Urbanizing the floodplain: Global changes of imperviousness in flood-prone areas

Konstantinos Andreadis (✉ kandread@umass.edu)

University of Massachusetts Amherst <https://orcid.org/0000-0002-3642-6615>

Oliver Wing

University of Bristol <https://orcid.org/0000-0001-7515-6550>

Emma Colven

University of Oklahoma

Colin Gleason

University of Massachusetts

Paul Bates

University of Bristol <https://orcid.org/0000-0001-9192-9963>

Casey Brown

University of Massachusetts

Physical Sciences - Article

Keywords: Urban Encroachment, Natural Hazards, Population Growth, Population Density, Flood Risk Management, Adaption Pathways

Posted Date: July 30th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-737556/v1>

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Urbanizing the floodplain: Global changes of imperviousness in flood-prone areas

Konstantinos Andreadis¹, Oliver Wing^{2,3}, Emma Colven⁴, Colin Gleason¹, Paul Bates^{2,3}, and Casey Brown¹

¹Civil and Environmental Engineering, University of Massachusetts Amherst

²School of Geographical Sciences, University of Bristol

³Fathom, Bristol, United Kingdom

⁴International and Area Studies, University of Oklahoma

Abstract

Cities have historically developed close to rivers and coasts, increasing human exposure to flooding. That exposure is exacerbated by changes in climate and population, and by urban encroachment on floodplains. Although the mechanisms of how urbanization affects flooding are relatively well understood, there have been limited efforts to assess the magnitude of floodplain encroachment globally and how it has changed in both space and time. Highly resolved global datasets of both flood risk and changes in urban area from 1985-2015 are now available, enabling the reconstruction of the history of floodplain encroachment at high spatial resolutions. Here we show that the urbanized area in floodplains that have an average probability of flooding of 1/100 years, has almost doubled since 1985. Further, the rate of urban expansion into these floodplains increased by a factor of 1.5 after the year 2000. We also find that urbanization rates were highest in the most hazardous areas of floodplains, with population growth in these urban floodplains suggesting an accompanying increase in population density. These results reveal the scope, trajectory and extent of global floodplain encroachment. With tangible implications for flood risk management, these data can be directly used with integrated models to assess adaptation pathways for urban flooding.

Main

More than half (55%) of the world's population lives in urban areas and that percentage is projected to increase to 68% by 2050¹. While centers of wealth and economic activity, cities host impoverished and vulnerable communities. In addition, urban areas also have a high density of transportation, telecommunications infrastructure, and energy assets. Any disruption to urban areas caused by flooding and other natural disasters therefore has the potential to impact human welfare². The intensity of flooding is generally expected to increase globally with climate change³⁻⁵. At the same time, exposure to flood hazards is increased due to the urbanization of flood-prone areas and the concomitant population growth. The effects of urbanization on floods are generally well understood⁶⁻⁸, but it is also imperative to understand how urbanization has varied globally in relation to flood risk. Recent work shows that built-up areas on floodplains have increased⁹, although most studies have been regional^{10,11} without a global assessment

of floodplain encroachment in both space and time. Moreover, other recent studies have examined the relationship between population dynamics and flooding but have focused on the population response to flood events^{12–14}. In this paper, we combined maps of fluvial and pluvial flood inundation with maps of urban area changes to quantify floodplain encroachment globally as a function of flood probability rather than the actual occurrence of flooding. Although urbanization in flood-prone areas has increased overall, the magnitude, rates and associated risk of floodplain encroachment have varied both in space and time and have not yet been systematically quantified globally.

Recent big-data computational technologies have facilitated efficient processing and generation of global geospatial datasets at relatively high resolution¹⁵, enabling our analysis of urbanization and flood risk. We estimated floodplain encroachment by combining the Global Annual Urban Dynamics (GAUD) dataset¹⁶ that comprises of annual (1985–2015) 30-m maps of urban areas, and a model-derived floodplain delineation that assigns flood risk to ~90-m pixels globally¹⁷. Both of these datasets offer better accuracy and higher spatial resolution compared with previously available datasets, improving our ability to resolve the localized impacts of flooding in urban areas on a global scale¹⁸. Flood hazard was defined from its return period (T), which ranged from 5 to 1000 years, corresponding to a $1/T$ average annual probability of exceedance (e.g., the 100-year flood has an average annual probability of 1/100, or 1%). We then generated an annual time series of floodplain encroachment from 1985 to 2015 for different levels of flooding probability by overlaying the urban area and floodplain maps (see Extended Data Fig. 1). In addition to estimating the area of floodplain encroachment, we used population grids for 1990, 2000, and 2015, to determine the population potentially exposed to flooding of different probabilities given the urban sprawl on the floodplain. There are a number of factors that can introduce uncertainty into the estimates of flood inundation^{19,20} and mapping of urban areas²¹, while variability in population datasets can significantly affect estimates of population exposure to flooding²². In order to ameliorate those potential uncertainties, we used all available population datasets that had global and multi-temporal coverage with a threshold of 1 km for spatial resolution (see [Methods](#) for details). On the other hand, GAUD implicitly incorporates (via data fusion) multiple global urbanization datasets while the model-derived floodplain delineation is unique in terms of spatial coverage, resolution, and explicit accounting of flood risk. Therefore, we only used single datasets for mapping the floodplain and urbanization but report the results in a regional context (e.g., per country) to abate the effects of local-scale errors²³.

As of 2015, 16.2% of the world's urban area was within the 100-year floodplain (105,657 km²). The extent of urban development on the 100-year floodplain was similar for each continent with the notable exception of Asia: 12.0% and 12.7% for North and South America, 7.9% for Oceania, 12.5% for Europe, 13.1% for Africa, and 22.7% for Asia. When examining the spatial distribution of the 100-year floodplain urbanization (Fig. 1a), eastern China, Korea, southeast Asia, central Europe, parts of the middle East, the Nile River basin, parts of sub-Saharan and southern Africa, Pakistan, northern India, Colombia and parts of Mexico, and a number of cities in the United States all stand out as hotspots.

On average, the urban area with a 1/100 annual probability of flooding increased by 2.5% per year, and this rate of encroachment was relatively constant for the Americas, Europe and Africa (Extended Data Fig. 2). Asia had an average 5.6% encroachment rate with a peak of 8.9% during the 30-year study period. These relatively high rates were also evident when assessing the proportion of urbanization that occurred after 1985 (Fig. 1b). Almost all encroachment in the 100-year floodplain occurred after 1985 in India, Philippines, Thailand, Vietnam, Indonesia and parts of China as well as parts of the Middle East, sub-Saharan Africa, Spain, Mexico, Brazil, and United States. On the other hand, increased levels of urbanization in the 100-year floodplain for some regions like central Europe, western United States,

Japan and southeastern China appears to have occurred prior to 1985 with little additional encroachment in the past three decades.

As well as quantifying floodplain encroachment as a fraction of the total urbanized area, we can also examine the associated population occupying those areas. As of 2015, 457.1 ± 134.7 million people in urban areas are exposed to floods with a 1% annual exceedance probability (i.e., 1/100-year floodplain). Most of that population lives in Asia as expected, however the proportion of population in the floodplain is higher in Asia as well. Relative to their total population, the urban population residing in the 1/100-year floodplain varies substantially: $6.8 \pm 2.6\%$ for Asia, 8.0 ± 0.7 and $6.5 \pm 2.2\%$ for North and South America, $5.6 \pm 1.6\%$ for Europe, $3.6 \pm 1.5\%$ for Africa, and $3.8 \pm 0.2\%$ for Oceania. The 2015 population in both urban and non-urban areas that is potentially exposed to a 1/100-year flood is 1.49 ± 0.03 billion, which is consistent with recent studies²⁴.

We also assessed the urban areas exposed to different levels of flood hazard. Almost half of the 2015 urban area in the 1/100-year floodplain resides in the 1/20-year floodplain (i.e., on land with a higher flood frequency by a factor of 5). All continents had about the same proportion of their urban area within the 1/20-year floodplain in 2015 except for Asia (highest) and Oceania (lowest). Similar results were found for floodplain encroachment when examining other annual flooding probabilities in terms of proportion of each continent's total urban area (Extended Data Table 1).

The proportion of urban areas exposed to flooding through time is shown in Fig. 2, which further breaks down the proportions by the highest frequency at which a given area is inundated. The urbanized area in the 1/100-year floodplain appears to have practically doubled between 1985 and 2015 (from 8.2 to 16.2%), which is also the case for all flood frequencies. In addition to the increase of floodplain encroachment globally, the magnitude of the annual urban expansion has increased since 2000 for all flood probabilities ($p \leq 0.01$). In fact, it appears that urban areas on floodplains have been expanding about 1.5 times faster on average during 2000-2015 compared to the 1985-2000 period. Floodplains corresponding to return periods less than 100-years had the highest rates of urbanization globally throughout the study period with average rates between 2.3 and 2.4% per year. The urban expansion rate was slightly slower for floodplains with smaller annual flooding probabilities at 2.2 and 2.1% per year.

We have established that as of 2015, 28.3% of the total global urban area occupied the floodplain (up to 1/1000 annual flooding probability), 46.7% of which was urbanized after 1985. This development varied both geographically and in terms of corresponding flooding probability, and therefore it is important to examine the magnitude and trajectories of floodplain encroachment for different regions globally. In order to jointly characterize the degree of urbanization that occurred after 1985 and the associated increase in flood probability, we developed a 9-class compound urban flooding index (see [Methods](#) for details). Encroachment of relatively high flood probability areas appears to have intensified since 1985 in many regions in Asia, Europe, and North America (Fig. 3), while urban expansion on floodplains with lower flood probability has occurred in Europe, South America, and Africa. Eastern China has the largest area urbanized after 1985 on the floodplain with 1/20-year flood probability (Extended Data Fig. 3), with northern India and Indonesia also showing high degrees of urbanization over large areas of the frequently inundated floodplain. Parts of the Middle East, Egypt, Italy, and Mexico as well as many regions in the United States have also urbanized relatively high flood probability areas, while South American, African and some European areas have expanded either on non-floodplain land or areas with relatively lower flood probability. On the other hand, a number of countries in central Europe, South America and South-east Asia, as well as parts of China and the United States show relatively low urbanization but most of it occurring in floodplain areas with high flooding frequency. The explicit delineation of the floodplain

Fig. 1 | Fraction of urbanization on the 100-year floodplain. **a**, Map of urbanized area (percent fraction) as of 2015 that is in the 100-year floodplain. Fractions were calculated as the number of urban pixels overlapping the 100-year floodplain divided by the number of urban pixels within a 0.1° area (for display purposes). **b**, Percent fraction of the 2015 100-year floodplain encroached area (**a**) that was urbanized after 1985.

based on flood return periods in our dataset also allows the assessment of the degree of urbanization in terms of the total urban area on the floodplain (Extended Data Fig. 3), which shows similar results to the bivariate analysis in terms of total urbanization (both floodplain and non-floodplain) with a few differences. Some regions (e.g., Brazil, sub-Saharan Africa) had significant proportions of their floodplain encroachment on higher risk areas despite the total urban expansion being relatively low.

Finally, we assess global floodplain encroachment in conjunction with total population for different levels of flood hazard. The number of people in urban areas on floodplains (regardless of hazard level included here) increased from 0.45 (± 0.21) billion in 1990 to 0.87 (± 0.23) billion in 2015, while the corresponding numbers were 1.18 (± 0.15) and 1.48 (± 0.19) respectively for non-urban areas. Despite

Fig. 2 | Urbanized floodplain area for different risk levels. Annual time series of global urban area (in percentage, normalized by the 2015 total urban area) on the floodplain for different flood return periods (5 to 1000 years).

Fig. 3 | Floodplain urbanization and associated flood probability. Bivariate choropleth map of urbanization that occurred on the floodplain between 1985-2015 combined with a weighted estimate of flood probability that corresponds to the urbanized area.

the variability between the different datasets, there is consensus that the non-urban proportion of the population exposed to flooding is larger than the urban proportion (Fig. 4a). About 3/4 of the non-urban population on the floodplain are exposed to flooding probabilities of 1/100 years, while the same is true for about half the urban population. These proportions are consistent among the different datasets, while also remaining relatively constant for the three epochs (1990, 2000, and 2015) available in the population datasets used. On the other hand, we found a significant difference between the distribution of the overall population increase on the floodplain between urban and non-urban areas. Specifically, 33.2 ± 0.8 % of the population increase globally between 1990 and 2015 occurred on floodplains, and most of that increase was found in urban areas (20.7 ± 6.7 % of the total population increase).

Total population on the floodplain has increased at a slower rate when comparing the 1990-2000 and 2000-2015 periods, with the highest rates associated with elevated flooding probabilities (return periods of 100-years or less). The slower population growth after 2000 was true for both urban and non-urban areas on floodplains, but the discrepancy between the rates was significantly more pronounced for non-urban areas (Fig. 4b). More importantly, population growth was not only higher in urban areas compared to non-urban areas on floodplains but is also increased for higher flooding probabilities. The highest population growth rate in urban floodplain areas was 4.2 ± 0.6 % for the 1/20-year return period and the lowest was 3.2 ± 0.4 % for the 1/1000-year probability. The impact of these population growth rates is also evident from the ratio of urban to non-urban population on the floodplain. There was an increase of about 25% in that ratio from 1990 to 2000, and a subsequent increase for all population datasets from 2000 to 2015 although there was significant uncertainty in the actual percentage which ranged between 29 and 61%. Despite the variability in the datasets, we consistently found that the population size has increased in urban areas on the floodplain. It is difficult to attribute the accelerated urbanization rates on the floodplain as driven by population or related to commercial and industrial purposes¹⁶, but these results do agree with recent work that found that built-up areas and population on the floodplain have increased in most of the world's countries¹³.

Urbanization is driven by a number of factors including economics (e.g., job opportunities), industrialization, population pressure, political conditions, natural disasters in rural areas²⁵ and is expected to triple its 2000 extent by 2030²⁶. The link between urbanization and potential increase in flood risk stems from hydrologic alteration from impervious surface areas^{27,28}, effects on local climate²⁹, or changes in exposure (e.g., population distribution changes)³⁰. Recent studies found that urbanization can significantly exacerbate flood risk; for example, during Hurricane Harvey the probability of flooding was elevated by ~21 times due to urbanization³¹. Therefore, our results that showed the doubling of the urban area within the 1/100-year floodplain and the accelerated rate of urbanization since 2000 have significant implications despite some potential limitations.

Although the simulation that we used to delineate the floodplain globally relied on a state-of-the-art hydrodynamic model, it only approximately accounted for flood protection measures (see [Methods](#) for details). The presence of flood defenses such as dams and levees would reduce the flood risk to the exposed population³², and there have been recent efforts to improve their representation in high-resolution, large-area models³³. On the other hand, there have been a number of studies positing that the installation of structural protection measures changes the perception of risk at an institutional level leading to the further urbanization and population increase (or resettling after a flood event) in flood-prone areas¹². In the context of this “safe development paradox”, the actual efficacy of flood defenses is further complicated when considering issues such as effects of levees³⁴, damages and maintenance requirements, or the socio-economic conditions of the population suffering flood losses or benefiting from protection

Fig. 4 | Global population dynamics for different flood risk levels. a, Population size (in millions) exposed to different levels of flooding probabilities (indicated by the return period T , 10 to 1000 years) from 1990, 2000, and 2015. Population size was estimated for both the non-urban and urban portions of the floodplain. **b,** Population growth rates (% per year) for different subsets of the study period (1990-2015, 1990-2000, and 2000-2015) in relation to flood annual probability (expressed in terms of the return period T).

measures^{35,36}. Furthermore, even areas that are protected by defenses build at a specific standard (e.g., 100 years) can become exposed in the near future due to increases of flood magnitudes for the same return period³⁷. For example, a recent study¹⁸ found that $\sim 2,200 \text{ km}^2$ of land currently defended from a 1/100-year flood will be at risk by 2050 in the United States under one of the intermediate climate change scenarios (RCP 4.5). In sum, we conclude that (i) human settlement on floodplains is increasing, with impervious surface area expansion rates accelerating; (ii) the total urban area in floodplains has nearly doubled since 1985; (iii) population size has grown on the floodplain with the highest rates in areas with 1/20 annual probability of flooding. We argue that our analysis can act as the baseline for assessing the relationship between urbanization and flood risk, as the resulting dataset is physically-based at sufficiently high spatial resolution with global coverage. Despite their potential value, such maps can only be a component of the integrated modeling frameworks¹⁸ required to correctly assess all aspects (socio-economic, engineering, policy etc.) of national and local flood management.

Methods

Mapping changes in impervious area

We reconstructed global changes in impervious area from 1985-2015 from an annual urban mask that maps changes from non-urban to urban areas. The annual urban maps were obtained from the Global Annual Urban Dynamics (GAUD) dataset¹⁶, which provides information on the year when urban expansion (i.e., increase in built-up areas) or reversal to increased vegetation (i.e., green recovery) occurred within the 1985-2015 period. GAUD is derived from Landsat imagery at 30m resolution by fusing four global urbanization datasets (Global Human Settlement Layer, Global Urban Footprint, Global Urban Land, and the Global Artificial Impervious Area) and then applying the normalized urban areas composite index (NUACI) to identify years of urbanization or green recovery. The fusion algorithm kept the urban areas that were consistent among the other products, and used a locally adaptive random forest classifier for the inconsistent pixels. The years of urban expansion and green recovery were identified with a temporal segmentation approach which fits a regression model to the NUACI time series and classifies the year with the largest residual as the year of change³⁸. When validated against 200,000 samples, GAUD was shown to have higher accuracy compared to other available global datasets with lower commission and omission errors. Specifically, GAUD had an accuracy of detecting years of urbanization between 76 and 82% for the majority (90%) of global urban areas, while green recovery years were identified with an accuracy of 78%.

Calculating floodplain encroachment

The annual maps of urbanization were overlaid on floodplain maps providing a quantitative estimate of floodplain encroachment at different flood probability levels. Global datasets of geolocated information on floodplains are not readily available with the exception of the recently developed GFPLAIN250m, which uses a morphometric approach to derive fluvial valley zones from elevation data³⁹. Despite the global coverage of the GFPLAIN250m dataset though, it does have some limitations which make it inappropriate for our analysis including its relatively coarse 250m spatial resolution that could produce unreliable floodplain maps⁴⁰ especially for flat alluvial plains as it most likely will work best in confined valleys. Moreover, the geomorphologic approach used to derive GFPLAIN250m does not incorporate any

of the physics governing water flow, while also not accounting for different levels of flood probability. An alternative approach could include mapping areas that became inundated from an adequately long-term dataset such as the Global Surface Water which classified 32 years of water surface dynamics from Landsat data⁴¹. Nonetheless, the ephemeral nature of flood events as well as the inherent limitations of optical sensors (e.g., obscuring cloud cover) imply that not all areas that could potentially inundate would be observed and similar to GFPLAIN250m information on flood probability would be difficult to extract. Consequently, the only viable approach to deriving a global floodplain map is to use a hydrodynamic model that can simulate flood inundation for events associated with different flooding probability levels.

Here, we delineated floodplains globally using the Fathom-Global flood inundation model¹⁷, which is based on the local inertial formulation of the shallow water equations in 2-D⁴². In order to account for different flood probability levels, we simulated ten discrete flood return periods including 5, 10, 20, 50, 75, 100, 200, 250, 500, and 1000 years for both fluvial and pluvial perils. River discharge for each of these simulations was estimated by a global regional flood frequency analysis⁴³, where the extreme flow behavior modeled in both gauged and ungauged catchments via transfer functions in the latter case. These flows were then routed in 1-D through river channels delineated from the MERIT-Hydro hydrography dataset⁴⁴, with a conveyance constraint of a 2-year return period discharge that corresponds to bankfull flow conditions. The model can resolve rivers of any size with a sub-grid channel formulation⁴⁵, and for these global simulations we explicitly simulated flow in rivers with a drainage area larger than 50 km². Once bankfull capacity is exceeded, the model simulates water flow in 2-D over the topography derived from the MERIT digital elevation model at 3 arc second (~90m at the equator) spatial resolution. The pluvial component of the model generates non-riverine surface runoff via a rain-on-grid approach and is used to simulate the inundation extent in catchments smaller than 50 km², with extreme rainfall represented by Intensity-Duration-Frequency relationships. Flood protection measures are estimated in the absence of a global inventory of such data. The FLOPROS database⁴⁶ is used to assign return period defense standards to river reaches, depending upon whether they are high-density urban, low-density urban, or suburban. Channels thus convey the 2-year discharge in rural areas, and the T-year discharge in other areas depending on the information in FLOPROS. Similarly, pluvial defense standards are assumed for different levels of urban density. For urban (high), urban (low), and suburban, assumed pluvial defenses correspond to the 2-, 5-, and 10-year in less developed regions and 5-, 10-, and 25-year in more developed regions. Rainfall boundary conditions in the pluvial model are then adjusted based on these assumed drainage design standards.

Output of the model (and the LISFLOOD-FP model on which the core numerical engine is based) has been successfully and extensively validated in many regional case studies globally^{47,48}. These studies show that the core numerical model can reproduce analytical solutions to the full shallow water equations⁴² and, when driven with gauged flows and high accuracy terrain data (e.g., airborne Lidar), can achieve accuracies of up to 90% against high-accuracy inundation data (as determined using a robust Critical Success Index metric). When used with lower quality data, such as those available globally, these methods can still achieve Critical Success Index values of up to 70% at ~90m resolution, with errors in fractional inundated area decreasing below 10% when data are aggregated to 1 km²¹⁷. The flood maps generated from the model represent the maximum depth of pluvial and fluvial flooding in a 3 arc second (~90m) area during a flood event of a specific return period, and therefore were compressed into a single global flood frequency layer where each pixel value corresponds to the highest frequency (i.e., lowest return period) flood when that pixel was inundated.

In order to quantify floodplain encroachment we overlaid the annual maps of impervious area change

onto the floodplain maps and then classified each pixel as encroached if the pixel became urban during the study period (1985-2015) and was inundated for any of the flood simulations. Each of these simulations corresponds to a specific event return period and therefore we were able to assign a flood probability level to the urbanized area, as well as the year that they were urbanized. Any areas where “green recovery” occurred were reclassified as non-encroached floodplain starting at the year when recovery was detected according to GAUD.

Flooding probability was defined as the return period of the simulation that was used to derive the corresponding floodplain (from the simulated inundation extent), but we also derived a flood risk index which was calculated for a predefined area (0.1° pixels for Fig. 3). This aggregate risk index was simply computed by multiplying the number of pixels (n_f) within the predefined area that were encroaching the floodplain for each return period, with the mean probability of occurrence

$$\sum_f \frac{1}{T_f} n_f \quad (1)$$

where $T_f \in (5, 10, 20, 50, 75, 100, 200, 250, 500, 1000)$. The aggregate risk index values along with the total encroachment area expansion for each 0.1° pixel were binned into 3 classes each, with the bounds of each class derived from the 33th and 66th percentiles of the corresponding values. These classes were subsequently combined to form 9 classes that represented a compound urbanization and flood risk indicator.

In addition to urbanized area on the floodplain we examined the population exposed to the different levels of flood probability. Due to the variability of the available population datasets and the potential impact on estimates of population exposed to flood risk²², we used multiple datasets that satisfied the requirements of global coverage, spatial resolution less than 1 km, and multiple epochs. These datasets included: the 9 arc-second ($\sim 250\text{m}$) Global Human Settlement (GHSL) dataset that represents population during 1990, 2000, and 2015⁴⁹; the Global Rural Urban Mapping Project (GRUMP) that has 30 arc-second ($\sim 1\text{km}$) resolution and represents 1990 and 2000⁵⁰; the Worldpop dataset that provides annual data from 2000-2020 on global population at a 3 arc-second spatial resolution⁵¹; the Gridded Population of the World (GPW) dataset that represents population at 30 arc-seconds resolution every 5 years since 2000⁵²; and LandscanTM that provides annual population data since 2000 at 30 arc-seconds resolution globally⁵³. Each dataset is adjusted to match United Nations Population Division (UNDP) national population estimates, but derived with a range of approaches that combine dasymetric algorithms and spatial data (e.g., nighttime lights, built-up area). Due to the scale discrepancy between the derived floodplain encroachment data (3 arc-seconds) and all the population datasets (9 and 30 arc-seconds) with the exception of Worldpop, we calculated the fractional areas of floodplain encroachment per flood probability as the number of 3 arc-second floodplain pixels for each return period T (masked to retain only pixels that were urbanized) divided by the number of non-null pixels within each 9 or 30 arc-second pixel. The population size for a given flood probability was then derived by multiplying the fractional area by the number of people in each 9 or 30 arc-second pixel. In the case of Worldpop, we just aligned the population and floodplain encroachment grids as their spatial resolutions matched resulting in a direct calculation of the population exposed to flooding.

We also calculated the growth rates for both urbanization and population for the entire and subsets of the study period as

$$R_t = \frac{x_t - x_b}{(t - b)x_b} 100\% \quad (2)$$

where x is the urban area or population for the ending and beginning years, t and b respectively. When assessing population changes the periods we used were 1990-2000, 2000-2015, and 1990-2015, whereas urbanization rates were calculated either for each year or the 1985-2000, 2000-2015, and 1985-2015 periods.

Comparison with reference dataset

Although both the GAUD dataset and the floodplain delineation (via the simulated flood inundation proxy) from the LISFLOOD-FP hydrodynamic model have been successfully validated, it is useful to assess the robustness of the floodplain encroachment results. An independent, large-scale urbanization dataset was needed to calculate floodplain encroachment and compare with our results. The National Land Cover Database (NLCD) is a dataset that contains information about urban imperviousness across the United States at high spatial resolution of 30 m⁵⁴ and four eras (2001, 2006, 2011, and 2016). NLCD is derived from Landsat satellite observations and has been shown to have accuracy of 89% for overall land cover classification and 84% for urban classification⁵⁵. We used the NLCD dataset for 2016 and the same approach of overlaying the urban area and floodplain maps to calculate encroachment for different flooding probabilities. In comparison to NLCD, GAUD appears to underestimate floodplain encroachment at higher flooding probabilities, and overestimate at return periods greater than 100 years (Extended Data Fig. 4). Nonetheless, agreement between the GAUD and NLCD results was relatively high with a Mean Absolute Error (MAE) of 1.09 in terms of percent area for 2016 (MAEs were similar for the other years and are not shown).

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Extended Table 1 | Floodplain encroachment per continent and flooding probability. Area of urbanized floodplain (expressed as percentage of the 2015 total urban area) for each continent and different flooding return periods (in years).

<i>T</i>	Africa	Asia	Europe	North America	Oceania	South America
5	2.19	3.45	2.47	3.23	1.07	2.08
20	6.37	10.41	5.91	6.70	2.77	5.84
50	10.33	17.19	9.42	9.66	5.22	9.82
100	13.10	22.65	12.52	12.03	7.92	12.67
200	15.72	28.23	15.72	14.86	10.82	15.28
500	18.86	35.03	19.56	18.43	14.51	18.44
1000	21.04	39.66	22.23	21.02	17.02	20.61

Extended Data Fig. 1 | Floodplain encroachment for different cities. Urbanized floodplain areas for different flooding probabilities (i.e., return period in years) and four cities at the beginning and end of the study period (1985 and 2015). **a**, Houston, USA. **b**, Shanghai, China. **c**, Bangkok, Thailand. **d**, Bogotá, Colombia.

Extended Data Fig. 2 | Urbanization rate of change on 100-year floodplain. Relative expansion rate of the 100-year floodplain encroachment, expressed as percent area per year, for each continent over the 1986-2015 period.

Extended Data Fig. 3 | Floodplain area at different flooding probabilities, urbanized after 1985. Maps of floodplain area that was urbanized between 1986-2015 for different return period intervals (i.e., flooding probability), with areas calculated as the percent fractions of the 2015 total urban area on the floodplain per 1° pixel. The fraction of the 2015 urban area on the floodplain that was non-urban in 1985 (i.e., changed to impervious between 1986-2015) is also shown in the bottom right panel.

Extended Data Fig. 4 | Comparison of floodplain encroachment with NLCD. Urban area of floodplain (expressed as percentage of the total urban area) for different levels of flooding probability, calculated from the GAUD and NLCD datasets.