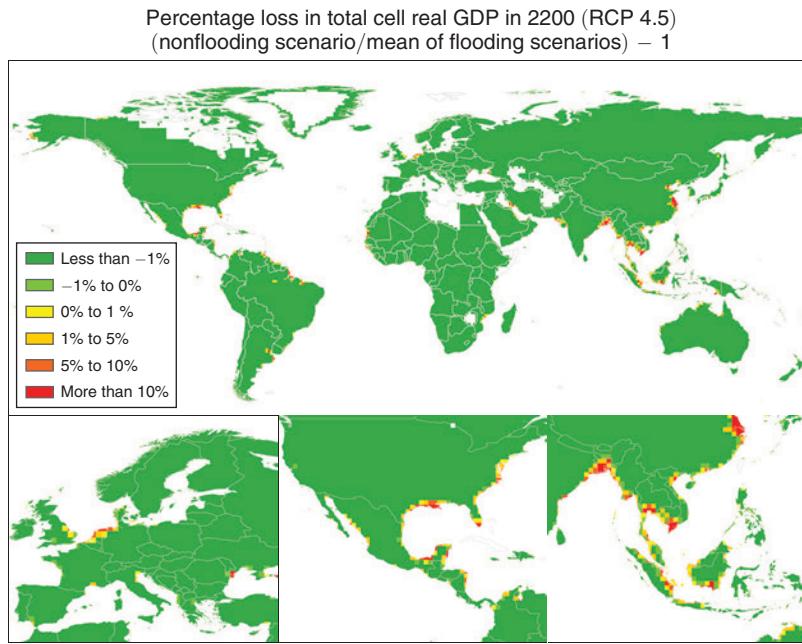
FIGURE 4. PERCENTAGE MEAN LOSS IN TOTAL CELL REAL GDP IN 2200 UNDER RCP 4.5

A. *Cell-Level Effects*

Figure 4 displays a world map of the mean loss in total real GDP across realizations in the year 2200. As expected, coastal areas suffer significant losses across the globe, but the effects are unevenly distributed. The negative effects tend to be larger in Southeast Asia and Northwest Europe, while they are more contained on the Pacific coast of the Americas. Flooding also affects areas that are not directly impacted by the sea level rise. In particular, in the year 2200, inland regions tend to gain around 1.5 percent of GDP. These results underscore the importance of our spatially disaggregated general equilibrium analysis: focusing only on flooded areas would ignore this redistribution. In present discounted value terms, around 20 percent of coastal cells lose. In contrast, almost all inland cells gain (see Figure 5, panel A, which presents the CDF of the present discounted value of real GDP losses for coastal and inland cells).

A map that depicts for each grid cell the flooding-induced percentage loss in population in the year 2200 looks very similar to Figure 4. Not surprisingly, the areas with the greatest share of displaced population are the same as those that lose most in terms of real GDP. In the year 2200, close to 20 percent of all coastal cells lose population (see Figure 5, panel B, which depicts the CDF of 2200 population losses in coastal and inland cells).

B. *Country-Level Effects*

We further illustrate our findings by looking at the fate of some particular countries. Appendix A presents, as an example, the evolution of real GDP and welfare

Panel A. Percentage real GDP loss

Panel B. Percentage population loss
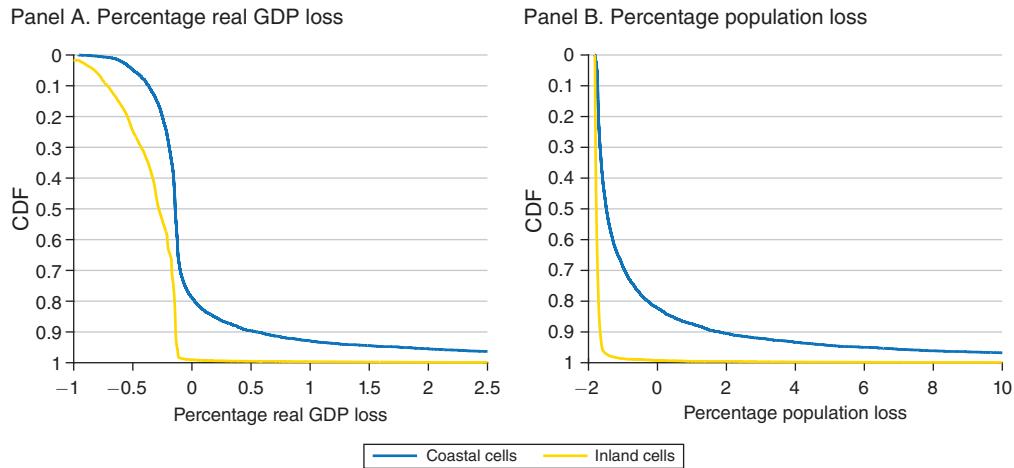
FIGURE 5

Note: Cumulative density functions of the PDV of total percentage losses in real GDP (panel A), and the population losses for coastal and inland cells in 2200 (RCP 4.5) (panel B).

for China and the United States. The figures show that China and the United States experience a similar evolution of welfare costs but the losses in GDP per capita are larger and are much more persistent in China. In Table A1 in Appendix A, we also present losses in real GDP, welfare, and population for most countries in the world—for example, China's loss in real GDP per capita due to permanent inundation peaks in 2121 at 0.94 percent. For the United States, the PDV of real GDP losses amounts to 0.03 percent with a population loss that peaks in 2021 at 0.01 percent. Another interesting case is the Netherlands.[11] It loses more from flooding than most other countries, with total real GDP declining 0.41 percent and the welfare in the country dropping 1.05 percent in present discounted value terms. The country loses 3.0 percent of its population in 2200, and as a result economic activity declines.

C. *City-Level Effects*

Coastal flooding is bound to have an important effect on many of the world's largest cities. Table 4 reports the estimated effect of flooding on population and real GDP in a sample of 25 large coastal metropolitan areas in the year 2200. We use the built-up area in 2016 and assign the proportion of the cells covered by this area to the metropolitan area for the entire 200-year period. For our estimation, we assume that the share of land lost to flooding in a city is the same as the share of land lost to flooding in the cells that overlap the city. Compared to a world without flooding, Ho Chin Minh City is predicted to lose 40.5 percent of its area, 21.8 percent of its population, and 21.5 percent of its real GDP. Other metropolitan areas that stand

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[11] In our simulations, the Netherlands inundates immediately since we do not consider existing dikes or other forms of protection against inundation. As mentioned before, the numbers we find should be compared with cost estimates of mitigation and other forms of adaptation.

TABLE 4—POPULATION AND REAL GDP LOSS IN A SAMPLE OF 25 LARGE CITIES IN 2200

Metropolitan area	Real GDP loss (percent)		Population loss (percent)		Area cells flooded (percent)
	Mean	95 percent credible interval	Mean	95 percent credible interval	
Amsterdam	6.5	(−0.3, 19.5)	6.6	(0.0, 18.3)	14.1
Bangkok	167.1	(134.0, 188.3)	162.0	(128.9, 187.5)	87.0
Barcelona	−2.4	(−5.2, −0.4)	−1.7	(−3.8, −0.2)	0.1
Buenos Aires	0.3	(−1.6, 7.6)	0.7	(−0.2, 2.7)	5.3
Ho Chi Minh City	21.5	(−1.7, 37.6)	21.8	(−0.4, 37.9)	40.5
Hong Kong	−0.8	(−1.9, −0.3)	−0.4	(−1.2, −0.1)	2.5
Houston–Galveston–Brazoria	0.1	(−1.2, 1.0)	0.5	(−0.4, 1.2)	5.2
Karachi	3.8	(0.1, 8.8)	4.9	(0.7, 10.9)	17.0
Kolkota	6.9	(−1.1, 38.2)	6.6	(−0.9, 36.2)	15.0
Kuala Lumpur	1.5	(−0.5, 3.3)	1.5	(−0.2, 3.5)	6.5
Lagos	−1.8	(−2.8, −0.4)	−1.2	(−2.1, −0.2)	1.2
Lima	−1.8	(−3.5, −0.4)	−1.4	(−2.6, −0.2)	0.2
Los Angeles–Riverside–Orange County	−1.9	(−4.1, −0.4)	−1.4	(−3.0, −0.1)	0.4
Manila	0.3	(−0.7, 1.2)	0.7	(0.1, 1.3)	4.7
Miami–Fort Lauderdale	6.7	(0.2, 55.1)	6.7	(0.5, 51.1)	12.2
Mumbai	1.4	(−0.3, 2.7)	1.8	(0.1, 3.2)	6.5
New York-Northern New Jersey–Long Island	0.0	(−1.5, 1.1)	0.4	(−0.9, 1.4)	3.2
Rio de Janeiro	−1.5	(−3.9, −0.4)	−1.0	(−2.6, −0.1)	1.8
San Francisco–Oakland–San Jose	−1.6	(−3.8, −0.3)	−1.1	(−2.5, 0.0)	1.7
Seoul	−0.4	(−0.9, 0.7)	−0.1	(−0.5, 0.9)	3.3
Shanghai	159.1	(10.5, 799.9)	149.7	(11.1, 745.0)	82.2
Singapore	−1.4	(−2.7, −0.5)	−1.0	(−1.8, −0.2)	1.2
Sydney	−1.9	(−4.1, −0.4)	−1.3	(−2.9, −0.1)	0.7
Tianjin	19.8	(−0.6, 45.8)	20.3	(−0.2, 47.7)	37.9
Tokyo	0.7	(−0.9, 3.1)	1.1	(−0.5, 3.2)	5.9

Notes: The geographic extent of metropolitan areas is defined as their built-up areas in 2016 and come from the Atlas of Urban Expansion (http://www.atlasofurbanexpansion.org/). Percentage loss refers to (nonflooding scenario/mean of flooding scenarios) − 1, where the flooding scenarios are based on RCP 4.5. Calculations assume that the share of a city's land flooded is the same as that of the 1° by 1° cells the city belongs to.

to lose an important share of their population are Amsterdam, Bangkok, Miami, Shanghai, and Tianjin. The corresponding real GDP losses are commensurate. The uncertainty of the effects is often substantial. For example, Miami is projected to lose between 0.5 percent and 51.1 percent of its population when using a 95 percent credible interval. Table C2 of Appendix C reports estimates for alternative sea level rise projections and alternative elevation maps.

V. Physical Structures

Our model does not include physical structures. We have argued that the losses of physical structures due to sea level rise are likely to be relatively minor for two reasons. First, sea level rise is a slow-moving process, and the damage it causes plays out over longer time periods than capital depreciation. As a result, by the time a structure becomes permanently inundated, standard depreciation would probably have required it to be rebuilt anyway. If so, the structure could simply be moved to higher ground. Second, the physical damage from flooding in large coastal cities has more to do with the loss in agglomeration economies than with the cost of the physical capital per se. As a result, the actual cost of rebuilding those structures is bound to be substantially less than their market value.

To test our intuition, we quantitatively analyze whether the paper's main insights hold when accounting for the loss in physical capital. Using data for the United States, we perform two exercises: a first one compares the present discounted value of total losses, with and without physical capital. A second exercise traces the flooding-induced losses in the value of physical capital over time and compares them to our earlier results.

A. *Measuring the Loss in Physical Structures*

We start by briefly discussing how we measure the loss of physical capital over time. To be clear, we do not formally incorporate physical capital into our theoretical model. Doing so would involve introducing a rival long-lasting asset and so the associated investment decisions would require creating expectations over the future evolution of economic activity in all locations and scenarios.[12] There are no available methods to solve such a complex dynamic problem in a rich spatial setup like ours. Instead, we limit ourselves to providing a simple measurement framework to assess these losses.

Suppose the observed value of physical capital in location r in the initial period, $K_0(r)$, is the present discounted value of a stream of depreciated future rents in the absence of flooding given by

$$(9) \qquad K_0(r) = \sum_{t=0}^{\infty} \beta^t \delta^t \bar{k}(r) = \frac{\bar{k}(r)}{1 - \beta\delta},$$

where δ is one minus the depreciation rate, β is the inverse of one plus a constant interest rate, and $\bar{k}(r)$ is the per-period rent gross of depreciation.

The loss of initial physical capital due to flooding in location r in period t can be written as the rent net of depreciation, $\delta^t \bar{k}(r)$, times the share of initial land lost to permanent inundation, $(H_0(r) - H_t(r))/H_0(r)$:

$$(10) \qquad \delta^t \bar{k}(r) \frac{H_0(r) - H_t(r)}{H_0(r)} = \delta^t K_0(r)(1 - \beta\delta) \frac{H_0(r) - H_t(r)}{H_0(r)}.$$

The total flooding-induced loss of initial physical capital in all locations in period t is then

$$(11) \qquad \sum_r \delta^t K_0(r)(1 - \beta\delta) \frac{H_0(r) - H_t(r)}{H_0(r)}.$$

Dividing (11) by GDP in every period t allows us to trace the time path of the share of income lost due to the flooding of physical capital. The loss of physical capital in present discounted value terms is then simply

$$(12) \qquad \sum_{t=1}^{\infty} \sum_r \beta^t \delta^t K_0(r)(1 - \beta\delta) \frac{H_0(r) - H_t(r)}{H_0(r)}.$$

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[12] This is unlike technology which is long-lasting but eventually nonrival since it diffuses spatially and becomes available for anyone producing in a given location. This property is essential to make our model tractable.

This calculation assumes that current valuations of physical capital do not incorporate the possibility of future flooding. That is, expression (9) assumes that today's observed market value of structures ignores future losses due to inundation. This is reasonable if either people are ignorant about future sea level rise or if the owners of physical capital believe the government will cover the costs of future flooding. Of course, it would be straightforward to adopt the alternative assumption that the current value of physical capital incorporates future losses from inundation. In that case, the current value of physical capital would be

$$(13) \qquad K_0'(r) \; = \; \sum_{t=0}^{\infty} \beta^t \delta^t \bar{k}(r) \frac{H_t(r)}{H_0(r)},$$

where we use a prime superscript to distinguish this equation from (9). The rest of the expressions can then be derived by analogy.

B. The Quantitative Effect of Including Physical Structures

To quantitatively assess the impact of the loss of physical structures due to flooding, we focus on the United States, where we have detailed geographic data on the value of the housing stock. For each census block group, the 2006–2010 American Community Survey (ACS) from the US Census Bureau gives data on the number of houses for 24 different value classes. This allows us to estimate a value for the total stock of housing at the level of census block groups. We then combine this with data on the share of land flooded at the same level of geographic resolution for each one of the 40 sea level paths under RCP 4.5 for all time periods. With these two pieces of information, we can compute the total loss in physical capital for each time period, as expressed in (11), and the present discounted value of physical capital lost, as expressed in (12).

We start by estimating the present discounted value of losses in housing as a share of GDP. The average of these losses across the 40 sea level paths for RCP 4.5 is 0.10 percent of real GDP in the United States (95 percent credible interval of 0.05–0.15 percent). This calculation assumes an annual depreciation rate of 2.5 percent (Harding, Rosenthal, and Sirmans 2007). Even if we substantially lower the depreciation rate to 1 percent per year, the average losses hardly increase to 0.11 percent of real GDP. These estimates are based on (9); i.e., we are assuming that the current valuation of the housing stock does not incorporate future losses from flooding. If, instead, we were to assume that today's housing value already accounts for future flood damage, as in (13), then the average present discounted value of the loss in housing would increase from 0.10 percent of real GDP to 0.12 percent of real GDP in the United States. The assessment increases since both estimations are based on the same current housing valuation observed in the data, but the latter assumes that this value already incorporates future destruction, which implies a more valuable housing stock absent flooding. Note that, although these costs are modest, they are large relative to the present discounted value of losses without considering capital. In the United States, the present discounted value of real GDP losses from permanent inundation when not taking into account physical structures is only 0.03 percent. However, as we show next, and consistent with our main argument, even
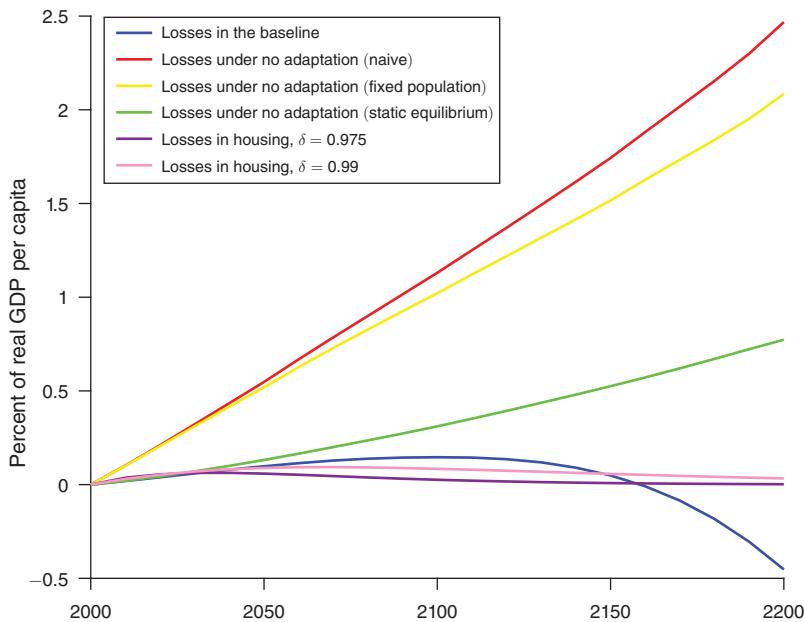
FIGURE 6. DIFFERENT LOSSES AS A SHARE OF US REAL GDP PER CAPITA, AVERAGE ACROSS 40 PATHS

these larger costs remain tiny in comparison to the cost of flooding in the absence of economic adaptation.

Figure 6 represents losses in the value of housing as a share of income for the United States over the time period 2000 to 2200, using either a depreciation rate of 2.5 percent or 1.0 percent per annum. Both time paths of the losses in physical capital indicate small and stable losses over time. Similar to Figure 3, and to ease comparison, Figure 6 also depicts the time paths of losses in the United States in the model's baseline without taking into account housing and in various alternative models with limited or no adaptation.[13] Recall from Figure 3 the main insight of the paper: when taking into account adaptation through migration, trade, and innovation, the impact of sea level rise is substantially reduced compared to a world without those margins of adaptation. Incorporating the losses from housing leaves this basic insight unchanged. If we add the damage from flooding to the housing stock, the baseline path of losses continues to exhibit small losses. In particular, these losses are substantially less than in a world without the possibility of flooding-induced moving, represented in the graph by the so-called "naive" scenario.

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[13] To be precise, it adds three alternatives with limited or no adaptation: a scenario that does not allow for any migration due to flooding (naive); a scenario with movement, but without changes in the incentives to innovate (static); and a scenario with zero mobility (fixed).

VI. Conclusion

Permanent coastal inundation is an important consequence of anthropogenic climate change. Evaluating the economic consequences of any climate-related phenomenon raises the challenge of accurately accounting for the dynamic spatial adjustment of the economy and the uncertainty inherent in environmental projections. To address this challenge, this paper combines recently developed economic modeling with probabilistic flooding projections for different emissions pathways.

The results indicate that the economic cost of coastal flooding is shaped by spatial dynamics. Under RCP 4.5, we estimate that sea level rise will induce an average decline in real GDP of 0.19 percent (with 95 percent credible interval of 0.07–0.37 percent) and an average drop in welfare of 0.24 percent (with 95 percent credible interval of 0.08–0.45 percent). In some countries, the effects are more than an order of magnitude larger, with an estimated decline in real GDP of 7.60 percent in Vietnam, 9.37 percent in Thailand, and 5.37 percent in Bangladesh. In terms of population, in the year 2200, flooding is predicted to displace an average of 1.46 percent of world population (with a credible interval of 0.15–3.54 percent). At a national level, population displacement in the year 2200 is 14.60 percent in Vietnam, 2.28 percent in Thailand, and 12.38 percent in Bangladesh.

The magnitude of our findings depends crucially on the dynamic spatial adjustment of the economy to coastal flooding. When faced with rising sea level, people in our model have the possibility of moving to higher ground, albeit at a cost. As this occurs, the destruction of existing economic clusters is at least partly compensated by the emergence of new clusters of economic activity. The higher concentration of people in interior regions in turn enhances the incentives of local firms to innovate. When ignoring these mitigating factors, the expected real GDP loss is substantially larger. If people faced insurmountable barriers to moving when experiencing coastal flooding, the real GDP loss would be around 4.5 percent in the year 2200, compared to 0.11 percent in our model.

To lend further credibility to our findings, it is important to understand to what extent the quantitative predictions depend on the choices of some of the parameter values. To that end, Appendix B conducts extensive sensitivity analysis. As a further robustness check, Appendix C also analyzes whether the results change when using alternative sea level rise projections and elevation data. None of these additional exercises change the paper's main conclusions. The insights of this paper also do not change when accounting for the flooding-induced damage to physical structures. Although this adds to the overall cost of sea level rise, in the United States its impact is minimal relative to the mitigating effects introduced by the dynamic adaptation through migration and investment. Performing similar exercises for the rest of the world is challenging due to data limitations, but the magnitude of the differences between the role of adaptation and the role of physical capital destruction for the United States suggests that the conclusions for other countries are unlikely to change significantly.

Given the complexity of the issue at hand, our model necessarily leaves out some important aspects. First, although we account for the uncertainty in flooding

scenarios and we demonstrate the robustness of our evaluation to a variety of economic parameters, our evaluation does not include potential measurement error in economic variables or model misspecification. Second, we do not account for feedback loops between economic outcomes and flooding through changed emissions pathways. Third, nonlinear effects beyond those coming from agglomeration economies may aggravate the effect of flooding. Examples include partial flooding leading to contamination of freshwater supplies and the possibility of political stress and violent conflict. Fourth, we only analyze the impact of permanent, albeit gradual, inundation and not temporary flooding caused by extreme weather events. Coastal locations will likely experience increasingly frequent flooding before they fall below the high tide line, causing migration and its ensuing economic impacts to occur faster than modeled here. Finally, and conversely, we do not model efforts to mitigate flooding using a variety of methods such as barriers and dikes, which might delay migration. Future work should focus on extending our research in these directions in order to further improve our estimates of the economic consequences of coastal flooding.

Appendix

A. *Country Effects*

Panels A and B of Figure A1 display the losses in real GDP per capita and welfare in China. These effects are in per capita terms, and hence measure the impact on an individual resident. The mean loss in real GDP per capita due to flooding peaks at 0.94 percent in the year 2121 and declines thereafter. Panels C and D of Figure A1 display the behavior of real GDP per capita and welfare in the United States over the next 200 years. The overall effects are small. As the country receives flooding refugees from other countries, the spatial concentration of economic activity increases, leading to more innovation and higher GDP per capita in the long run. The welfare effects are negative though, because of the crowding out of amenities. Given the size of the country and the high internal mobility, there is enough scope for economic adaptation.

Table A1 presents the total real GDP, total welfare, and total population changes that result from flooding, as well as the peak losses in real GDP per capita and total population for all countries in our analysis. We here limit ourselves to describing the results for a few countries. In PDV terms, calculated over the period 2000 to 2200, Vietnam's total GDP drops by 7.60 percent because of flooding. This negative effect is due not only to the losses in real GDP per capita, but also to Vietnam's drop in total population relative to other countries. In the year 2200, Vietnam's population is 14.60 percent lower, compared to a world without flooding. A contrasting case is the Democratic Republic of the Congo (DRC). There the peak per capita income losses are negligible given that the country is not directly affected by flooding. However, it attracts migration from flooded areas, leading to an increase in population by around 1.79 percent in 2200. These gains in population imply that both total output and the total utility generated in the country increase.
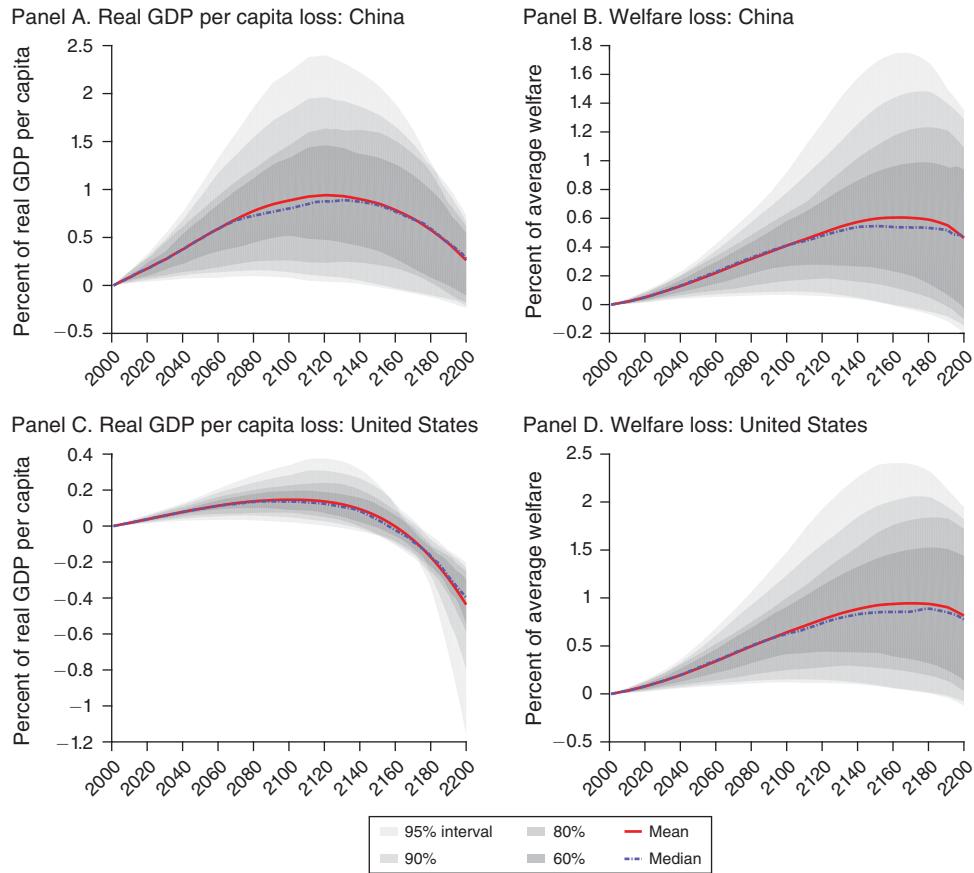
FIGURE A1

Note: This figure displays real GDP per capita losses in China (panel A), welfare losses in China (panel B), real GDP per capita losses in the United States (panel C), and welfare losses in the United States (panel D).

B. *Parameter Robustness*

The quantitative results depend on the parameter values governing the forces of the economic model. These parameters were chosen as in the benchmark scenario in Desmet, Nagy, and Rossi-Hansberg (2018). That paper estimates the parameters of the model using a variety of data and finds that the resulting economic model is successful in matching other, nontargeted, empirical moments. Still, there is uncertainty about the true values of these parameters. Hence, we conduct a number of robustness checks related to the degree at which the future is discounted, the importance of mobility and trade frictions, the cost of innovation, the intensity of the spatial diffusion of technology, and the strength of production externalities and congestion. In all of them, we keep the same selection of the 40 sea level paths for RCP 4.5. The results, reported in Table B1 and Table B2, demonstrate that our evaluation of the cost of permanent inundation is quite robust to changes in these parameters.

TABLE A1—COUNTRY LOSSES IN REAL GDP, WELFARE, AND POPULATION

Countries	PDV of real GDP	PDV of total welfare	Peak difference in real GDP per capita		Population, 200-year average	Population, 2200	Peak difference in population	
			Magnitude	Year			Magnitude	Year
Albania	−0.11%	0.18%	0.14%	2100	−0.27%	−0.92%	0.00%	2001
Algeria	−0.36%	−0.07%	0.05%	2081	−0.60%	−1.76%	0.00%	2001
Angola	−0.52%	−0.10%	0.05%	2082	−0.71%	−1.73%	0.00%	2001
Anguilla (1)	0.05%	0.36%	0.13%	2108	0.06%	0.69%	0.69%	2200
Argentina	−0.06%	0.13%	0.26%	2121	−0.28%	−0.86%	0.00%	2001
Armenia	−0.57%	−0.12%	0.05%	2079	−0.74%	−1.80%	0.00%	2001
Australia	−0.09%	0.08%	0.10%	2101	−0.25%	−1.11%	0.00%	2001
Austria	−0.17%	−0.05%	0.05%	2079	−0.41%	−1.80%	0.00%	2001
Azerbaijan	−0.55%	−0.12%	0.05%	2079	−0.73%	−1.80%	0.00%	2001
Bahrain	0.84%	1.33%	0.71%	2149	1.60%	8.27%	8.27%	2200
Bangladesh	5.37%	4.54%	1.33%	2181	5.34%	12.38%	12.38%	2200
Belarus	−0.36%	−0.08%	0.05%	2079	−0.60%	−1.80%	0.00%	2001
Belgium	0.23%	0.86%	0.15%	2101	0.23%	0.09%	0.39%	2073
Belize	0.81%	2.50%	0.50%	2131	0.88%	2.02%	2.02%	2200
Benin	−0.37%	0.02%	0.12%	2111	−0.47%	−0.79%	0.00%	2001
Bhutan	−0.48%	−0.07%	0.08%	2096	−0.68%	−1.64%	0.00%	2001
Bolivia	−0.44%	−0.09%	0.05%	2079	−0.66%	−1.80%	0.00%	2001
Bosnia and Herzegovina	−0.35%	−0.06%	0.05%	2080	−0.59%	−1.73%	0.00%	2001
Botswana	−0.26%	−0.07%	0.05%	2081	−0.55%	−1.77%	0.00%	2001
Brazil	−0.25%	0.05%	0.04%	2087	−0.46%	−1.27%	0.00%	2001
Brunei	−0.08%	0.07%	0.22%	2131	−0.23%	−0.68%	0.00%	2001
Bulgaria	−0.35%	−0.07%	0.05%	2081	−0.59%	−1.77%	0.00%	2001
Burkina Faso	−0.79%	−0.15%	0.05%	2079	−0.87%	−1.80%	0.00%	2001
Burundi	−1.07%	−0.21%	0.05%	2079	−1.01%	−1.80%	0.00%	2001
Cambodia	1.45%	1.32%	0.66%	2136	1.15%	2.07%	2.07%	2200
Cameroon	−0.60%	−0.12%	0.05%	2081	−0.76%	−1.78%	0.00%	2001
Canada	−0.15%	−0.01%	0.05%	2080	−0.37%	−1.69%	0.00%	2001
Cabo Verde	−0.43%	0.06%	0.08%	2084	−0.55%	−1.33%	0.00%	2001
Central African Republic	−0.83%	−0.17%	0.05%	2079	−0.90%	−1.80%	0.00%	2001
Chad	−0.87%	−0.17%	0.05%	2079	−0.92%	−1.80%	0.00%	2001
Chile	−0.27%	−0.04%	0.05%	2079	−0.52%	−1.72%	0.00%	2001
China	0.48%	0.21%	0.94%	2121	−0.15%	−0.60%	0.01%	2018
Colombia	−0.24%	0.04%	0.05%	2087	−0.43%	−1.27%	0.00%	2001
Comores/Mayotte	−0.69%	0.00%	0.06%	2082	−0.73%	−1.50%	0.00%	2001
Republic of the Congo	−0.50%	−0.10%	0.05%	2081	−0.70%	−1.77%	0.00%	2001
Costa Rica	−0.24%	0.03%	0.07%	2089	−0.45%	−1.40%	0.00%	2001
Cote d'Ivoire	−0.61%	−0.12%	0.05%	2081	−0.76%	−1.73%	0.00%	2001
Croatia	−0.26%	−0.04%	0.05%	2081	−0.51%	−1.75%	0.00%	2001
Cyprus	−0.18%	0.01%	0.07%	2093	−0.40%	−1.53%	0.00%	2001
Czech Republic	−0.24%	−0.06%	0.05%	2079	−0.49%	−1.80%	0.00%	2001
DRC	−1.11%	−0.21%	0.05%	2079	−1.03%	−1.79%	0.00%	2001
Denmark	−0.01%	0.29%	0.07%	2080	−0.10%	−0.72%	0.00%	2011
Djibouti	−0.48%	0.00%	0.08%	2095	−0.61%	−1.35%	0.00%	2001
Dominican Republic	−0.31%	0.04%	0.06%	2084	−0.52%	−1.49%	0.00%	2001
Ecuador	−0.27%	0.02%	0.08%	2096	−0.47%	−1.39%	0.00%	2001
Egypt	0.25%	0.54%	0.65%	2138	0.10%	0.70%	0.70%	2200
El Salvador	−0.35%	0.00%	0.06%	2084	−0.53%	−1.33%	0.00%	2001
Eritrea	−0.77%	−0.05%	0.06%	2085	−0.83%	−1.66%	0.00%	2001
Estonia	−0.25%	−0.02%	0.05%	2080	−0.50%	−1.70%	0.00%	2001
Ethiopia	−0.93%	−0.18%	0.05%	2080	−0.94%	−1.80%	0.00%	2001
Fiji (2)	0.09%	0.42%	0.16%	2097	−0.02%	−0.43%	0.08%	2080
Finland	−0.16%	−0.04%	0.06%	2081	−0.39%	−1.75%	0.00%	2001
France	−0.14%	0.04%	0.05%	2082	−0.34%	−1.50%	0.00%	2001
Gabon	−0.15%	0.00%	0.10%	2099	−0.34%	−1.15%	0.00%	2001
The Gambia	1.60%	1.56%	0.37%	2111	1.53%	2.27%	2.27%	2200
Germany	−0.14%	0.04%	0.06%	2081	−0.34%	−1.52%	0.00%	2001
Ghana	−0.69%	−0.02%	0.07%	2090	−0.79%	−1.61%	0.00%	2001
Greece	−0.16%	0.04%	0.04%	2076	−0.34%	−1.34%	0.00%	2001
Greenland	−0.09%	0.00%	0.07%	2082	−0.29%	−1.63%	0.00%	2001

TABLE A1—COUNTRY LOSSES IN REAL GDP, WELFARE, AND POPULATION (*continued*)

Countries	PDV of real GDP	PDV of total welfare	Peak difference in real GDP per capita		Population, 200-year average	Population, 2200	Peak difference in population	
			Magnitude	Year			Magnitude	Year
Grenada	−0.20%	0.11%	0.08%	2087	−0.37%	−1.14%	0.00%	2001
Guatemala	−0.37%	0.10%	0.06%	2089	−0.57%	−1.51%	0.00%	2001
Guadeloupe (3)	−0.35%	−0.01%	0.07%	2085	−0.55%	−1.51%	0.00%	2001
Guinea	0.04%	0.24%	0.34%	2131	−0.21%	−0.58%	0.00%	2011
Guinea-Bissau	0.54%	0.81%	0.28%	2138	0.45%	1.47%	1.47%	2200
Guyana	1.88%	1.29%	0.93%	2144	1.79%	3.46%	3.46%	2200
Haiti	−0.62%	−0.02%	0.06%	2080	−0.69%	−1.45%	0.00%	2001
Honduras	−0.33%	0.24%	0.08%	2095	−0.50%	−1.21%	0.00%	2001
Hungary	−0.26%	−0.07%	0.05%	2079	−0.52%	−1.80%	0.00%	2001
Iceland	−0.15%	−0.03%	0.06%	2081	−0.38%	−1.73%	0.00%	2001
India	−0.28%	0.12%	0.21%	2120	−0.49%	−1.04%	0.00%	2001
Indonesia/Timor-Leste	0.23%	0.57%	0.26%	2128	0.13%	0.20%	0.26%	2166
Iran	−0.24%	0.03%	0.07%	2081	−0.46%	−1.46%	0.00%	2001
Ireland	−0.13%	0.03%	0.06%	2082	−0.34%	−1.57%	0.00%	2001
Israel	−0.20%	−0.03%	0.07%	2098	−0.43%	−1.58%	0.00%	2001
Italy	−0.13%	0.02%	0.08%	2082	−0.36%	−1.50%	0.00%	2001
Jamaica/Cuba	−0.27%	0.09%	0.07%	2086	−0.45%	−1.23%	0.00%	2001
Japan	−0.08%	0.11%	0.11%	2120	−0.20%	−0.45%	0.00%	2001
Jordan	−0.43%	−0.09%	0.06%	2087	−0.65%	−1.74%	0.00%	2001
Kazakhstan	−0.36%	−0.08%	0.05%	2079	−0.60%	−1.80%	0.00%	2001
Kenya	−0.71%	−0.09%	0.07%	2083	−0.85%	−1.74%	0.00%	2001
Kuwait	0.51%	0.83%	1.04%	2191	1.02%	6.28%	6.28%	2200
Kyrgzstan	−0.63%	−0.13%	0.05%	2079	−0.79%	−1.80%	0.00%	2001
Laos	−0.55%	−0.07%	0.10%	2102	−0.72%	−1.62%	0.00%	2001
Latvia	−0.28%	−0.05%	0.06%	2081	−0.54%	−1.71%	0.00%	2001
Lebanon	−0.33%	−0.07%	0.05%	2085	−0.57%	−1.72%	0.00%	2001
Lesotho	−0.70%	−0.14%	0.05%	2080	−0.82%	−1.79%	0.00%	2001
Liberia	−0.91%	−0.09%	0.06%	2086	−0.91%	−1.66%	0.00%	2001
Lithuania	−0.25%	−0.03%	0.06%	2081	−0.49%	−1.71%	0.00%	2001
Macedonia	−0.30%	−0.07%	0.05%	2083	−0.55%	−1.77%	0.00%	2001
Madagascar	−0.65%	0.02%	0.08%	2093	−0.73%	−1.48%	0.00%	2001
Malawi	−0.85%	−0.16%	0.05%	2080	−0.90%	−1.79%	0.00%	2001
Malaysia	0.31%	0.62%	0.44%	2133	0.28%	0.99%	0.99%	2200
Mali	−0.78%	−0.15%	0.05%	2079	−0.86%	−1.80%	0.00%	2001
Malta	−0.20%	0.01%	0.06%	2084	−0.41%	−1.43%	0.00%	2001
Mauritania	6.10%	1.87%	3.98%	2111	3.18%	3.16%	3.89%	2081
Reunion/Mauritius	−0.23%	0.08%	0.07%	2086	−0.42%	−1.29%	0.00%	2001
Mexico	−0.10%	0.32%	0.04%	2090	−0.22%	−0.80%	0.00%	2001
Moldova	−0.63%	−0.11%	0.06%	2082	−0.77%	−1.72%	0.00%	2001
Mongolia	−0.52%	−0.10%	0.05%	2082	−0.72%	−1.78%	0.00%	2001
Morocco	−0.47%	−0.07%	0.06%	2084	−0.67%	−1.70%	0.00%	2001
Mozambique	−0.27%	0.37%	0.16%	2111	−0.36%	−0.81%	0.00%	2001
Myanmar	0.67%	0.64%	0.91%	2191	0.36%	1.63%	1.63%	2200
Namibia	−0.38%	−0.07%	0.06%	2084	−0.65%	−1.75%	0.00%	2001
Nepal	−0.79%	−0.15%	0.05%	2082	−0.86%	−1.77%	0.00%	2001
Netherlands	0.41%	1.05%	0.22%	2111	0.67%	3.00%	3.00%	2200
New Zealand	−0.05%	0.11%	0.12%	2104	−0.19%	−0.90%	0.00%	2001
Nicaragua	−0.35%	0.21%	0.10%	2111	−0.49%	−1.12%	0.00%	2001
Niger	−0.89%	−0.17%	0.05%	2079	−0.92%	−1.80%	0.00%	2001
Nigeria	−0.66%	−0.12%	0.06%	2085	−0.79%	−1.69%	0.00%	2001
Norway	−0.12%	−0.01%	0.06%	2083	−0.33%	−1.68%	0.00%	2001
Oman	−0.17%	0.03%	0.08%	2093	−0.39%	−1.47%	0.00%	2001
Pakistan	−0.31%	0.06%	0.15%	2104	−0.49%	−1.24%	0.00%	2001
Panama	−0.16%	0.09%	0.10%	2092	−0.34%	−1.12%	0.00%	2001
Papua New Guinea	−0.48%	0.04%	0.08%	2093	−0.65%	−1.52%	0.00%	2001
Paraguay	−0.44%	−0.09%	0.05%	2079	−0.66%	−1.80%	0.00%	2001
Peru	−0.34%	−0.06%	0.08%	2094	−0.60%	−1.64%	0.00%	2001
Philippines	−0.07%	0.40%	0.18%	2119	−0.20%	−0.47%	0.00%	2001
Poland	−0.25%	−0.01%	0.06%	2082	−0.50%	−1.71%	0.00%	2001

(*continued*)

TABLE A1—COUNTRY LOSSES IN REAL GDP, WELFARE, AND POPULATION (*continued*)

| Countries | PDV of real GDP | PDV of total welfare | Peak difference in real GDP per capita | | Population, 200-year average | Population, 2200 | Peak difference in population | |
			Magnitude	Year			Magnitude	Year
Portugal	−0.16%	0.11%	0.07%	2087	−0.38%	−1.50%	0.00%	2001
Puerto Rico	−0.13%	0.13%	0.09%	2092	−0.28%	−0.94%	0.00%	2001
Romania	−0.31%	0.04%	0.05%	2082	−0.55%	−1.64%	0.00%	2001
Russia (4)	−0.28%	−0.05%	0.05%	2082	−0.53%	−1.68%	0.00%	2001
Rwanda	−0.92%	−0.18%	0.05%	2079	−0.93%	−1.80%	0.00%	2001
Saudi Arabia	−0.18%	−0.01%	0.08%	2094	−0.42%	−1.61%	0.00%	2001
Senegal	0.04%	0.57%	0.11%	2097	0.02%	0.00%	0.06%	2115
Serbia	−0.34%	−0.08%	0.05%	2080	−0.58%	−1.79%	0.00%	2001
Seychelles	0.08%	0.36%	0.13%	2095	0.04%	−0.17%	0.11%	2111
Sierra Leone	0.64%	0.60%	0.76%	2168	0.15%	0.49%	0.49%	2200
Singapore	−0.10%	0.05%	0.11%	2115	−0.28%	−1.03%	0.00%	2001
Slovakia	−0.25%	−0.07%	0.05%	2079	−0.51%	−1.80%	0.00%	2001
Slovenia	−0.20%	−0.05%	0.05%	2080	−0.44%	−1.79%	0.00%	2001
Solomon Islands	−0.35%	0.11%	0.08%	2088	−0.48%	−1.19%	0.00%	2001
South Africa	−0.33%	−0.08%	0.05%	2081	−0.64%	−1.76%	0.00%	2001
South Korea	−0.07%	0.15%	0.12%	2110	−0.21%	−0.67%	0.00%	2001
Spain	−0.14%	0.04%	0.06%	2085	−0.34%	−1.47%	0.00%	2001
Sri Lanka	−0.33%	0.13%	0.10%	2116	−0.48%	−0.91%	0.00%	2001
Sudan	−0.67%	−0.14%	0.05%	2082	−0.84%	−1.78%	0.00%	2001
Suriname	1.10%	1.01%	0.28%	2088	1.29%	2.39%	2.39%	2200
Swaziland	−0.42%	−0.09%	0.06%	2084	−0.65%	−1.75%	0.00%	2001
Sweden	−0.15%	−0.02%	0.07%	2085	−0.38%	−1.66%	0.00%	2001
Switzerland	−0.17%	−0.04%	0.05%	2079	−0.40%	−1.80%	0.00%	2001
Syria	−0.45%	−0.10%	0.05%	2082	−0.68%	−1.78%	0.00%	2001
Tanzania	−0.66%	−0.11%	0.12%	2103	−0.80%	−1.64%	0.00%	2001
Thailand	9.37%	1.42%	12.79%	2081	2.82%	2.28%	4.11%	2091
Togo	−0.71%	−0.11%	0.07%	2094	−0.77%	−1.46%	0.00%	2001
Trinidad and Tobago	−0.09%	0.14%	0.10%	2094	−0.24%	−0.89%	0.00%	2001
Tunisia	−0.19%	0.26%	0.12%	2098	−0.39%	−1.24%	0.00%	2001
Turkey	−0.28%	−0.05%	0.06%	2084	−0.55%	−1.70%	0.00%	2001
Uganda	−0.85%	−0.17%	0.05%	2079	−0.90%	−1.80%	0.00%	2001
Ukraine	−0.40%	0.00%	0.05%	2081	−0.60%	−1.61%	0.00%	2001
UAE	−0.05%	0.11%	0.14%	2111	−0.21%	−1.01%	0.00%	2001
UK	−0.07%	0.16%	0.06%	2085	−0.22%	−1.15%	0.00%	2001
USA	0.03%	0.19%	0.15%	2103	−0.10%	−0.73%	0.01%	2021
Uruguay	−0.20%	0.05%	0.09%	2090	−0.43%	−1.51%	0.00%	2001
Uzbekistan	−0.65%	−0.13%	0.05%	2079	−0.79%	−1.80%	0.00%	2001
Vanuatu	−0.40%	−0.01%	0.06%	2083	−0.59%	−1.54%	0.00%	2001
Venezuela	−0.15%	0.15%	0.10%	2076	−0.37%	−1.28%	0.00%	2001
Vietnam	7.60%	5.38%	2.12%	2171	7.69%	14.60%	14.60%	2200
Yemen	−0.38%	0.09%	0.17%	2118	−0.60%	−1.43%	0.00%	2001
Zambia	−0.74%	−0.15%	0.05%	2080	−0.85%	−1.80%	0.00%	2001

Notes: Calculated using a simulation over 200 years and an annual discount rate of 4 percent. (1) Anguilla, Antigua, and Barbuda; (2) Fiji, Wallis, and Futuna, Tuvalu; (3) Guadeloupe, Montserrat, Saint Vincent and the Grenadines, Saint Lucia, Barbados, Saint Kitts, and Nevis; (4) Russia, Svalbard (NO), Jan Mayen (NO).

Discounting.—Discounting is central to any assessment of climate change. In this subsection, we entertain the possibility of lower discount rates and Ramsey discounting. The results can be found in panel A of Table B1.

Discount Rate: In a first robustness check, we lower the discount rate from 4 percent to 3 percent. This is the central discount rate used by the US government when

TABLE B1—AGGREGATE WORLD LOSSES IN REAL GDP AND WELFARE: DISCOUNT RATES
AND MOBILITY FRICTIONS

Scenario	Real GDP PDV		Welfare PDV	
Benchmark				
1. Medium benchmark (RCP 4.5)				
Mean (percent)	0.19		0.24	
95 percent credible interval (percent)	0.07	0.37	0.08	0.45
Panel A. Discount rates				
2. Lower discount factor of 3 percent				
Mean (percent)	0.26		0.34	
95 percent credible interval (percent)	0.06	0.55	0.09	0.69
3. Ramsey discounting with coefficient of relative risk aversion of 2				
Mean (percent)	0.13		0.14	
95 percent credible interval (percent)	0.07	0.23	0.06	0.24
Panel B. Moving and trade costs				
4. 25 percent higher moving costs				
Mean (percent)	0.23		0.22	
95 percent credible interval (percent)	0.06	0.48	0.08	0.41
5. 25 percent lower moving costs				
Mean (percent)	0.14		0.25	
95 percent credible interval (percent)	0.08	0.24	0.08	0.50
6. 25 percent higher trade costs				
Mean (percent)	0.23		0.26	
95 percent credible interval (percent)	0.09	0.43	0.09	0.50
7. 25 percent lower trade costs				
Mean (percent)	0.14		0.21	
95 percent credible interval (percent)	0.05	0.29	0.07	0.40

Notes: Calculations based on 4 percent annual discount rate, except in exercise 2 (discount rate of 3 percent) and exercise 3 (Ramsey discounting based on equation (30) in Weitzman 2012, using the path of predicted growth in real GDP under nonflooding and a coefficient of relative risk aversion of 2). Percentage change in PDV refers to (PDV of nonflooding scenario/mean of PDV of flooding scenarios) − 1 using a simulation over 200 years.

calculating the social cost of carbon. This parameter change increases the importance of future years in our present discounted value calculations. Giving more weight to later years increases the losses, from 0.19 percent to 0.26 percent for real GDP and from 0.24 percent to 0.34 percent for welfare. Note that the discount rate cannot fall below the equilibrium balanced growth rate in the economy, which is between 2 and 3 percent depending on the scenario.

Ramsey Discounting: In a second robustness check, we use time-varying Ramsey discounting. The Ramsey equation is often used in cost-benefit analysis and relates the discount rate to the growth rate of the economy. For example, a future benefit is discounted more in a fast-growing economy than in a slow-growing economy because of diminishing marginal utility, and a future benefit is discounted less if there is more uncertainty about future growth if agents are risk averse. As a result, in a world where future growth rates may be changing over time, the discount rate will be time-varying. To generate Ramsey discount rates for the next 200 years, we

take the predicted growth path of real GDP in the nonflooding scenario, and plug this into equation (30) in Weitzman (2012), together with a coefficient of relative risk aversion of 2 and a rate of pure time preference of zero (so as not to favor any particular generation in the calculation of present discounted values). In the baseline quantification, our model predicts that growth rates first increase and then decline slowly to their balanced growth level, so discount rates exhibit a similar pattern. With Ramsey discounting, the predicted loss in real GDP decreases from 0.19 percent to 0.13 percent, whereas the welfare loss decreases from 0.24 percent to 0.14 percent.

Moving and Trade Costs.—Mobility and trade are key to adaptation. In this subsection, we analyze how our results depend on mobility and trade frictions. Panel B of Table B1 reports the results.

Moving Costs: We calculate counterfactual migration scenarios where we either relax or enhance existing migration frictions in the world. To allow for the possibility of different migration costs, we generalize the cost of moving by raising it to the power ϑ so that the cost of moving to location r is $m_2(r)^\vartheta$, where in the baseline $\vartheta = 1$. Hence, $\vartheta > 1$ corresponds to increasing moving costs above their current levels, whereas $\vartheta < 1$ indicates lowering existing migration frictions. If we make it harder for people to move by increasing the moving cost parameter ϑ by 25 percent to 1.25, the real GDP losses from flooding increase, from 0.19 percent to 0.23 percent, because it becomes more costly to move to higher ground. In contrast, we see a slight drop in the welfare loss, from 0.24 percent in the benchmark to 0.22 percent when moving costs are higher. This occurs because greater mobility frictions imply a more dispersed distribution of population. Hence, when people are forced to move because of sea level rise, they cause less congestion in amenities in the host regions. This positive effect of lower congestion on welfare compensates the negative effect of higher moving costs on welfare. Needless to say, there is a limit to this argument. For example, in the extreme case of zero mobility, the negative effect is bound to dominate. Consistent with this, Figure 3 shows that welfare losses are up to five times larger in a world with no mobility, compared to a situation where we maintain migration frictions at their current levels. Not surprisingly, if instead of increasing the moving cost parameter, we lower ϑ by 25 percent to 0.75, we see the opposite patterns. With lower migration costs, the real GDP losses drop, whereas the welfare losses show a slight increase.

Trade Costs: Understanding changes in trade costs is more straightforward. We run counterfactual trade scenarios where we either increase or decrease existing transport costs. Formally, and by analogy with what we did in the case of moving costs, we raise transport costs to the power ϑ so that the transport cost between locations r and s equals $\varsigma(r,s)^\vartheta$, where in the baseline $\vartheta = 1$. An increase in trade costs by 25 percent to $\vartheta = 1.25$ worsens the losses from flooding, both in terms of real GDP and welfare. The PDV losses in real GDP rise from 0.19 percent to 0.23 percent, and the PDV losses in welfare rise from 0.24 percent to 0.26 percent. A drop in trade costs by 25 percent to $\vartheta = 0.75$ has the opposite effect.

TABLE B2—AGGREGATE WORLD LOSSES IN REAL GDP AND WELFARE:
INNOVATION, PRODUCTIVITY, AND CONGESTION

Scenario	Real GDP PDV		Welfare PDV	
Benchmark				
1. Medium Benchmark (RCP 4.5)				
Mean (percent)		0.19		0.24
95 percent credible interval (percent)	0.07	0.37	0.08	0.45
Panel A. Innovation and productivity				
2. 25 percent higher innovation costs				
Mean (percent)		0.18		0.23
95 percent credible interval (percent)	0.07	0.36	0.08	0.44
3. 25 percent lower innovation costs				
Mean (percent)		0.19		0.24
95 percent credible interval (percent)	0.07	0.38	0.08	0.47
4. 20 percent increase in spatial diffusion parameter				
Mean (percent)		0.17		0.23
95 percent credible interval (percent)	0.06	0.33	0.08	0.44
5. Local spatial technology diffusion				
Mean (percent)		0.24		0.30
95 percent credible interval (percent)	0.07	0.48	0.09	0.60
6. No production externalities				
Mean (percent)		0.19		0.24
95 percent credible interval (percent)	0.07	0.37	0.08	0.46
Panel B. Congestion costs				
7. 50 percent increase in amenities congestion parameter				
Mean (percent)		0.18		0.29
95 percent credible interval (percent)	0.08	0.35	0.10	0.57

Notes: Calculations based on 4 percent annual discount rate. Percentage change in PDV refers to (PDV of nonflooding scenario/mean of PDV of flooding scenarios) − 1 using a simulation over 200 years.

In this case, we see a slightly larger impact on real GDP losses, which drop to 0.14 percent.

Innovation and Productivity.—In this subsection, we analyze the sensitivity of our results to the magnitude of innovation costs, the strength of the spatial diffusion of technology, and the importance of agglomeration economies and congestion costs. Panel A of Table B2 reports the results.

Cost of Innovation: We start by focusing on the fixed cost of innovation. Recall that innovating an amount ϕ requires a labor investment of $\nu\phi^\xi$. To increase or lower the cost of innovation, we raise ν to the power ϑ, where once again $\vartheta = 1$ in the baseline. If we increase innovation costs by 25 percent to $\vartheta = 1.25$, we observe slightly smaller losses, both in terms of real GDP and welfare. The present discounted value losses in real GDP drop from 0.19 percent to 0.18 percent. When, instead, we decrease innovation costs by 25 percent, there is no observable change. The finding of smaller losses from flooding when increasing the cost of innovation is not immediately transparent. There are two countervailing forces. On the one hand, as local innovation is more costly, over time there

is less local productivity embodied in the world's largest clusters. This mitigates the losses from flooding, as leaving Manhattan or Miami behind is less costly. On the other hand, as local innovation is more costly, it is harder to build new productive clusters. Our results show that these two forces roughly balance each other out.

Strength of Technology Diffusion: A second robustness check increases the strength of technology diffusion. In the model, the degree of spatial diffusion of technology is given by $1 - \gamma_2$. In this exercise, we decrease γ_2 from 0.993 in the benchmark to 0.991. This amounts to an increase in the degree of spatial diffusion of 20 percent. This has two effects: on the one hand, it gives places better access to best-practice technology, and on the other hand, it reduces the incentive to agglomerate. How does this affect the losses from flooding? The rise in the sea level forces economic activity to move out of some previously highly productive places. However, if other locations have easier access to best-practice technology through spatial diffusion, that loss is less pronounced. As a result, in present discounted value terms, the loss in real GDP drops slightly from 0.19 percent in the benchmark to 0.17 percent when the diffusion of technology is stronger. The welfare effects of flooding remain virtually unchanged.

Spatial Scope of Technology Diffusion: Technology diffusion in the model is slow, but it reaches the whole world simultaneously, since we assumed η to be a constant. To explore what happens if technology diffusion is stronger locally, we assume that $\eta(r,s) = \bar{\eta}\exp\left(-\varkappa\delta(r,s)\right)$, with $\varkappa > 0$ and $\delta(r,s)$ denoting the distance between locations r and s measured in kilometers. Based on Comin, Dmitriev, and Rossi-Hansberg (2012), we use $\varkappa = 0.0015$. When moving from a world with global diffusion to one with local diffusion, we observe greater losses. In present discounted value terms, the real income loss from flooding increases from 0.19 percent to 0.24 percent, and the welfare loss increases from 0.24 percent to 0.30 percent. This makes sense: less spatial diffusion of technology implies a greater role for local innovation, implying there is more local productivity embodied in the large population centers. This increases the losses from flooding, as leaving Manhattan or Miami behind becomes more costly.

Production Externalities: To further understand the role of static production externalities, we analyze what happens when we eliminate them. That is, we no longer assume that local density has a direct positive effect on local productivity. Since this affects the spatial concentration of economic activity both under the flooding and the nonflooding scenarios, we would probably expect the effect of inundation on real income and welfare not to change much. There is one subtle change that might potentially worsen the negative impact of flooding though. As we discussed before, in a world with production externalities, the greater geographic concentration that comes with sea level rise partly compensates the direct negative impact of flooding on real income. By eliminating static production externalities, this mitigating effect is no longer present. However, our analysis

shows that this change is quantitatively negligible: both the real income effects and the welfare effects of flooding are essentially left unchanged compared to the benchmark case.

Congestion.—As a last robustness check, we increase the congestion parameter by 50 percent. That is, we increase the elasticity of amenities to population density by one-half, implying that local amenities suffer more from congestion than before. This reduces the incentives for people to geographically concentrate. As in the previous robustness check, the mitigating effect of the increased spatial concentration due to flooding weakens. On the other hand, higher congestion in amenities implies that fewer people choose to live in coastal regions, hence reducing the negative impact of coastal flooding. The results are reported in panel B of Table B2. The overall effect on real GDP per capita is very slight: the negative effect drops from 0.19 percent to 0.18 percent. The increase in congestion costs also has a direct impact on the utility that people derive from amenities. As a result, the greater geographic concentration that comes from land loss implies a somewhat larger negative welfare effect from flooding: in present discounted value terms, it increases from 0.24 percent in the benchmark to 0.29 percent when the congestion parameter is 50 percent larger.

C. *Alternative Datasets on Sea Level Rise Projections and Elevation*

In this section, we compare how our findings change when using alternative datasets on elevation and sea level rise projections. For elevation, we consider JAXA's ALOS World 3D 30m mesh (AW3D30) for the entire globe. For sea level rise projections we consider DP16 (Kopp et al. 2017). These replace the Antarctic projections of K14 (Kopp et al. 2014), which are based on the "likely" range assessment of Church et al. (2013) and the structured expert judgement of Bamber and Aspinall (2013), with ensembles of Antarctic simulations developed with a physical model, as described by DeConto and Pollard (2016). This model incorporates multiple modes of Antarctic instability involving ice shelves and ice cliffs, which leads to more rapid mass loss from the Antarctic ice sheet in the second half of this century and beyond, particularly under higher emissions scenarios.

Table C1 reports our findings for GDP and welfare losses, as well as for the share of population that gets displaced by flooding. When using DP16, real GDP losses rise to 0.32 percent in present discounted value terms, compared to 0.19 percent in our benchmark case. We see a similar pattern for welfare losses, which increase from 0.24 percent in the benchmark to 0.39 percent. The percentage of the population displaced by flooding in 2200 is also higher: 3.25 percent of the world's population, compared to 1.46 percent in the benchmark case. The effects of flooding are larger in Kopp et al. (2017) because the sea level rise projections include a less stable Antarctic ice sheet and thus tend toward faster sea level rise after 2050 (DeConto and Pollard 2016).

When using AW3D30 elevation data, the effects are smaller. Real GDP losses in present discounted value terms drop to 0.07 percent. These alternative elevation data also generate smaller displacements of the world's population: 0.46 percent in

TABLE C1—ROBUSTNESS TO DIFFERENT ELEVATION DATA

Elevation data	Real GDP PDV		Welfare PDV	
Panel A. Percentage flooding losses in the world				
1. Benchmark K14 coastal DEM (RCP 4.5)				
Mean (percent)		0.19		0.24
95 percent credible interval (percent)	0.12	0.44	0.14	0.55
2. DP16 Coastal DEM (RCP 4.5)				
Mean (percent)		0.32		0.39
95 percent credible interval (percent)	0.16	0.49	0.18	0.69
3. K14 AW3D30 DEM (RCP 4.5)				
Mean (percent)		0.07		0.09
95 percent credible interval (percent)	0.02	0.16	0.03	0.20
4. DP16 AW3D30 DEM (RCP 4.5)				
Mean (percent)		0.14		0.17
95 percent credible interval (percent)	0.05	0.27	0.07	0.35
Elevation data	2100		2200	
Panel B. Percentage of population displaced by flooding in the world				
1. Benchmark K14 CoastalDEM (RCP 4.5)				
Mean (percent)		0.58		1.46
95 percent credible interval (percent)	0.13	1.30	0.15	3.54
2. DP16 coastal DEM (RCP 4.5)				
Mean (percent)		0.96		3.25
95 percent credible interval (percent)	0.19	2.14	2.00	4.53
3. K14 AW3D30 (RCP 4.5)				
Mean (percent)		0.17		0.46
95 percent credible interval (percent)	0.03	0.40	0.03	1.47
4. DP16 AW3D30 (RCP 4.5)				
Mean (percent)		0.30		1.33
95 percent credible interval (percent)	0.05	0.73	0.57	2.41

Notes: Panel A: Calculations based on 4 percent annual discount rate. Percentage change in PDV refers to (PDV of nonflooding scenario/mean of PDV of flooding scenarios) − 1, using a simulation over 200 years. Panel B: Percentage of population displaced refers to the sum of differences in absolute value of cell population under non-flooding scenario and cell population under the mean flooding scenario divided by twice the total population. In both panels, K14 and DP16 refer to sea level rise projections according to Kopp et al. (2014) and Kopp et al. (2017), whereas CoastalDEM and AW3D30 refer to digital elevation models from JAXA's ALOS World 3D 30m mesh and Kulp and Strauss (2018). The benchmark in the paper corresponds to K14 CoastalDEM. All simulations are for the medium RCP 4.5.

2200. These smaller numbers are due to the higher positive vertical bias, compared to CoastalDEM. For completeness, Table C1 also includes an additional robustness exercise where we simultaneously use DP16 for the sea level rise projections and AW3D30 for the elevation data.

Figures C1 through C3 display the cell-level effect on real GDP in the year 2200 using the alternative flooding projections and elevation data. The DP16 projections increase losses in coastal areas, whereas AW3D30 reduces coastal losses. These findings are confirmed in Table C2, which reports population losses in 25 major coastal cities. Using the benchmark K14 and CoastalDEM data, Miami loses 6.7 percent of its population. When using DP16 sea level rise projections that include more rapid Antarctic ice sheet loss, Miami loses 49.8 percent of its population. In contrast, when using AW3D30 elevation data that include greater vertical bias, Miami experiences no losses.

Percentage loss in total cell real GDP in 2200 (RCP 4.5)
(nonflooding scenario/mean of flooding scenarios) − 1
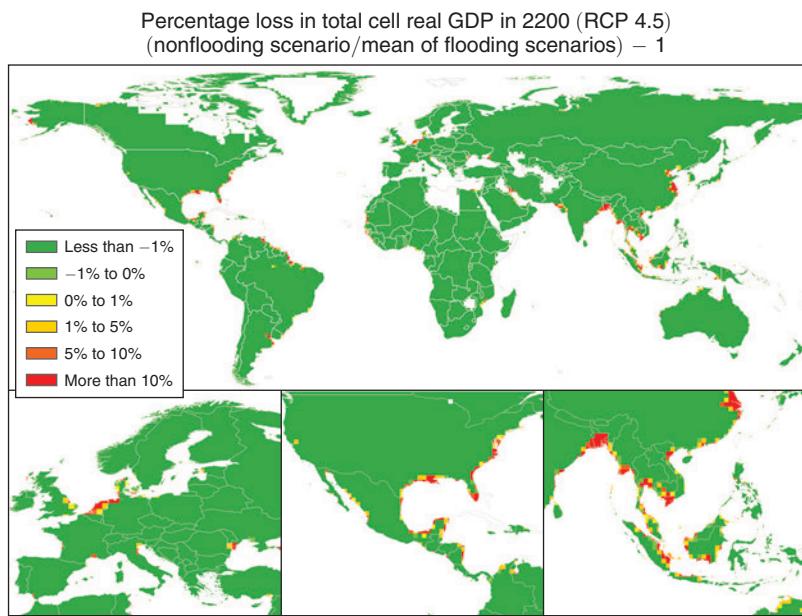
FIGURE C1

Note: Percentage mean loss in total cell real GDP in 2200 under RCP 4.5 using Kopp et al. (2017) SLR projections (DP16) and CoastalDEM elevation data.

Percentage loss in total cell real GDP in 2200 (RCP 4.5)
(nonflooding scenario/mean of flooding scenarios) − 1
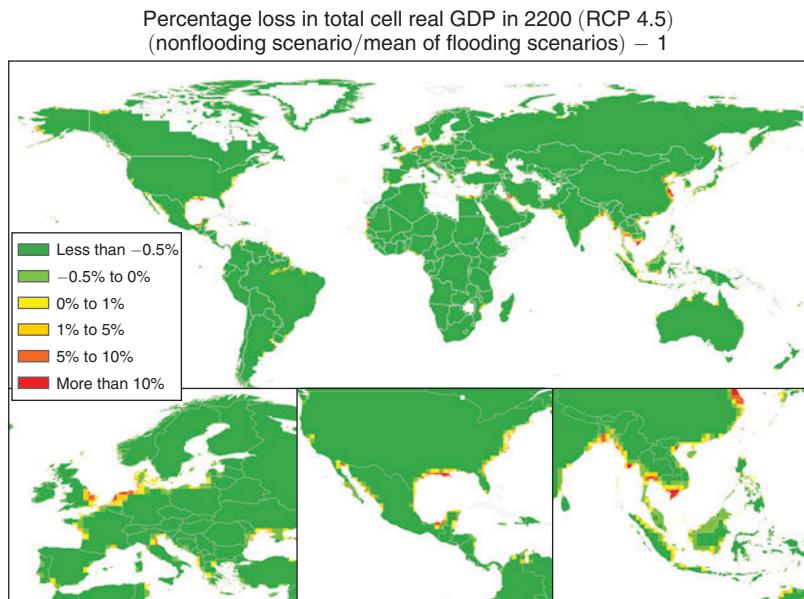
FIGURE C2

Note: Percentage mean loss in total cell real GDP in 2200 under RCP 4.5 using Kopp et al. (2014) SLR projections (K14) and JAXA's AW3D30 elevation data.

Percentage loss in total cell real GDP in 2200 (RCP 4.5)
(nonflooding scenario/mean of flooding scenarios) − 1

Legend:
- Less than −1%
- −1% to 0%
- 0% to 1%
- 1% to 5%
- 5% to 10%
- More than 10%
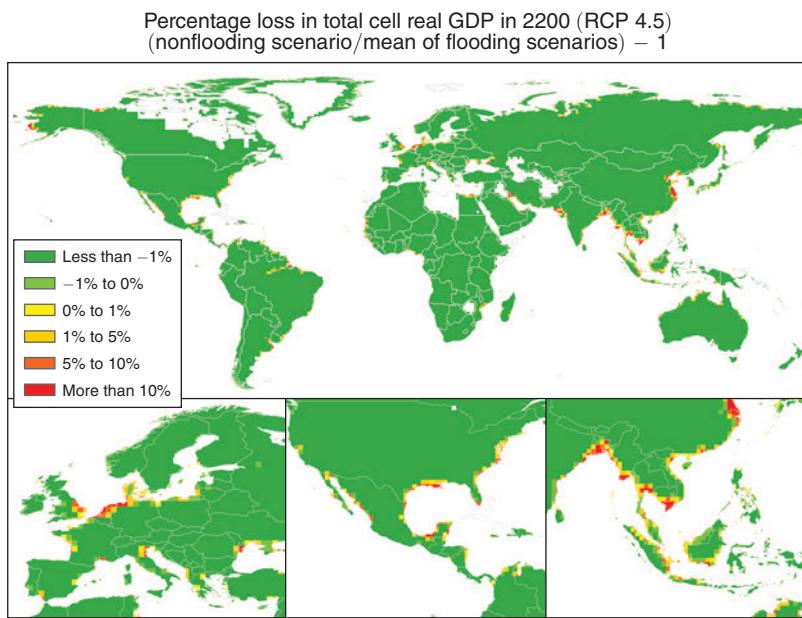
FIGURE C3

Note: Percentage mean loss in total cell real GDP in 2200 under RCP 4.5 using Kopp et al. (2017) SLR projections (DP16) and JAXA's AW3D30 elevation data.

TABLE C2—POPULATION LOSS IN A SAMPLE OF 25 LARGE CITIES IN 2200 USING ALTERNATIVE ELEVATION DATA

Metropolitan area	Coastal DEM (percent)		AW3D30 DEM (percent)	
	K14	DP16	K14	DP16
Amsterdam	6.6	46.3	8.7	24.8
Bangkok	162.0	187.6	58.2	116.7
Barcelona	−1.7	−3.5	−0.5	−1.5
Buenos Aires	0.7	5.6	0.3	2.2
Ho Chi Minh City	21.8	37.1	24.4	61.6
Hong Kong	−0.4	−0.9	0.0	−0.2
Houston–Galveston–Brazoria	0.5	0.4	0.4	0.9
Karachi	4.9	11.7	2.4	7.8
Kolkota	6.6	34.1	0.9	7.9
Kuala Lumpur	1.5	3.3	−0.2	−0.3
Lagos	−1.2	−1.2	−0.2	−0.1
Lima	−1.4	−2.3	−0.4	−1.1
Los Angeles–Riverside–Orange County	−1.4	−2.5	−0.5	−1.2
Manila	0.7	0.6	−0.1	0.2
Miami–Fort Lauderdale	6.7	49.8	−0.2	3.6
Mumbai	1.8	3.5	1.8	3.9
New York–Northern New Jersey–Long Island	0.4	1.0	0.7	1.3
Rio de Janeiro	−1.0	−2.3	−0.5	−1.4
San Francisco–Oakland–San Jose	−1.1	−2.1	0.3	0.4
Seoul	−0.1	0.9	−0.1	0.2
Shanghai	149.7	688.2	18.4	73.5
Singapore	−1.0	−1.7	−0.3	−0.8
Sydney	−1.3	−2.6	−0.4	−1.1
Tianjin	20.3	45.5	6.9	24.9
Tokyo	1.1	3.1	0.2	0.7

Notes: The geographic extent of metropolitan areas is defined as their built-up areas in 2016 and come from the Atlas of Urban Expansion (http://www.atlasofurbanexpansion.org/). Percentage loss refers to (nonflooding scenario/mean of flooding scenarios) − 1, where the flooding scenarios are based on RCP 4.5. Calculations assume that the share of a city's land flooded is the same as that of the 1° by 1° cells the city belongs to. K14 and DP16 refer to sea level rise projections according to Kopp et al. (2014) and Kopp et al. (2017), whereas CoastalDEM and AW3D30 refer to digital elevation models from JAXA's ALOS World 3D 30m mesh and Kulp and Strauss (2018). The benchmark in the paper corresponds to K14 CoastalDEM.

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