Greenprint for Chennai – Integrating Natural Infrastructure in City Planning

PRELIMINARY REPORT

Acknowledgement

We sincerely appreciate the support of the Chennai Metropolitan Development Authority (CMDA), Department of Town and Country Planning (DTCP), Chennai Metropolitan Water Supply and Sewerage Board (CMWSSB), Greater Chennai Corporation (GCC) and experts in the field of planning and biodiversity. We are also thankful to al the donors who made this effort possible.

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“First we shape the cities - then they shape us”

- Jan Gehl

Through the LiFE (Lifestyle for Environment) movement, the Government of India is focusing on changing individual lifestyles to benefit the environment and make people more aware and sensitive towards protecting and connecting with our natural environment. This is a key step towards meeting our lofty goals of reducing carbon emissions by 2030. In fact, according to the United Nations Environment Programme (UNEP), if one billion people out of the global population of eight billion adopt environment-friendly behaviors in their daily lives, global carbon emissions could drop by approximately 20 per cent.

While focusing on people behavior is vital in achieving our climate goals, it is equally important to focus on how our cities are planned. The two have to go hand in hand! A sustainable and eco sensitive city masterplan will go a long way in supporting mission LiFE. Integrating our natural wealth of wetlands and urban forests into our cities spatial plan and grey infrastructure development while keeping development goals in sight will help citizens benefit from the various ecosystem services that nature offers us through wetlands and urban forests like water security, better air, cooler temperatures, better mental and physical health of people and restored biodiversity habitats. Once we have sensitively planned cities, changing lifestyles towards environment will also begin to happen more easily.

1. Introduction

India is a country undergoing rapid transformation. Home to 1.3 billion people - 18% of the world's population. By 2024, it will overtake China as the world's most populous country. India adds the equivalent of a New York City to its urban population annually. In 2021, approximately a third of the total population in India lived in cities. The trend shows an increase in urbanisation by almost four percent in the last decade, meaning more people moved away from rural areas to find work and make a living in the cities. This growth has been accompanied by an infrastructure expansion that is remaking the country and fueling a trajectory of industrial advancement and modernisation that has positioned South Asia as one of the fastest-growing regions in the world, while also lifting millions out of poverty.

In India there are several megatrends that will impact cities, but two of them are the most important. The first one is climate change, which is now a reality. Influenced by the monsoonal climatic system, India, and in particular Indian cities, are starting to witness extreme events of flooding and drought.

The second trend is the rapid increase in urbanisation. Cities are an important opportunity from the perspective of development. If cities are managed well, businesses grow, people have better access to services and job opportunities are boosted. We know that 55% of the world population lives in cities and it is expected that this trend will continue for another 20-25 years. The number of people living in cities will increase by one and a half - to 6 billion by 2045.

The developing world is currently experiencing the highest migration of human population to urban spaces. India is at the forefront of the urbanisation movement, with the second largest urban system in the world. From 350 million people already living in 5,000 cities, the population is expected to reach 600 million by 2030 and 800 million by 2050. We currently add 90000 ha of urban space each year; in fact, some of the large cities are adding up to 4000 ha of urban

space each year. Seven out of the 50 most populous cities in the world are in India and the numbers are only growing. Nearly 60% of India's GDP comes from the cities and is expected to reach 70% in 2030. This human and economic infrastructure will be threatened if cities do not strengthen their resilience to the impacts of climate change.

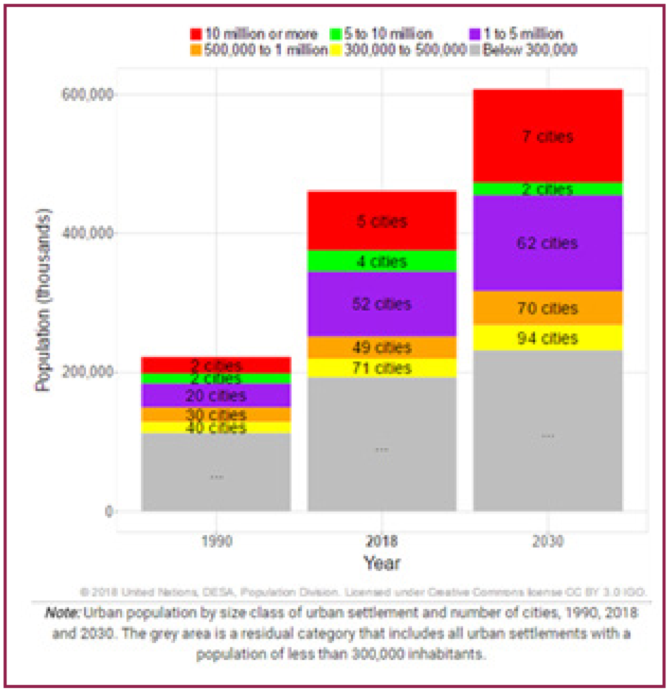

Fig 1: Urbanisation by number and size of cities in India

Given this background of urban growth, the government has begun to take several steps in the direction of making cities resilient. India's National Mission on Sustainable Habitat (NMSH) under the National Action Plan on Climate Change (NAPCC) and Nationally Determined Contributions (NDCs) towards achieving an economy-wide reduction of carbon emissions by 45% by 2030 from the 2005 levels and attaining carbon neutrality by 2070, are some of the ambitious goals of the country, urging people from both top-down and bottom-up towards taking necessary measures for the development of inclusive and climate-resilient cities. With cities known to contribute a major share of greenhouse gases, the country's initiative with the Smart City Mission encourages to take up planning and implementation of environment-friendly measures for the sustainable development of cities. The Climate Smart Cities Assessment Framework 2.0 (CSCAF 2.0) developed by the National Institute of Urban Affairs (NIUA) under the NMSH aims to guide cities' development in a holistic, inclusive, and climate-responsive manner by measuring its development performance against a set of environmental indicators broadly including

Fig 2: Climate Smart Cities Assessment Framework developed by NIUA

While these efforts are commendable, a lot remains to be done to make our cities resilient to impacts of climate change. In most cities, poorly designed land use plans have meant that development has proceeded in a largely haphazard way, resulting in urban sprawl and limited provision of needed infrastructure. Development both by individual owners and large-scale developers fail to consider the wider impact of their investments. Limited coordination between various government departments involved in planning also result in incoherent and overlapping regulations on land use. This model has meant that there are few broader conversations about where growth should or should not go to undo the harms of the city's historically piecemeal approach to planning and zoning, citywide. Without structural mechanisms to proactively plan for growth or development, communities are pushed into reactionary and defensive positions, contributing to a contentious land use review process that fails to foster or encourage equitable growth.

2. Greenprinting: 4-step Framework for Resilient Cities

Recognising these deficiencies, The Nature Conservancy (TNC) India, and partners, developed a framework for urban planning, based on experiences with other development sectors through its Development by Design approach (https://qdra-tnc.org/) to address expected urban development more effectively in the coming years.

The four-step framework called ‘greenprinting’ was developed to address the key deficiencies in urban mitigation and mesh with existing environmental assessments and regulatory approaches. The emphasis was on blending landscape/watershed level conservation planning and the urban planning and urban development process to identify situations where development plans and conservation outcomes may be in conflict. Greenprinting seeks to promote the value that natural habitats deliver to urban environments and how to envision alternatives development approaches that can accommodate both development and conservation outcomes.

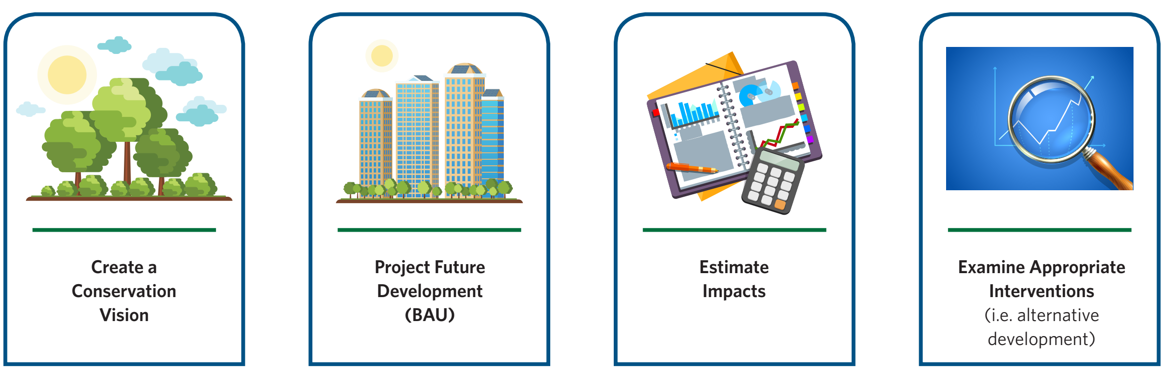

Fig 3: The four step process for developing a greenprint

With dozens of successful examples, including,

San Francisco Bay Area, California, USA

- A tool, the Bay Area greenprint, to support decision-makers and local stakeholders in determining what areas are of highest environmental value, based on relevant local needs.
- It is the go-to resource for land use planning and management decisions by a range of government agencies at the local and state level. For example:
    - **Metropolitan Transportation Commission:** using greenprint to assess Priority Conservation Area grant proposals and to assess the impacts and benefits of the growth network and transportation projects in non-urbanised areas.
    - **Santa Clara Valley Water Agency:** using greenprint to assess the health of watersheds in their region, to consider conservation investments and strategies to protect the water resources and find partners through the multi-benefit assessment.
    - **Local Area Formation Commissions:** a group of agencies in the nine Counties of the Bay Area that approve urban expansion into agricultural land. They are using the greenprint to run reports on proposals for expansions and make decisions.
- San Francisco Bay Area greenprint: https://www.bayareagreenprint.org/

Cape Town, South Africa

- A business case was established for Nature-based Solutions to address the water crisis issue.
- The results of this business case demonstrated that restoring the ecological infrastructure of priority sub-catchments is a cost-effective and sustainable means of augmenting water for the Greater Cape Town Region.
- The business case established that an expenditure $25.5 million USD on catchment restoration will generate annual water gains of 50 billion liters (50 Mm3) eventually increasing to 100 billion liters (100 Mm3) annually within 30 years.
- This was one-tenth of governments estimate of $540 million USD on desalination, aquifer drilling, increased surface water storage etc.
- In addition to security in water supply, catchment restoration brought wider benefits in terms of job creation, community empowerment, reduced fire risk, the restoration of native biodiversity, and climate change resilience.
- The Greater Cape Town water fund: https://www.nature.org/content/dam/tnc/nature/en/documents/GCTWF-Business-Case_2018-11-14_Web.pdf

Bridgeport, Connecticut, USA

- Main goal of the greenprint led by TNC, was to identify specific areas where investments in green stormwater infrastructure, open space and trees would have the greatest social and ecological value.
- Completed in 2018, the greenprint was able to pinpoint neighborhoods where trees, green stormwater systems and open spaces will make the biggest difference for people and nature.
- The Bridgeport Eco-Urban Assessment model is now being replicated in other cities in Connecticut.
- Bridgeport eco-urban assessment: http://tnc.maps.arcgis.com/apps/MapJournal/index.html?appid=4912af1e58394129be9f7a895a755c66

Melbourne, Victoria, Australia

- Development of an urban greening strategy.
- Convening metro-wide stakeholders to create a shared vision for sustaining nature
- Technical aspects of mapping urban nature, setting greening goals by local conditions, and assessing long-term financing needs to achieve these goals.
- Living Melbourne greenprint: https://www.natureaustralia.org.au/newsroom/living-melbourne/

Chicago, Illinois, USA

- A whole-system approach to achieve lasting impact across the metropolitan area.
- This was a spatial planning tool called the "Green Infrastructure Vision" (GIV).
- Chicago Metropolitan Agency for Planning – began to incorporate the GIV into its regional planning and in its technical assistance to local municipalities.
- CMAP began to fund incremental improvements in the GIV, including better GIS and modelling capabilities and the addition of ecosystem service valuation.
- Green infrastructure vision: https://www.cmap.illinois.gov/programs/sustainability/open-space/green-infrastructure-vision

Restoring Sembakkam Lake in Chennai, Tamil Nadu

The Nature Conservancy (TNC) India has been working in the urban landscape of Chennai for the last few years. Demonstrating a pilot on eco-restoration at the Sembakkam Lake in Chennai (100 acre), using Nature-based Solutions to restore the lake habitat and treat seven minimal liquid discharge (mld) of wastewater entering the lake daily. The lake, with its encroachment and dumping of sewage and solid waste, is a living example of what is happening to the city's natural infrastructure due to the way urbanisation has progressed. In fact, the city has already lost many of its wetlands to urbanisation and the city's vegetation cover has fallen by 22% in the last 20 years.[1]

While TNC India is restoring the Sembakkam Lake to demonstrate what a science-based restoration approach entails, it is crucial to recognise that to achieve scale an integrated and holistic solution is required to address the urban challenges the city of Chennai continues to face and to build long term resiliency and water security.

Based on TNC's global experience, nature is often undervalued in solving problems in cities - improving city services (nature as infrastructure), improving human well-being, and improving resilience (water, heat, air, etc.)

1 Study by Care Earth Trust – a biodiversity research organization

3. Embedding Greenprint in City's Master Planning

The most opportune time to consider the benefits of nature in creating more sustainable and livable cities is during the master planning process. This is much more cost effective than trying to retrofit nature into a city once it is entirely built. Work on the development of the third master plan for Chennai has already begun. This will come into force by 2026 and this masterplan will shape the city's next 20 years of development. Therefore, this is a timely opportunity for TNC India to work in support of the Housing and Urban Development Department and Chennai Metropolitan Development Authority (CDMA) to help shape the city's urban growth through the preparation of a greenprint for Chennai.

A key component of greenprinting is scenario planning that allows the city to envision multiple different pathways for city growth and to simultaneously assess consequences of various patterns of growth. Scenario planning enables governments, and the public, to assess and respond dynamically to an unknown future. It assists them with thinking, in advance, about the many ways the future may unfold and how they can be responsive, resilient, and effective, as the future becomes reality.

TNC India along with its partners, Care Earth Trust, and Indian Institute of Technology, Madras is supporting CMDA to develop different scenarios of development for the Chennai region. Workshops were conducted with officials from CMDA, Directorate of Town and Country Planning (DTCP), Greater Chennai Corporation (GCC) and Metro Water to gather and incorporate feedback on Chennai's projected growth and grey infrastructure development. Brainstorming with group of experts having background in urban planning, biodiversity, and hydrology to understand what an ideal growth scenario may look like. This feedback aided the development of two scenarios for Chennai which were simulated against a baseline scenario of Business-as-Usual (BAU) development to see their impact and how they performed against a situation where

no action is taken, and growth continues the way it has been over the last two decades. These results were presented to the planning officials and recommendations discussed. Refining of the analysis is ongoing and so is work on the cost of inaction as well understanding the benefits of sustainable and eco-sensitive planning.

Stakeholder consultations for developing Chennai greenprint

The greenprint will inform the master planning process which is currently underway and help in preparing a spatial plan that integrates wetlands and urban forests along with conserving watersheds and river basins. This will ensure that ecosystem services we receive from nature such as water security, cooler temperatures, improved biodiversity, better mental and physical health of people is realized as the new plan comes into effect.

Chennai region has seen a vast change in impervious cover due to urbanisation over the last few decades. This trend was analysed to make future projections, which formed the base of the study. Figure 4 illustrates the extent of the study area that was considered for the analysis and shows the extent of development that took place between 1988 to 2019.

Here the results of two scenarios intended to examine are presented below:

- the influence of existing policy
- regulations regarding land development and conversion

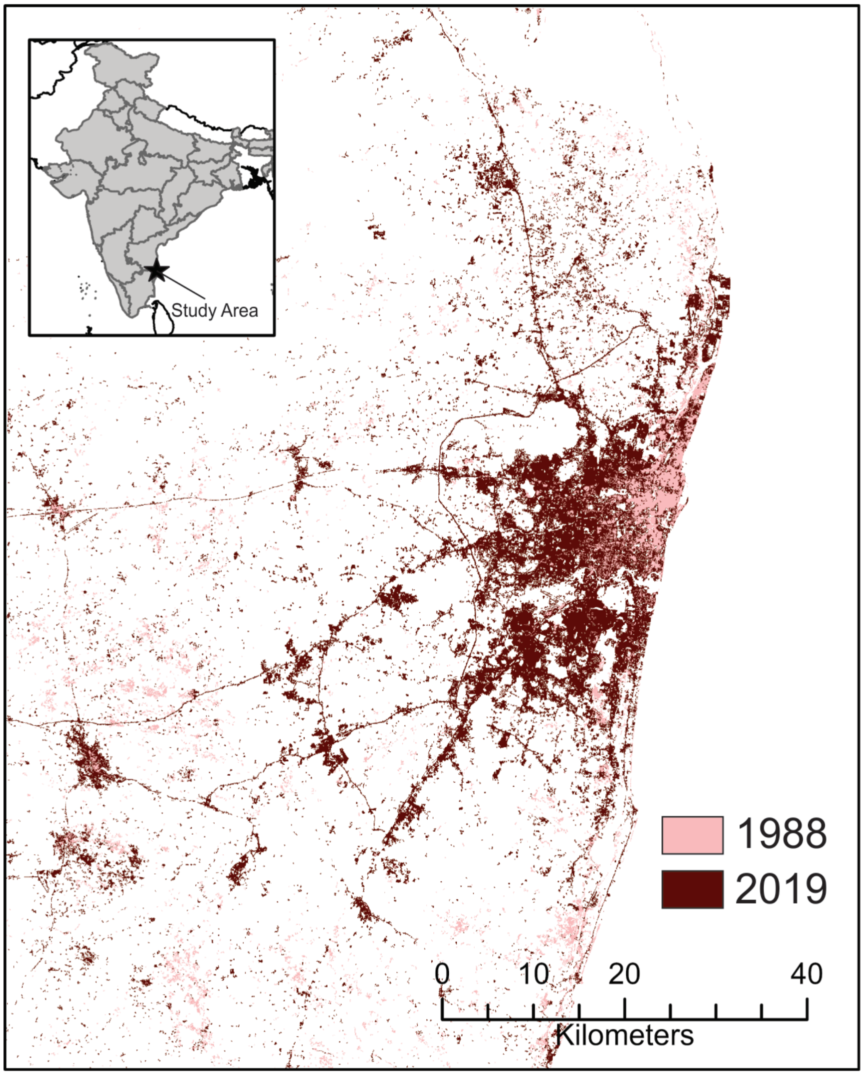

Fig 4: Changes in urban development, as indicated by impervious surface, between 1988 (light red) and 2019 (dark red) with inset study area map.

The BAU scenario represents what unchecked growth will look like in 30 years with no policy intervention. Whereas the policy scenario constrains growth patterns following existing regulations on conversion as well as avoidance of wetland conversion to address ecological and water security assets.

4. Analysis

To help proactively inform the Chennai city planning process and understand how interventions may improve the ability to manage water resources, a simulation model to explore scenarios of future land use change was built.

Modelling efforts were divided into two phases:

- **Phase I:** a model that estimates the transition probabilities for each land use class, based on patterns observed from 1988 to 2019.

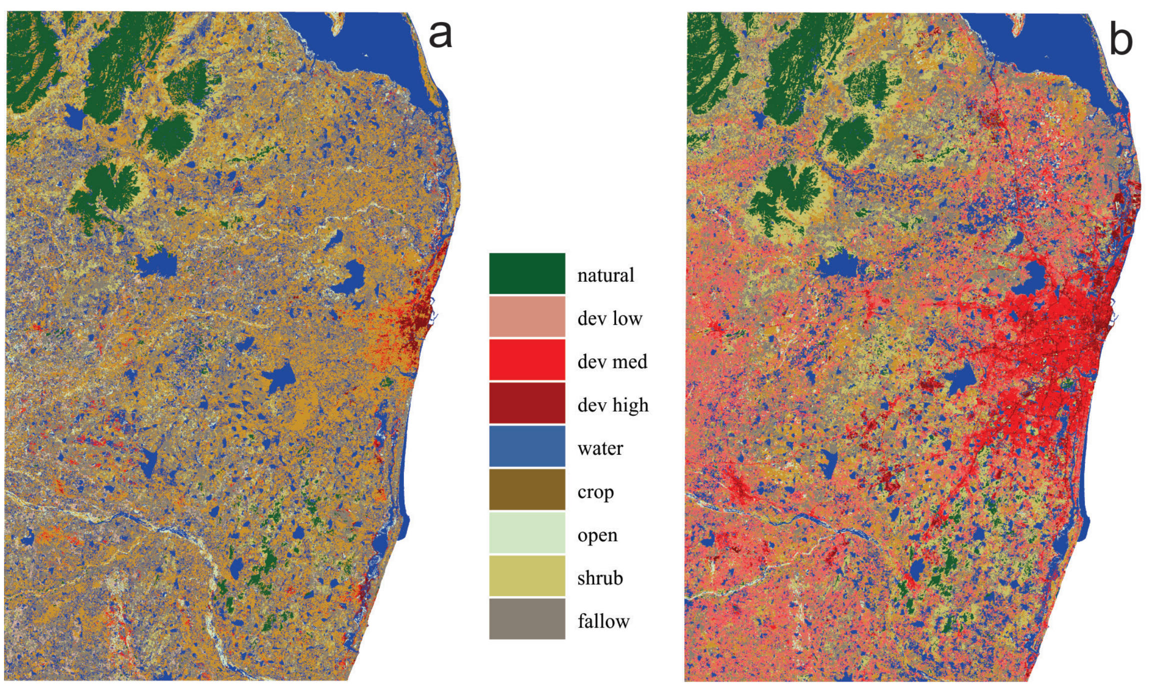

Fig 5: Results of the nine-class LULC classification model; a) 1988 classification and, b) 2019 classification.

- **Phase II:** a simulation model that allowed us to produce future projections of different LULC allocations.

To accommodate the time for the Chennai city plan, currently being developed for a 30-year period, a projection of future patterns of land use change to 2050 using two scenarios was used.

- **Scenario 1:** BAU where no constraints were specified thus, allowing urban expansion to follow past patterns i.e., into natural and agricultural classes.
- **Scenario 2:** Policy constrained, where transitions were only allowed into classes that allow development under current jurisdictional policy constraints.

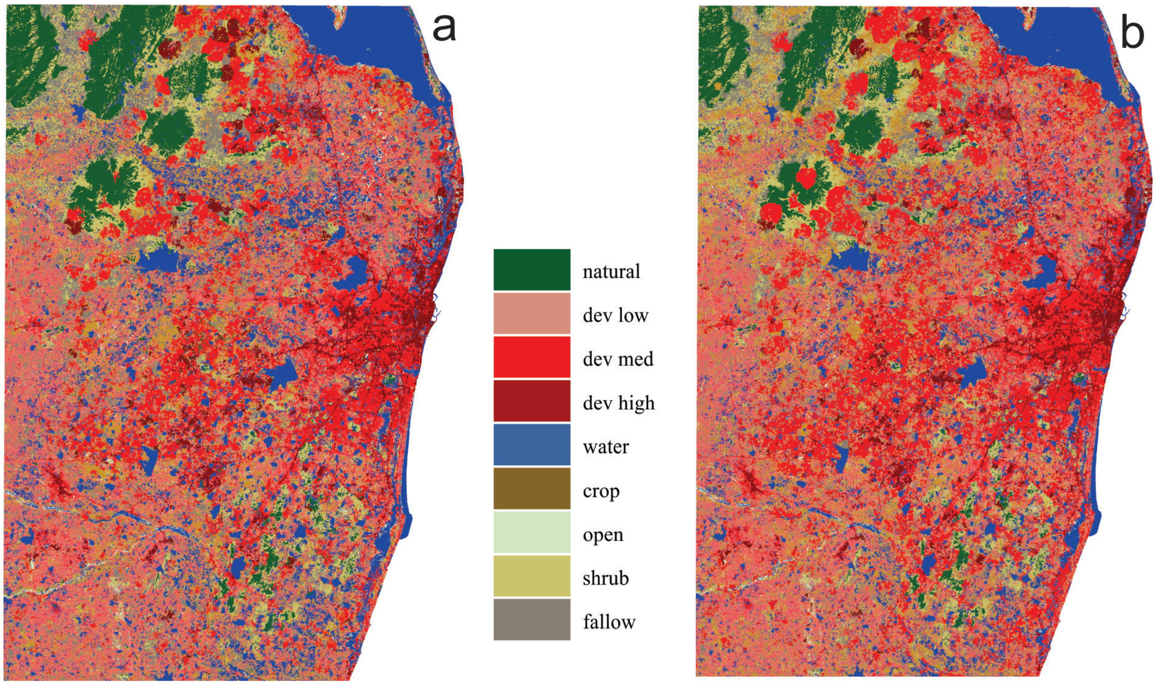

Fig 6: Results of our scenarios using two simulation conditions; a) Policy scenario, where agricultural, natural systems and wetlands transitions are constrained and, b) Business As Usual (BAU) scenario where no constraints are applied.

For both scenarios had some spatially discrete areas (i.e., military lands, protected areas, university campus) that precluded any development and were locked out of the analysis entirely. For additional details on methods see Appendix 1.

5. Results

In accounting for urban sprawl using both unconstrained growth and that constrained by state and federal policies, such as amount of allowed agricultural conversion and impacts to wetlands, a framework for testing the influence of policy adherence and prioritization of ecosystem service assets was developed.

- In terms of loss to natural systems a BAU scenario equates to considerable loss and increased development intensification.
- Looking at 2050 projections, and comparing BAU scenario with scenario with policy constraints

130 km^2
forest loss in BAU scenario

302 km^2
wetland/water loss (734 km^2 if compared to 1988 situation) in BAU scenario

43 km^2
open/shrub loss in BAU scenario

Between a BAU and policy scenario, a 510 km^2 increase in urban intensification occurs under BAU is witnessed, thereby leading to increase of impervious surfaces impacting in turn impacting water security due to increased runoff and lower percolation into ground

The change and "flow" of class transitions using Sankey diagrams (Schmidt 2008) which gives both the direction and magnitude of landcover transitions (fig 7) can be visually evaluated. For instance, looking at historic changes the small loss of forest can be attributed to urban development and agriculture (fig 7-a Sankey diagram). The net loss or gain in different classes is given by the bar graphs and (fig 7-a bar chart) does not provide insight to what that loss is attributed to.

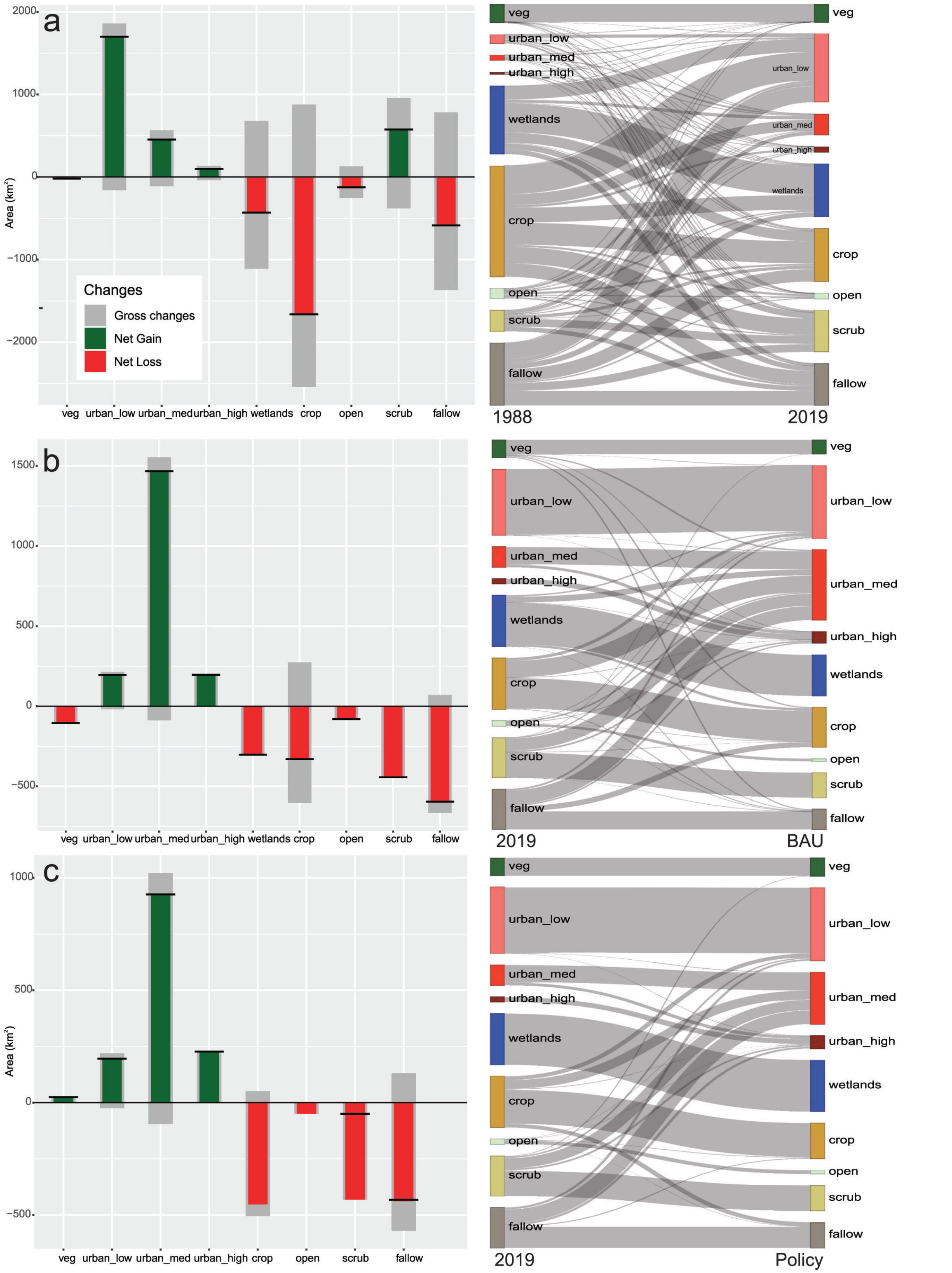

Fig 7: Net and Gross change (left) with flow diagrams (right) for a) 1988-2019, b) 2019-BAU scenario and c) 2019-policy scenario.

Where a small amount of forest attributed to agriculture is visible, one can simultaneously notice a considerable amount of agricultural loss to low and medium development as well as moving into fallow status (fig 7-a). In the BAU scenario, this trend continues with a large amount of agriculture continuing to move into urban development thus, threatening food security (fig 7-b). This is largely mitigated in in the policy scenario (fig 7-c), an equal number of fallow lands moving into development showing agricultural lands being removed from production that are not part of standard accounting is still visible. Looking at the flow through the observed change periods (1988 & 2019) then the two scenarios (fig 8) it becomes alarming to observe the continuing trend of loss in wetlands and agriculture and how a BAU approach would continue this trend.

The spatial distribution of the growth patterns yielded some interesting insights to indirect development effects of the rapid growth that Chennai has undergone. Often, considering the sprawl in terms of growth intensity around the city periphery and where this is certainly the case, an associated pattern is increasing development intensity around villages that occur along the new highways and its major intersecting arteries (fig 6). This development pattern is visible in the contemporary data but, it shows notable spread in the future projections, regardless of scenario, even many kilometers outside of the city. These associated growth patterns represent an opportunity, for city planners and policy makers, for developing incentives and new policy that head of issues such as water security and quality.

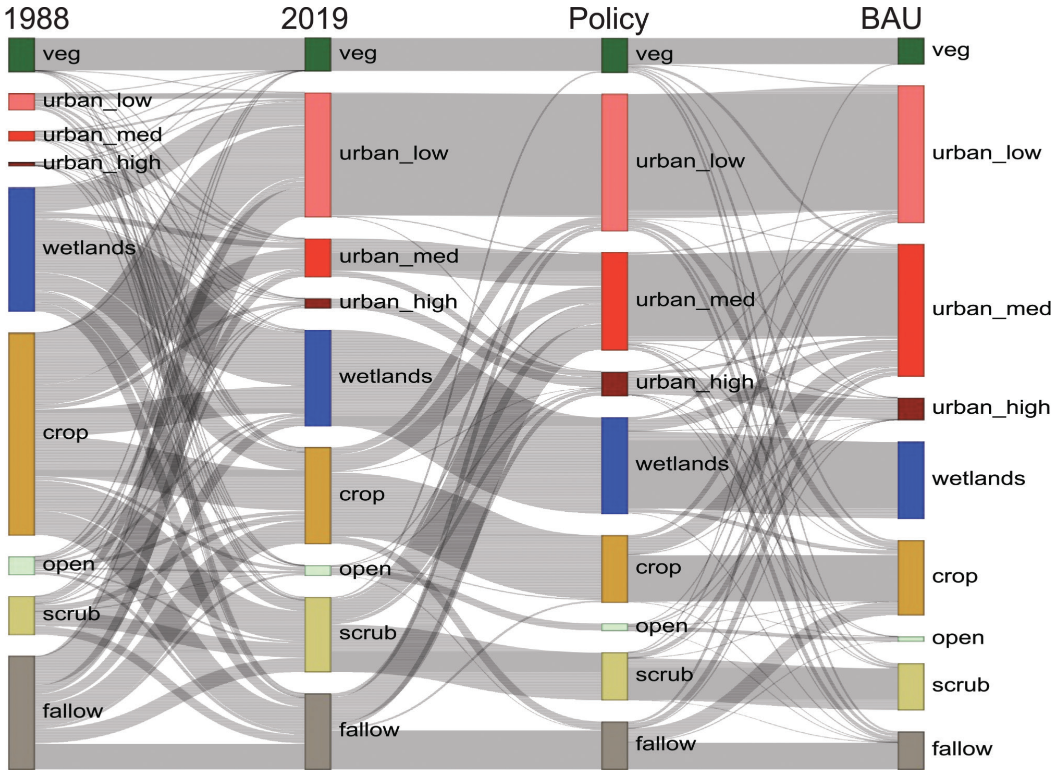

Fig 8: Flow diagram of differences between 1988, 2019, policy and BAU scenarios.

The analysis evaluated the amount of impervious surface (fig 9) as a means of evaluating watershed impairment. Distributions across the study area indicate a notable shift from low impairment of watershed in 1988 towards high watershed impairment in 2019.

This trend is seen to carry on and a BAU scenario would result in non-functioning urban watersheds across the study area. Even without direct interventions, a policy constrained scenario brings down the impairment across the region by seven percent. A spatial assessment indicates that some watersheds may still be in a functional condition (fig 9) but, would require proactive interventions to retain function relating to water quality and security, climate resiliency and biodiversity.

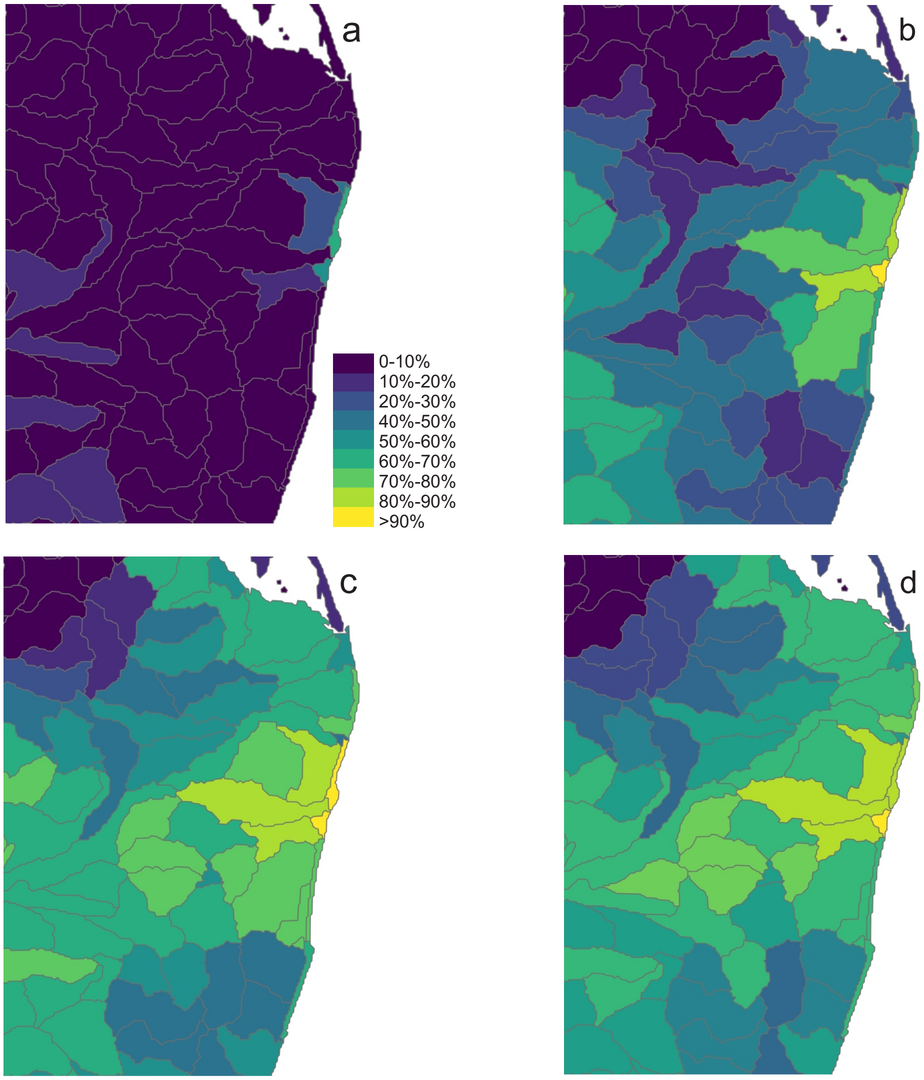

Fig 9: Watershed impairment (percent impervious in watersheds), a) 1988, b), 2019 c) policy scenario, d) BAU scenario

6. Recommendations

Some topline recommendations are provided below, that based on the scenarios coming out of the greenprinting analysis, that could help shape aspects of Chennai's city plan.

- Patterns of development suggest shift in urbanisation will be concentrated in several key places. Data from such analysis can be used to highlight areas where development changes will be significant. Areas expected to shift towards more urban land cover classes should have requirements that drive the use of construction materials and building designs that reduce impervious cover. This can be accomplished with building codes that:
    - Disconnecting impervious surfaces and roof drains to suitable pervious areas.
    - Using pervious pavement materials wherever feasible.
    - Installing green roofs on buildings.
    - Reducing the length and width of parking spaces, and other pavements.
    - Clustering project components (such as buildings) closer together to reduce the amount of road, and other impervious surfaces needed.
    - Prioritising redeveloping of existing disturbed properties as part of the Chennai land use and development plan map.
- Expansion of the urban footprint in Chennai is likely inevitable. As result city planners and city officials will need to seek novel mechanism to manage and mitigate for changes both within and outside of the city. To avoid the consequences of increasing urbanisation and associated impervious cover, city planners can seek to achieve a net positive reduction in impervious cover and net positive increase in wetland cover and function at the watershed scale – this will need to focus on areas outside of the city.
    - Wetland creation, restoration and protection plays an important role in ecosystem health and watershed dynamics. Among their valuable services, wetlands recycle nutrients, filter certain pollutants, recharge groundwater, and provide habitat for fish and wildlife.

Additionally, wetlands reduce peak flows and flood damage, store water, allowing for slower release of water resources during droughts, and provide recreational opportunities and amenities. There are multiple co-benefits to committing to increase wetland area and function for Chennai residents.

- Target the creation of new wetlands and restoration of existing wetlands in watersheds where urbanisation and increased impervious cover are projected to increase.
- Develop a "water fund" for watersheds where urbanisation and increased impervious cover are projected to increase. A water fund is a governance and finance mechanism that improves water security by allowing downstream water users **to invest collectively in upstream water and land conservation.** Water funds use a collective action and governance platform that brings together different water users – usually utilities, businesses, agriculture, and local government – **to invest in ecosystem protection and upstream communities** within the catchments they depend on. The greenprint is an ideal tool to identify such areas in the watershed for protection and development of water fund.
- Despite the presence of existing regulations that prevent conversion of wetlands and other natural habitats conversion of these areas has continued. Building the capacity to ensure enforcement of existing regulation can be useful. This capacity can be targeted at the municipalities where urban development is projected to expand the most.

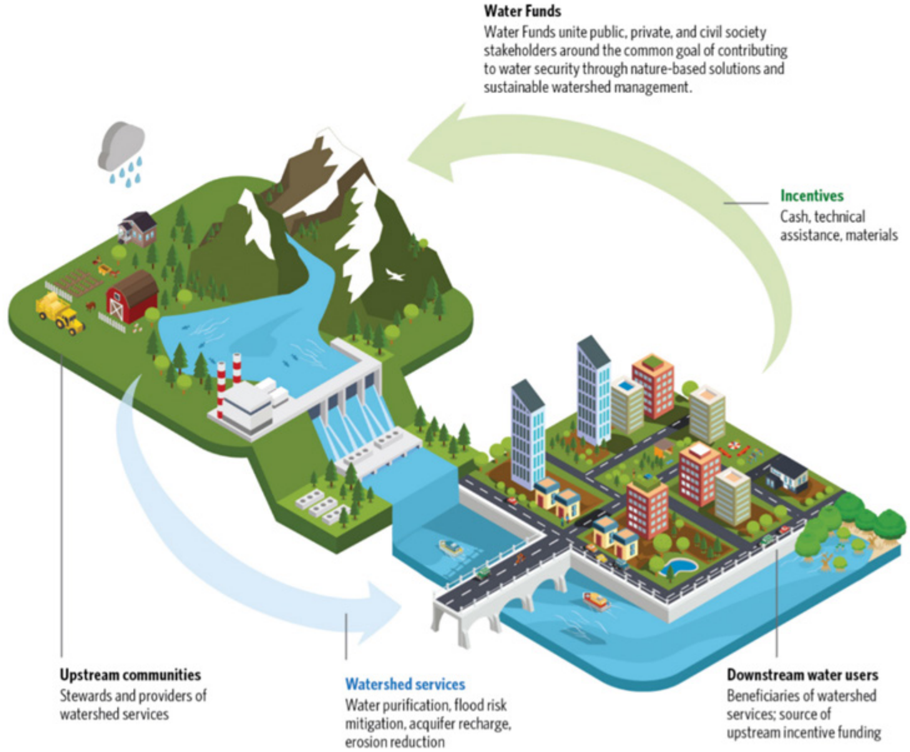

Fig 10: Functioning of a water fund

7. Conclusion

The conservation movement cannot afford to overlook the impact demonstrated in the study analysis. The loss of this natural habitat not only affects biodiversity but also affects human well-being. For example, remnant natural habitat patches along coastlines or floodplains play a crucial role in mitigating flood risk. Natural habitat can help maintain drinking water quantity and quality. Vegetation can help mitigate climate change by sequestering and storing carbon dioxide and lowering temperatures. The only way to safely support such numbers of urban growth is if cities can be planned and built sustainably. Greenprinting or development by design is a tool that can help to reduce the loss of nature when grey infrastructure is being built and to assure that the functional role of nature as a solution to urban challenges is evaluated on equal footing as traditional grey infrastructure approaches. For example, natural features like tree canopies in cities can serve as a climate adaptation strategy, helping provide shade that cools air temperatures and mitigates the urban heat island effect. Finally, nature in cities provides recreational, health and aesthetic benefits to urban residents, making our cities healthier and more resilient places to live. Greenprint supports better decision-making by revealing where important functioning natural systems exist and should be protected, by demonstrating where nature-based strategies and others could be implemented and by highlighting nature's benefits.

8. Appendix

This section gives a detailed overview of the analysis methods used to develop the projections of growth based on the two different scenarios considered. One with Business-As-Usual (BAU) growth and the other with policy measures of land use and growth built in. The future projections were created by using the state of art land use change simulation models. This includes the Land Expansion Analysis Strategy (LEAS) and Patch Generating Landuse Simulation models (PLUS) and how they helped in generating the future growth projections.

Methods

The first step in the definition of a classification scheme was to identify the prevalent land use /landcover (LULC) types that would affect and be affected by development across the region. We polled stakeholders with a list of potential LULC types as well as their definitions (e.g., high development represents high-density cityscapes where impervious cover accounts for >= 80% of total cover). After evaluating input from stakeholders and domain experts we choose 9 LULC classes/definitions (table 1) that would most influence development patterns, policy and ecological outcomes.

A set of heuristics, following each class definition, that provided rules for an analyst to select "head-up" training point locations on contemporary high-resolution (<1m^2) imagery was developed. Once a training set was generated, a 10% subset of the training data was then compared to the mid-resolution (30m^2) imagery that was utilized in the analysis. This was done to ensure that the training selection rules applied consistently across high and mid resolution imagery and clearly represented the same classes. A ranking representing; "clear agreement", "disagreement" or "unclear" was assigned to each validation point. The Kappa confusion matrix

Table 1: Defined LULC (land use/landcover) classes

Class	Description
Natural	Forested vegetation – lands with ≥ 20% forests.
Dev low	Low intensity development - areas with a mixture of constructed materials and vegetation where impervious surfaces account for 20% to 49% percent of total cover.
Dev med	Medium intensity development - areas with a mixture of constructed materials and vegetation and impervious surfaces account for 50% to 79% of the total cover.
Dev high	High intensity development - high-density cityscapes where impervious cover accounts for >= 80% of total cover.
Water	Wetlands and open water – Open water, inundated wetlands, and water with high ephemerality.
Crop	Agriculture – Multi-crop irrigated and non-irrigated.
Open	Open lands, non-agricultural and non-natural vegetation with no other LULC.
Shrub	Shrub vegetation – non-forest natural lands with shrub/grass components.
Fallow	Fallow agriculture – agriculture lands with no crops for ≥ 2 years.

(percent agreement corrected for random chance) was calculated and found a high classification agreement k=0.94 between the high and mid resolution data.

The 30m^2 Landsat sensors (TM5, ETM+7, OLI) representing seven years (1988, 1995, 2000, 2005, 2010, 2015, 2019) were selected due to the long duration temporal availability. The data was geometrically corrected to ensure alignment through the timeseries, the QAQC band was applied to each image to remove clouds/shadows. Each image was radiometrically corrected, to at-surface reflectance, ensuring consistent spectral response and the data was processed into seasonal composites using an image averaging approach. Finally, a robust regression approach, against the 2019 OLI image, was used to harmonise the data through the entire timeseries accounting for differences in dynamic ranges of the sensors and any sensor-signal degradation. All image processing was performed in Google Earth Engine with the results being downloaded to local servers.

With training data created then validated and the image pre-processing completed, the robustness of the training data and specific classes was evaluated.

First, the spectral values to the training data based on the 2019 images was assigned. Then a K-means clustering on the 2019 image to evaluate the number of supported classes that could plausibly be derived from the multivariate data provided by the image was performed. This was done by testing a range of cluster solutions (n=2-30) and evaluating the silhouette widths of the clusters to find the best supported number of unique classes supported. It was found that, 5-16 clusters were well enough supported to be a viable number of classes defined in a classification model, with 8-11 yielding the best support. Next, the specific nine LULC classes were tested by performing a spectral separability analysis (SSA), which indicates how "identifiable" each class is given the spectral data collected by the sensor and helps identify potential class-confusion issues where two (or more) classes exhibit high potential for cross-classification errors. It was found that the high support for the classes with only agriculture and fallow exhibited potential for cross-classification error. Because of this the fallow was dropped temporally from the model and specified a separate model to address fallow lands. This decision was mostly due to fallow having a specific temporal component that needed to be addressed independently to ensure that the analysis was not just classifying resting or freshly tilled agricultural lands as fallow and missing the policy implications of LULC conversion. Even though the separability was quite high, the decision was made for water/wetlands as the periodicity of wetlands was not being adequality represented in the image averaging and the average/maximum spatial extents not being classified correctly. As such, three independently fit models were specified and then results were harmonized into a single classified image for each year.

For image classification a regularized Gradient Boosting model using XGBoost (ref) in R statistical software (R Core Team 2021) was implemented. Gradient Boosting is a weak learning approach that sequentially attempts to reduce misclassification rate in subsequent iterations by giving higher penalty weights to misclassified points in the previous iteration(s) thus, boosting the model. The algorithm partitions data up to the maximum defined depth and then prunes the tree backwards to remove splits beyond which there is no positive gain. Hyper-parameter tuning was performed using a grid search (table 2). Our boosting and cross-validation objective metric was the log loss (negative log-likelihood) function.

The grid search was performed for the 2019 training set and, once the final model parameters were selected, a final model was fit and validated. Then, the imagery estimated the probabilities, creating a raster surface, for each class. Since multitemporal spectral was harmonised across the timeseries, the contemporary model was also estimated at each timestep. By evaluating potential multiple memberships (high probabilities of more than one class at the pixel-level) there was an additional validation source for assessing uncertainty. We found that the classification was quite stable with little confusion across classes (data not shown).

For the final 7 class classification(s), the class associated with the highest probability was then assigned to each pixel. For water, Sentinal-1 (radar VV/VH polarization) and Sential-2 (spectral bands) data were acquired and then utilized Feature Analyst to perform a feature extraction. Care Earth Trust provided known wetland locations, giving a starting point for identifying training features. Additional training data was heads-up digitised from imagery and then used to run the Feature Analyst algorithm with excellent support for the results. For the fallow land classification (agricultural lands taken out of production for at least one growing season), a binominal

classification, follow the Gradient Boosting methods provided previously, on all available growing season images for 1988 and 2019 was performed. Any pixel that exhibited a high cumulative frequency was then classified as fallow. The water/wetland and fallow classes were then "burned" into the 7 class results using a simple rule set (i.e.., fallow only overwriting agriculture, open, shrub) so that any cross-classification errors would be mitigated.

Table 2: Gradient Boosting parameters. The control column represents what model component the parameter relates to, partitions or boosting. Values returned from grid search are in bold.

Control	Parameter	Value(s)
Partition	Minimum samples for split	0.5% - 5% of n by 0.5 **(1.25)**
Partition	Minimum samples for terminal node	Constant = **10**
Partition	Maximum partition depth	3 – 10 by 1 **(4)**
Partition	Maximum features	Constant = sqrt [7] **(3)**
Partition	Subsample size	Constant = **0.8**
Boosting	Learning rate (Eta)	0.01 – 0.30 by 0.1 **(0.03)**
Boosting	Number of Bootstrap replicates	100 – 500 by 50 **(200)**
Boosting	Gamma, regularization	0-5 by 1**(3)**
Boosting	Lambda, L2 ridge regression weights regularization	Constant = **0** (no Lambda)
Boosting	Alpha, L1 LASSO regression weights regularization	Constant = **1** (use Alpha)

Model fit was evaluated using percent correctly classified, log-loss, and Kappa whereas performance was evaluated using these accuracy metrics with a Bootstrap approach rather than using a single data withhold that is passed to an n-fold cross-validation. The model p=999 was bootstrapped, without replacement, to create an error distribution representing model performance. From these error distributions, the performance was represented as the median value of a metric as well as variance to illustrate uncertainty in relation to spread of the error (Evans et al., 2010). Opportunistic field data, including n=100 GPS locations and associated LULC type, was compiled as well.

Classification

The first step in the definition of a classification scheme was to identify the prevalent land use /landcover (LULC) types that would affect and be affected by development across the region. We polled stakeholders with a list of potential LULC types as well as their definitions (e.g., high development represents high-density cityscapes where impervious cover accounts for >= 80% of total cover). After evaluating input from stakeholders and domain experts we choose 9

LULC classes/definitions (table 1) that would most influence development patterns, policy and ecological outcomes.

A set of heuristics, following each class definition, that provided rules for an analysist to select "head-up" training point locations on contemporary high-resolution (<1m^2) imagery was developed. Once a training set was generated, a 10% subset of the training data was then compared to the mid-resolution (30m^2) imagery that was utilized in the analysis. This was done to ensure that the training selection rules applied consistently across high and mid resolution imagery and clearly represented the same classes. A ranking representing; "clear agreement", "disagreement" or "unclear" was assigned to each validation point. The Kappa confusion matrix (percent agreement corrected for random chance) was calculated and found a high classification agreement k=0.94 between the high and mid resolution data.

Simulation Model

The simulation model can be divided into two phases.

- **Phase I:** A model that estimates the transition probabilities for each class.
- **Phase II:** A model that allows to produce future projections of different LULC allocations.

Those parameters were selected that would influence changes to LULC, particularly urban growth to create class-transitions. The region is somewhat data poor in relation to spatial representation of complex socioeconomic characteristics with homogeneous terrain. This precluded some common indicators used in other studies (e.g., gridded population, GDP, slope) but, from OSM (Open Street Map) the robust data on infrastructure such as roads, transmission and from our LULC classification, development intensities along with other natural and anthropogenic features (table 3) was accessed. To address the evolution of LULC and mitigate issues such as persistence to create a response, dependent y variable, that represented transitions, a land expansion analysis following methods presented in Pontius et al., (2004) was implemented. All years of LULC data was overlaid and the matrix diagonals to compute the gains and losses thus, accounting for net change, persistence, and swap resulting in class-level rasters representing gain, loss, and persistence was used. These rasters were then reclassified into a binominal of [loss = 0, gain/persistence = 1] and used as response variables to model transition probabilities and represent dual states in our transition rules.

Table 3: Parameters used in modeling class-level LULC transition probabilities.

Parameter	Description	Source
Dev_high	Distance to high intensity development	LULC classification
Dev_med	Distance to medium intensity development	LULC classification
Ag	Distance to agriculture	LULC classification
Rds	Distance to roads	Open Street Map (OSM)
Mrds	Distance to major roads	Open Street Map (OSM)
Rail	Distance to railroad lines	Open Street Map (OSM)
Trans	Distance to electrical transmission	Open Street Map (OSM)
Village	Distance to villages	Open Street Map (OSM)
Natural	Distance to natural cover types	LULC classification

A 10% random sample of each binominal class was drawn and a random forests model to estimate probabilities of our gain/persistence based on correlative relationships with our independent variables (table 3) implemented. To ensure robustness in the simulation an error threshold was applied where any class-level model that exhibited > 10% error in either binominal class were flagged. Fortunately, this was never the case, and no models were rejected.

Phase two of the simulation model was to use the transition probabilities and specify a LULC change model to allocate future development scenarios. The Liang et al., (2021) Patch-generating Land Use Simulation (PLUS) model due to its ability to account for the evolutionary characteristics of LULC change, local land use dynamics and estimate realistic spatial structures was chosen. The development of patch growth simulation models has received increasing attention (Meentemeyer et al., 2013; Yang et al., 2020) however, PLUS expands these methods into accepting mixed class patches thus, accounting for complex LULC patterns and stochasticity. Two key parameters for the PLUS model are the transition matrix, controlling constraint and directionality of allowed transitions and the allocations, specifying target amounts for each resulting class. A global model was specified, using all our classified years and a simple linear MCMC, to project amounts at a specific future year as a means of empirically deriving LULC amount allocations. The Chennai city plan, currently being developed, is for a 30-year period so, the allocations estimated at 2050 for specifying development allocation amounts was used. Two transition matrices were specified to represent two initial scenarios. One was a business as usual (BAU) where no constraints were specified thus, allowing urban expansion into natural and agricultural classes. The second was policy constrained, where transitions were only allowed into classes that allow development under jurisdictional policy constraints. There was also the presence of some spatially discrete areas (i.e.., military lands, protected areas, university campus) that precluded any development and were locked out of the analysis entirely.

Results

The 2019 LULC classification mode all validated very well with high fit and performance measures. Based on fit yielded percent correctly classified of pcc=97, kappa=92, and logloss=0.03. In measures of performance the median metrics were pcc=95, kappa=87, and logloss=0.02 all with very low error variance indicating that there is extremely low uncertainty in the models. Based on field validation, model performance was also very well supported with a pcc=xx and kappa=xx. Given that the collected training samples that would typify LULC patterns through time, fit a model using this data and then back predicted the model to the spectrally and temporally harmonised imagery, without direct effort, the study is not able to directly validate these classifications. However, given the methodology and resulting LULC patterns, the performance characteristics are very similar to the evaluated model. The most critical classifications are the start and end dates (1988, 2019) as the intervening years (1995, 2000, 2005, 2010, 2015) are only used to derive class persistence in the land expansion analysis. This model would be quite resilient to small errors at a given point in time because these are exactly the types of issues the model is designed to account for. The intervening classification years in deriving future LULC allocations via a linear MCMC model was also used. Since these allocations represent linear trends of the total areas in each class any pixel-level errors are greatly mitigated and not much of a concern here.

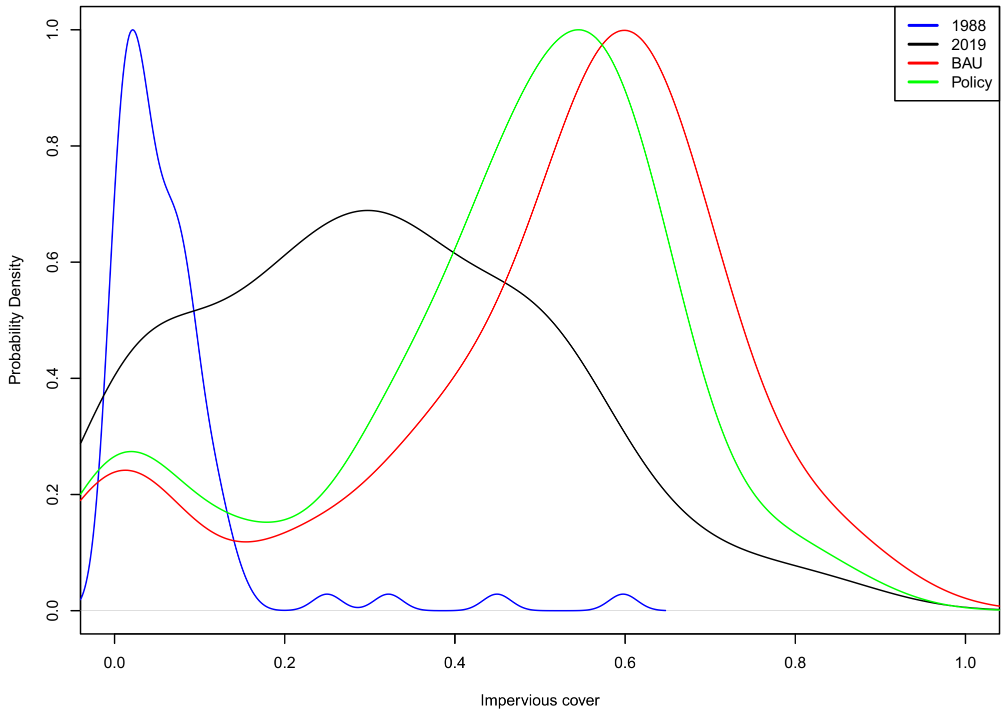

Fig 11: Distributions of watershed impervious surface impairment for the classified measurement years BAU, policy scenarios.

Using the LULC developed classes and HydroSheds sub-basin watersheds, defined as where two river branches meet which each have an individual upstream area of at least 100 km² (Lehner & Grill 2013), the amount of impervious surface (fig 9) as a means of evaluating impairment (Schueler et al., 2009) was evaluated. Distributions across the study area (fig 11) indicate a notable shift from low (median 0.045) impact in 198 towards high watershed impairment (median 0.304) in 2019. Continuing this trend under a BAU scenario would result in non-functioning urban watersheds across the study area (median 0.57). Even without direct interventions, a policy scenario brings down median impairment across the region by 7% (see distributions of our two scenarios in fig 11). A spatial assessment indicates that some watersheds may still be in a function condition (fig 9) but, would require proactive interventions to retain function relating to water quality and security, climate resiliency and biodiversity.

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9. References

Arsanjani, J.J., Kainz, W., and Mousivand, A.J., 2011. Tracking dynamic land-use change using spatially explicit Markov Chain based on cellular automata: the case of Tehran. International Journal of Image & Data Fusion, 2 (4), 329–345. doi:10.1080/19479832.2011.605397

Chen, T., C. Guestrin (2016). XGBoost: A Scalable Tree Boosting System. In Krishnapuram, B., M. Shah, A. Smola, C. Aggarwal, Charu, D. Shen, R. Rastogi (eds.). Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, CA, USA, August 13-17, 2016. ACM. pp. 785–794. arXiv:1603.02754. doi:10.1145/2939672.2939785.

Evans, J.S. and M.A. Murphy (2014) rfUtilities: An R package for model selection and validation of Random Forests. R package version 1.0-1. http://CRAN.R-project.org/package=rfUtilities

Evans J.S., M.A. Murphy, Z.A. Holden, S.A. Cushman (2011). Modeling species distribution and change using Random Forests *in Predictive species and habitat modeling in landscape ecology: concepts and applications.* eds Drew CA, YF Wiersma, F Huettmann. Springer, NY

Evans, J.S. and S.A. Cushman (2009) Gradient Modeling of Conifer Species Using Random Forest. *Landscape Ecology* 5:673-683.

Liang, X., Q Guan, K.C. Clarke, S. Liu, B. Wang, Y. Yao. (2021). Understanding the drivers of land expansion for sustainable land use using a patch-generating land use simulation (PLUS) model: A case study in Wuhan, China, Computers, Environment and Urban Systems, 85:101569. DOI: 10.1016/j.compenvurbsys.2020.101569

Liu, S., Su, H., Cao, G., Wang, S., & Guan, Q. (2019). Learning from data: A post classification method for annual land cover analysis in urban areas. ISPRS Journal of Photogrammetry and Remote Sensing, 154, 202-215. doi: 10.1016/j.isprsjprs.2019.06.006

Meentemeyer, R. K., Tang, W., Dorning, M. A., Vogler, J. B., Cunniffe, N. J., Shoemaker, D. A. (2013). FUTURES: Multilevel simulations of emerging urban-rural landscape structure using a stochastic patch-growing algorithm. Annals of the Association of American Geographers, 103(4), 785–807. https://doi.org/10.1080/00045608.2012.707591.

Pontius Jr, R.G., Shusas, E., McEachern, M. (2004). Detecting important categorical land changes while accounting for persistence. Agriculture, Ecosystems & Environment 101(2):251-268.

R Core Team (2022). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Reis, I., D. Baron, S. Shahaf (2019) Probabilistic Random Forest: A Machine Learning Algorithm for Noisy Data Sets. *The Astronomical Journal*, 157:1, article id. 16, 12 pp.

Yang, X., Zheng, X.Q., and Chen, R., 2014. A land use change model: integrating landscape pattern indexes and Markov-CA. Ecological Modelling, 283 (7), 1-7.doi:10.1016/j.ecolmodel.2014.03.011

Yang, J., Gong, J., Tang, W., & Liu, C. (2020). Patch-based cellular automata model of urban growth simulation: Integrating feedback between quantitative composition and spatial configuration. Computers, Environment and Urban Systems, 79, Article 101402. https://doi.org/10.1016/j.compenvurbsys.2019.101402.

Arsanjani, J.J., Kainz, W., and Mousivand, A.J., 2011. Tracking dynamic land-use change using spatially explicit Markov Chain based on cellular automata: the case of Tehran. International Journal of Image & Data Fusion, 2 (4), 329–345. doi:10.1080/19479832.2011.605397

Evans, J.S. and M.A. Murphy (2014) rfUtilities: An R package for model selection and validation of Random Forests. R package version 1.0-1. http://CRAN.R-project.org/package=rfUtilities

Evans J.S., M.A. Murphy, Z.A. Holden, S.A. Cushman (2011). Modeling species distribution and change using Random Forests *in Predictive species and habitat modeling in landscape ecology: concepts and applications.* eds Drew CA, YF Wiersma, F Huettmann. Springer, NY

Evans, J.S. and S.A. Cushman (2009) Gradient Modeling of Conifer Species Using Random Forest. *Landscape Ecology* 5:673-683.

Liang, X., Q Guan, K.C. Clarke, S. Liu, B. Wang, Y. Yao. (2021). Understanding the drivers of land expansion for sustainable land use using a patch-generating land use simulation (PLUS) model: A case study in Wuhan, China, Computers, Environment and Urban Systems, 85:101569. DOI: 10.1016/j.compenvurbsys.2020.101569

Liu, S., Su, H., Cao, G., Wang, S., & Guan, Q. (2019). Learning from data: A post classification method for annual land cover analysis in urban areas. ISPRS Journal of Photogrammetry and Remote Sensing, 154, 202-215. doi: 10.1016/j.isprsjprs.2019.06.006

Meentemeyer, R. K., Tang, W., Dorning, M. A., Vogler, J. B., Cunniffe, N. J., Shoemaker, D. A. (2013). FUTURES: Multilevel simulations of emerging urban-rural landscape structure using a stochastic patch-growing algorithm. Annals of the Association of American Geographers, 103(4), 785–807. https://doi.org/10.1080/00045608.2012.707591.

Pontius Jr, R.G., Shusas, E., McEachern, M. (2004). Detecting important categorical land changes while accounting for persistence. Agriculture, Ecosystems & Environment 101(2):251-268.

Yang, X., Zheng, X.Q., and Chen, R., 2014. A land use change model: integrating landscape pattern indexes and Markov-CA. Ecological Modelling, 283 (7), 1-7.doi:10.1016/j.ecolmodel.2014.03.011

Yang, J., Gong, J., Tang, W., & Liu, C. (2020). Patch-based cellular automata model of urban growth simulation: Integrating feedback between quantitative composition and spatial configuration. Computers, Environment and Urban Systems, 79, Article 101402. https://doi.org/10.1016/j.compenvurbsys.2019.101402.

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