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Urban Expansion into Natural Systems: Assessing Ecological Function Loss and AI-Driven Solutions for Sustainable Urban Development

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Abstract
Cities are spreading into landscapes that support water, heat and wildlife. Often, the ecological costs of such urban expansion are not exposed while technology is being promoted to address them. This chapter explores how urban expansion reduces the ecological functions of wetlands, floodplains and lakes and how Artificial Intelligence (AI) can support sustainable urban development. Drawing on published studies, institutional reports and tribunal orders, the chapter examines the cases of the Yamuna floodplain and Okhla wetland stretch in Delhi and the lake system of Bengaluru, and contrasts these with global trends. Using a structured narrative review, the chapter maps out the several loss mechanisms that are affecting these cities and relates these to corresponding AI methods described in the literature. The chapter distinguishes between what has been demonstrated for these cities and what can only be inferred. It argues that AI is best used as a monitoring and early warning layer that makes ecological limits visible and enforces them. It cannot, however, substitute for floodplain protection and effective governance. The chapter concludes with some practical recommendations for planners, regulators, designers and researchers.

Keywords: Urban Expansion, Ecological Function, Wetlands, Yamuna Floodplain, Artificial Intelligence, Land-Use Change, Sustainable Urban Development

1. Introduction

While urban expansion is often seen as being on ‘empty’ land, much of the world’s urban expansion is on wetlands, floodplains, agricultural land and lake bottoms that are currently providing ecological and economic services. Globally, an additional 1.2 million km² of urban land is projected to be added by 2030. This is almost three times the area of urban land that was present in 2000. It is likely that much of this urban expansion will take place in or near biodiversity-rich regions [1].

Wetlands cover about 6% of the Earth’s surface, yet they generate more than 7.5% of global gross domestic product (GDP) through water supply, flood protection, food production and carbon storage. The Convention on Wetlands reports that 22% of the world’s wetlands have been lost since 1970 and that wetlands are being destroyed at a rate of 0.52% per annum. At this rate, up to 20% of the remaining wetlands could be destroyed by 2050, resulting in a loss of benefits worth up to US$39 trillion [2]. Over

a longer time period, the loss of wetlands is even greater with a global reconstruction of wetlands since 1700 estimating that about a fifth of the world's wetlands have been lost since then [3], while an earlier synthesis of studies estimated that 64–71% of the world's wetland area was destroyed during the 20th century [4].

Urban areas, where most of the world's population resides, are places where most of the ecological loss is visible. When wetlands are filled in, floodplains are built over and lakes are polluted, the city loses services that it never paid for in the first place. These services include storing of flood water, recharging of ground water, cooling of air, dilution of waste and habitat for wildlife. This is true for two of India's most documented urban areas – Delhi, the city which has spent two centuries encroaching upon the river that gave it a site [5] and Bengaluru, the city that was once known for its chain of tank-lakes but where today most of the water bodies have been encroached upon and polluted [6].

The two gaps this chapter attempts to fill are: (a) evidence of ecological loss is scattered across several sources such as published papers, institutional reports, tribunal orders and civil society analyses, and is rarely read together; and (b) most discussions of Artificial Intelligence (AI) in urban planning remain general and fail to specify which tools can be used to address specific loss mechanisms and how strong the evidence is for a particular city.

The chapter pursues three objectives: (a) to document from traceable sources the ecological loss in the Delhi–Yamuna and the Bengaluru lake systems; (b) to map the various loss mechanisms to the different AI methods that have been described in the literature; and (c) to state clearly what has been demonstrated for these cities and what remains inference. The scope of this chapter is limited to secondary evidence and no field data was collected for this chapter.

2. Background and Literature Review

2.1 Global trajectory and loss of function

This chapter examines the ecological loss of function of wetlands, floodplains and lakes in urban areas and how AI can be used to support sustainable urban development. Urban expansion is usually seen as land conversion, but the land that is lost was providing services such as storing floodwater, recharging groundwater, cooling air, diluting and purifying waste and providing habitat for wildlife. This chapter examines how urban expansion has led to the loss of ecological function of the Yamuna floodplain and Okhla wetland stretch in Delhi and the lake system of Bengaluru, and how these can be monitored and managed using AI.

2.2 Evidence from Delhi and Bengaluru

The most recent evidence for the Yamuna is found in two studies from 2026, which were reported in the press. The first study by Neenu and Kansal [7] is a land-cover change analysis for the Upper Yamuna Basin. The second study by the same authors is a two-century reconstruction of the width of the river and the discharge of the Yamuna in Delhi [5]. The hydrodynamic model used for the Delhi reach of the river in the latter study found that the encroachment of the floodplain had caused an increase in the severity of floods. A 1-in-30-year flood is expected to cause an increase of about 12% in the area at risk compared to a 1-in-10-year flood. The Indian Institute of Science reports on the loss of lakes in Bengaluru and the almost total paving of the Bellandur catchment [6, 8]. The relevant numbers are given in Section 4.

2.3 AI methods and the research gap

The technology side is also well-documented in the literature. For extracting land use information from satellite imagery, Deep Learning (DL) approaches such as Encoder-Decoder architectures (e.g. U-Net)

have become the standard for image segmentation [9, 10]. For planetary scale analysis, Google Earth Engine (GEE) has become the standard tool [11]. A 32-year Landsat time series has been used to map global surface water and its changes [12]. For hydrological modeling, Long Short-Term Memory (LSTM) networks have shown to be competitive with traditional models for rainfall-runoff modeling [13]. A global hydrological model based on AI has also been shown to improve the prediction of extreme river flows in ungauged basins [14]. A broader review of the use of machine learning (ML) in environmental modeling concluded that ML approaches are best used in combination with physical process-based models [15], and can support climate action in various sectors [16], but can also enable some of the sustainable-development goals while inhibiting others [17].

The two bodies of literature, documentation of urban ecological loss and AI-based methods for urban monitoring, are rarely brought together for specific cities. This chapter attempts to do so for Delhi and Bengaluru.

3. Emerging Technology / Core Concepts

3.1 Ecological function and its loss

In this chapter, the term ecological function is used to describe the functions that natural systems can perform for the city. These functions include storing and slowing down flood water, recharging groundwater, cooling down the temperature, diluting and purifying waste and providing habitat for animals and plants. It is important to make a distinction between loss of function and loss of area. A floodplain that is cut off from the river by embankments still has the same area on paper, but it cannot perform its flood storage function anymore. Therefore, in the Delhi case study, the 45 km² of floodplain that was disconnected from the river between 1912 and 2024 is counted as lost function. The relative change in function can be calculated for two dates by using Equation (1).

$$RC = \frac{X_{t2} - X_{t1}}{X_{t1}} \times 100 \quad (1)$$

Here RC is the relative change in per cent, and X(t1) and X(t2) are the values of an indicator, such as the share of area under water, at the earlier and later dates.

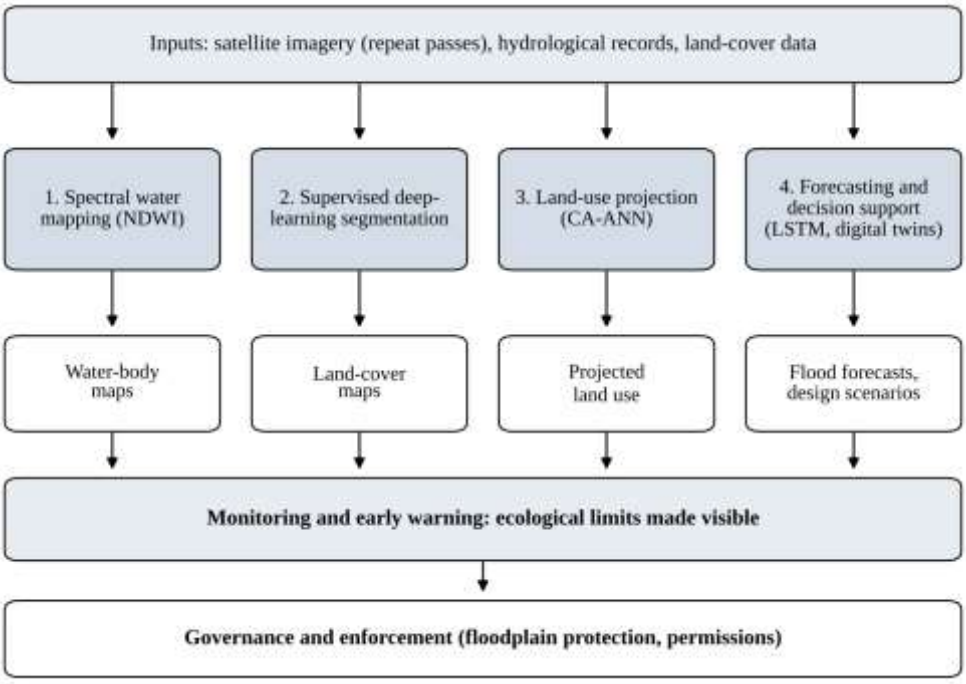
3.2 The AI building blocks

Spectral water mapping is the first of four building blocks used in the literature on the use of AI for ecological monitoring and enforcement. The Normalised Difference Water Index (NDWI) is used to map water based on the difference between green and near-infrared reflectance [18] (Equation 2).

$$NDWI = \frac{\rho_{green} - \rho_{NIR}}{\rho_{green} + \rho_{NIR}} \quad (2)$$

The second building block is the use of supervised deep learning for image segmentation. This type of deep learning model learns to classify different types of land use (e.g. water, vegetation, built-up area) from a large number of labeled images [9, 10]. The third building block is the use of AI for projection of land use change. This is typically done using cellular automata (CA) in combination with artificial neural networks (ANN) [7]. For example, such a model has been applied to the Upper Yamuna Basin to predict where future development is most likely to occur. The fourth building block is the use of AI for forecasting and decision support, such as LSTM-based flood models [13] or digital twins of urban systems that can be used to test different scenarios [19]. The four building blocks and their place in the monitoring and enforcement chain are shown in Figure 1.

Figure 1: Conceptual Framework Linking AI Methods to Ecological Monitoring and Enforcement



Source: methods discussed in this section [9, 10, 13, 19].

4. Applications and Multidisciplinary Perspectives

Two case studies of urban growth and ecological loss are presented in this chapter. The main indicators used in the two case studies are summarized in Table 1.

Table 1: Key Indicators of Ecological Function Loss Used in This Chapter

Parameter	Value	Source
Global wetland loss since 1970	22%; about 0.52% per year	[2]
Remaining wetlands at risk by 2050	Up to 20%; about US$39 trillion in benefits	[2]
Yamuna bankfull width, Delhi (1799 to 2024)	About 658 m to about 210 m (about 68% narrower)	[5]
Yamuna discharge, Delhi (1799 to 2024)	About 30,000 to about 3,900 m^3/s (reported as about 89% lower)	[5]
Floodplain disconnected by embankments (1912 to 2024)	About 45 km^2 (about 33% of floodplain)	[5]
Built-up area, Upper Yamuna Basin	+130% (2004–2014); +28% (2014–2024)	[7]
Water bodies, Upper Yamuna Basin (share of area)	1.36% (2004) to 0.62% (2024)	[7]
Urban land surface temperature, Delhi	36.58 °C to 41.81 °C (2001–2021)	[7]
Peak flood level, Old Railway Bridge, Delhi	208.66 m on 13 Jul 2023; 1.17 m above the 1978 record	[20]

Parameter	Value	Source
Water bodies, Greater Bengaluru	207 (1973) to 93 (2010)	[6]
Built-up share, Bellandur catchment	5.4% (1973) to 92.3% (2016)	[8]

Source: Percentages are as reported by the sources.

4.1 Case A: the Yamuna floodplain and Okhla wetland, Delhi

The downstream end of the Delhi reach of the river is the Okhla Bird Sanctuary, a wetland of about 5.5 km² created by the construction of the Okhla barrage in 1986. The Sanctuary is home to 302 species of birds and in winter up to 14,000 to 20,000 waterbirds can be found in the Sanctuary. The Key Biodiversity Area factsheet for the Sanctuary, last updated in 2004, describes the site as 'an island surrounded by development' and lists 'pollution', 'encroachment' and 'loss of feeding grounds' as threats to the Sanctuary [21].

Pollution is another problem that has been growing with the urban expansion. The Upper Yamuna Basin study reported that the volume of untreated effluent being discharged into the river in Delhi had gone up from 70 million gallons per day (MGD) in 2004 to 242 MGD in 2024. The 22 drains that enter the river in the Delhi stretch of the river carry 688 MGD of untreated effluent, with the Najafgarh drain alone carrying 453 MGD of it. Urban land surface temperature in the city has gone up from 36.58 °C in 2001 to 41.81 °C in 2021, largely due to decline in green cover. Groundwater levels in large parts of the city have gone down by 20–30 m. About 2,500 small farmers are operating on the floodplain and restoration of the ecological function of the floodplain would also affect their livelihoods [7].

Floodplain management in Delhi is a contentious issue and has been so for more than a decade. The floodplain of the Yamuna in Delhi covers some 9,700 ha of which more than 1,000 ha is covered by permanent structures on the river. The 22 km of the river in Delhi is crossed by 26 bridges and 3 barrages [20]. A landmark Tribunal order of January 2015 had prohibited dumping on the floodplain [22]. A subsequent order of 2019 had left the issue of permissibility of individual projects to be decided by the respective statutory authorities after an environmental study [23]. More recently, the Tribunal has directed the Delhi government to demarcate the floodplain on a 1-in-100-year flood basis as against the 1-in-25-year basis that the Delhi authorities had proposed [22].

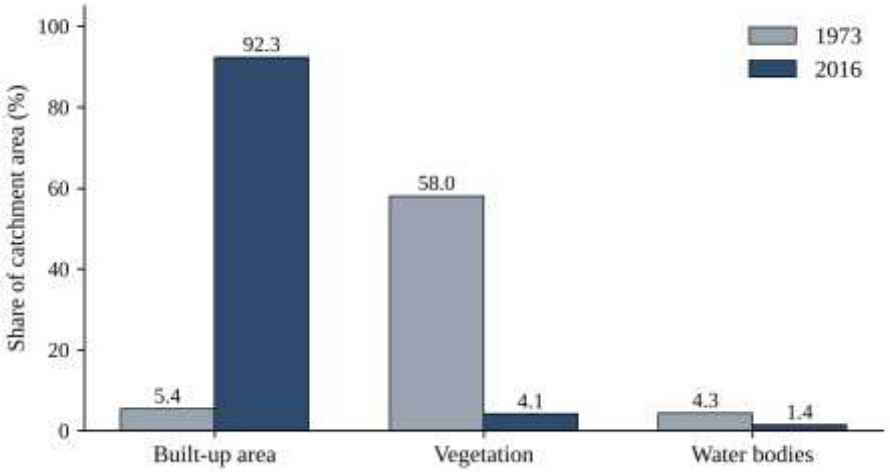
Hydrologists and remote sensing scientists provide the data, ecologists explain the ecological impacts of a shrinking wetland on birds and water quality, and planners and architects design what is built on the river edge. Design choices are critical and as reported by the South Asia Network on Dams, Rivers and People (SANDRP), riverfront and plantation works on about 1,515 ha of floodplain have added built-up cover in 'piece by piece' development [20]. Soil dumping to raise a roughly 19.5 ha patch near Shastri Park has reduced the space available for flood waters to spread and for groundwater to recharge [22].

4.2 Case B: the lake system of Bengaluru

Bengaluru is a large urban area of 69 km² in 1901 and 741 km² in 2006 [8]. The city had an engineered system of tanks to store and carry storm water out of the city. Today only 93 out of 207 lakes are left in the city. More than half of the remaining lakes (54%) are encroached upon. A field survey in 2007 found that about 66% of the remaining lakes are sewage fed. A pristine wetland in Bengaluru is valued at Rs 10,435 per hectare per day while the sewage fed Varthur wetland is valued at Rs 119 per hectare per day [6].

The proportion of built-up area in the Bellandur catchment has increased from 5.4% in 1973 to 92.3% in 2016. In the same period, the vegetation has decreased from 58.0% to 4.1% and the water bodies from 4.3% to 1.4% (Figure 2). This means that the built-up area has increased about seventeen-fold and the vegetation and water cover have decreased by about 93% and 67% respectively.

Figure 2: Land-Cover Shares in the Bellandur Lake Catchment, Bengaluru, 1973 and 2016



Source: values reported in [8].

5. Methodology / Research Approach

This chapter is a structured narrative review of secondary evidence combined with a comparative analysis of two cases. No primary data were collected, no field surveys were run and no models were trained for this chapter.

The sources for the chapter have been chosen against three criteria: they must be site-specific, they must be verifiable from public records, and they must be cited. The case study material has been opened and read in full for each figure used: institutional technical reports, a peer-reviewed modeling paper, a global database of biodiversity, a tribunal order, two 2026 studies published as peer-reviewed papers by civil society groups, and AI literature from widely cited peer-reviewed papers in remote sensing, hydrology and sustainability.

The analysis has two parts. First, the reported indicators for the proposed use of AI are tabulated. Where there are two dates for the indicators, the relative change is also computed using the Equation (1). Then, the evidence for each of the proposed uses of AI is graded on a three-point scale: demonstrated (shown in peer-reviewed literature for at least one case), applied locally (used in one of the two study areas), or inference (the chapter's own reasoning for the use of AI in Delhi or Bengaluru).

6. Results, Findings and Discussion

6.1 Observed findings

There are three very important patterns that are observed in the two cases. Firstly, the built-up cover is increasing at the cost of the land that is meant to handle water. In the Upper Yamuna Basin the increase in built-up area is mainly in the cropland and the water bodies [7]. In the case of Bellandur, the water bodies have decreased by about two-thirds [8]. The other two patterns are of connectivity being lost before

there is any decrease in the area. The embankments have disconnected about 45 km² of Delhi's floodplain [5]. The bridges and the barrages are fragmenting the remaining areas of the floodplain [20].

6.2 How AI responds to each problem

Table 2 matches each of the above problems with corresponding AI approaches and assesses the extent of evidence available for each. For instance, the above problem of wetland and water-body loss can be projected into the future using CA-ANN as was done for the Upper Yamuna Basin [7], where the projected water bodies in the basin decrease by more than 40% between 2024 and 2034. Note that this is a stress test of current course and not a forecast as it relies on a host of assumptions built into the model.

Table 2: Mapping of Loss Mechanisms to AI Approaches and the Status of the Evidence

Problem	AI approach	Evidence status
Wetland and water-body loss is slow, patchy and disputed	Deep-learning segmentation of satellite imagery; NDWI; long-term surface-water layers	Demonstrated elsewhere [9, 10, 11, 12]; for Yamuna floodplain, inference
Land-use change outruns planning cycles	CA-ANN projection of land use and land cover	Applied locally: Upper Yamuna Basin [7]
Floods arrive faster than warnings	LSTM and hybrid physics–machine-learning forecasting	Demonstrated at scale [13, 14, 15]; Delhi shortfalls documented [20]; Delhi use is inference
Encroachment is found late	Automated change detection on repeat satellite passes	Manual image comparison already used as evidence [22]; automation is inference
Where to place flood storage and recharge	Scenario testing with digital twins and hydrodynamic models	Concept [19]; sponge-city practice [24]; hydrodynamic baseline for Delhi [25]; AI coupling is inference
Plans carry no ecological limit	AI-assisted trade-off analysis against sustainability targets	Demonstrated as a concept [16, 17]; local use is inference

Source: evidence status graded as described in Section 5.

The issue of flood warning, where AI can be of great value to bridge the visible gap, was exposed in July 2023 when the national forecasting agency failed to predict the arrival time as well as the peak of the flood at Old Railway Bridge. The hourly discharge records for the three barrages in Delhi are not available in the public domain and an error of peak entry on a published hydrograph was not corrected for days [20]. Though machine-learning based flood forecasting has shown good results in other basins [13, 14], it requires continuous and open data which is the biggest bottleneck in Delhi as described by SANDRP.

Detection is also something that can be done using the same method that is currently used as evidence, i.e. comparing two images of the same area. This would allow for an automated change detection of all floodplain parcels after every satellite pass. The soil-dumping case near Shastri Park was documented by comparing two Sentinel-2 images, from July 2023 and March 2024 [22].

6.3 Discussion

The first point to note is the distinction between what is observed, what is interpreted and what is inferred. The indicators in Table 1 are based on the studies cited. The interpretation of these indicators as reflecting land-use governance as opposed to wastewater or rainfall is that of the Upper Yamuna study authors [7] and is consistent with the results of the modeling exercise which found that encroachment had increased flood severity [25]. Rainfall is clearly also an issue as was seen in July 2023 [20] and the effect of wetlands on floods can vary between different locations [26]. What is inferred is that the use of AI tools would improve monitoring and warning of these problems in the cities studied.

The main finding of the above discussion is that AI mostly reveals the ecological limits of development and not more. Thus, even the best of AI models cannot create political will to enforce ecological limits. The demarcation of Delhi's floodplains is based on whether the 1-in-25 year flood or the 1-in-100 year flood is used as the basis [22]. No amount of AI can decide this for Delhi.

7. Challenges, Ethical Considerations and Limitations

The first challenge is that of data. Hydrological and barrage data for Delhi are not available in any form that can be used for independent forecasting [20]. Ecological baselines for various parameters are very old, such as the Okhla factsheet that was last updated in 2004 [21]. Land-cover classification using satellite images requires local ground-truth data, such as water, wet vegetation, etc. to be manually annotated and used as training data for the classifier [9].

The second issue is that of governance. Even if AI provides good maps, these will not stop construction. The results of the CA-ANN projection for the Upper Yamuna Basin have to be translated into changes in permissions. AI can also go wrong, as it can enable many of the sustainable development goals and yet inhibit others [17]. AI can also be used to approve more things, and thus can also increase the loss of space.

Ethical Considerations – Floodplain farmers and people living in informal settlements must be given due consideration in any campaign to enforce laws to protect floodplains and lakes. Alerts on automated detection must not be used to harass the poor while large institutional encroachments are not detected and dealt with. Images and outputs from AI models must be made available for communities to check and use. Model opacity, high energy consumption and dependence on private cloud platforms are issues that need to be addressed while planning for the use of AI for sustainable development.

As with any secondary research, there are limitations. The studies referenced have been used from press reports, so the actual figures may vary from what has been reported. Also, the different sources have used different baselines and definitions. For example, the population comparison for Bengaluru has been based on the city and metropolitan boundaries [8]. The figures for discharge reduction have been quoted as reported [5]. No AI model has been tested on local data for the two cities.

8. Future Scope and Research Directions

Three directions for future work are outlined. First, the segmentation and forecasting models presented here should be validated on local data and their accuracy reported. Second, the land-use projection can be coupled with a hydrodynamic model of the Yamuna, as was done for the Delhi reach [25], to create a flood-risk map from the CA-ANN's land-cover forecast. Third, the hybrid physics–machine-learning forecasting of the Yamuna's discharge depends on the hourly data that is currently not publicly available [15, 20].

In terms of future research the above points can be used as a starting point. There are also a number of interdisciplinary questions, such as how to include the value of ecosystem services in planning decisions, how to use digital twins to inform architects and regulators about sustainable development and how the above patterns are reflected in other cities. A multi-city comparison would provide valuable insights.

9. Conclusion

In both cases built-up land is increasing at the expense of water, vegetation and floodplain with negative effects on flood risk, water quality, heat and wildlife. Built-up area in the Upper Yamuna Basin increased by 130% within a decade [7]. The Yamuna in Delhi is reported to have decreased in width by about 68% [5]. The proportion of built-up area in the Bellandur catchment has increased from 5.4% in 1973 to 92.3% in 2016 [8]. This is not a matter of lack of technology but of not incorporating ecological limits in land use planning.

AI can help in mapping water and built-up area, projecting future land use, flood forecasting, and testing design scenarios before they are built. The application of AI for the Yamuna has already been explored [7]. The remaining uses of AI, such as flood forecasting and testing design scenarios, are well supported by existing research but need to be tested for the two cities. Therefore, the use of AI can provide better visibility of ecological limits and earlier warnings of ecological degradation, and must be paired with effective floodplain protection.

10. Recommendations / Practical Implications

1. Publish a public map of water bodies and floodplain with regular updates and use the stricter criterion of 1-in-100-year flood as asked by the Tribunal [22].
2. Release hourly data of discharge and level at barrages and gauges as is required for any machine-learning flood forecasting [20].
3. Municipal bodies should run automated change detection on floodplains and lake catchments and publish alerts together with the underlying imagery, so that communities and courts can verify them [22].
4. Floodplain and lake margins should be treated as flood storage space by designers and architects, and therefore should be avoided for fill and hard riverfront development [20, 22].
5. Validate the models for segmentation and forecasting on local data and report the accuracy of the models before using them in policy [9, 13].

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