AI + Climate Futures in Asia

Community Participation in  India

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AI for Climate Action: Community Participation in India

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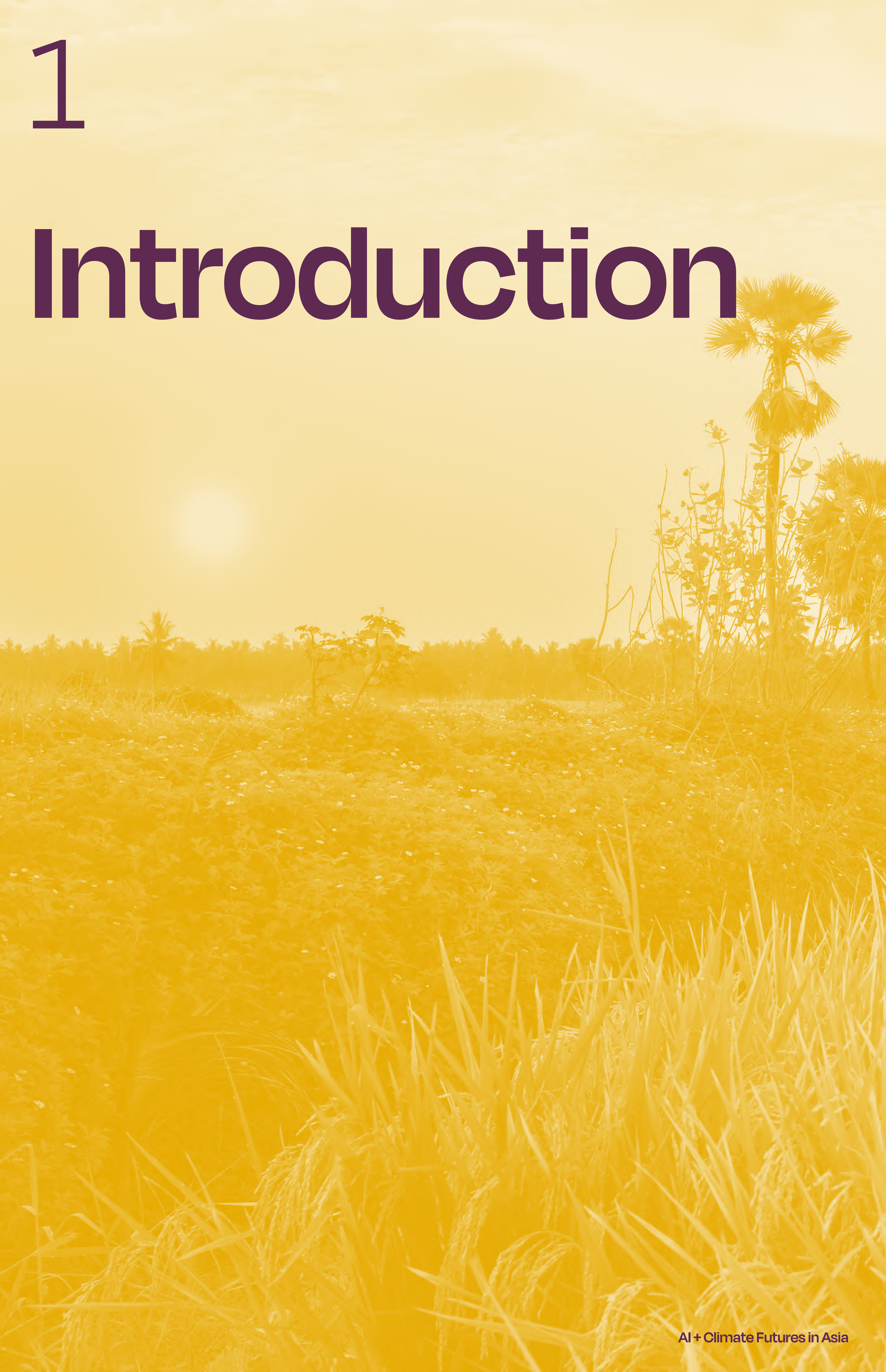
1

Introduction



The world is witnessing an increased frequency of environmental crises, largely arising from anthropogenic changes caused by human activity.[1,2]

Social groups marginalized along class and caste lines are often the ones most vulnerable to such crises.[3] In this brief, we broadly look at three areas where environmental health and human livelihood intersect in India and discuss the opportunities and challenges related to the use of AI technologies in these areas.

First, in the context of forests, we discuss methods to track and improve forest health.

Second, in the context of agriculture, we discuss methods to improve groundwater management.

Third, we examine flood management. In all these domains, we specifically discuss AI-based tools that can assist communities in managing their natural resources, while acknowledging that community participation is essential for robust environmental health.

2

Applications

Forests

Remote sensing data is being actively used to classify forest and non-forest areas and track forest degradation and deforestation.[4]

High-resolution data can potentially even detect local logging events[5], and LIDAR (Laser Imaging, Detection, and Ranging) measurements from GEDI can be used to train machine learning models to produce accurate wall-to-wall assessments of tree height and canopy density.[6] Forest classification and change detection methods can, thus, objectively assess the status of forests and are useful in monitoring.

Knowledge of the dominant tree species in an area, collected through crowdsourcing, can further help estimate the biomass and carbon sequestration performed by the forest[7] and identify sites for restoration or afforestation.[8] Such forest conservation initiatives can also provide an additional revenue stream through carbon offsets[9] and help plan land use by suggesting suitable combinations of cropping and forestry.[10] Site assessment for new tree planting activities could also be improved by taking soil type, soil moisture, water planning, and other factors into account[11] and monitoring the outcomes over time.

One problem that is encountered frequently while planning forest restoration activities is the identification of a suitable mix of tree species local to each region that can improve biodiversity, instead of creating monoculture plantations. A time series of satellite images could help with the tracking and classification of tree species in an area[12], aided by self-supervised super-resolution techniques as a preprocessing step.[13]

Further, agent-based simulation models can be used to predict the prevalence of different tree species based on the dynamics of species populations, their interactions such as predation, competition, and mutualism, and the effects of environmental factors such as climate, habitat availability, and resource availability. This can be used to create optimal tree plantation plans for different regions.

Ground water

Almost half the Indian population is facing groundwater stress,[14] which is likely to be aggravated with climate change.[15]

It is imperative to consider groundwater as a commons resource[16] and allocate it equitably by planning both supply-side interventions, such as water structures, and demand-side interventions, such as changes in cropping patterns. District-level vulnerability indices for climate change and water stress have been prepared for India[17], but these reports are infrequently updated and rely on coarse spatial and temporal data. High-resolution data sets are available, however, to obtain measurements of precipitation, surface run-off, water storage, evapotranspiration, soil moisture, and so on.[18]

Regional calibrations can be improved by making use of intra-annual land use and land cover (LULC) maps obtained through machine learning–based classification of satellite data to determine areas under single cropping (one crop planted in a year, in the *kharif* season) and multiple cropping (more than one crop planted in a year, in the *kharif* and *rabi* seasons)[19] as well as other more static classes such as forest cover, surface water, and built-up areas.[20] Area-wise assessments of ground-water can thus be made in a time series–based manner.[21]

Based on these area-wise assessments, specific plans to identify sites for rainwater harvesting can also be made by taking into account factors such as the soil type, slope, precipitation, soil moisture, and LULC[22]. New methods such as causal machine learning, with machines trained on past data of rainwater harvesting structures, can be predictive of the future potential of different sites for water management and may be better at identifying good sites than methods based on thumb rules. These methods require the computation of variables such as changes in cropping intensity on farm lands lying in close proximity to water structures and the specific times in a year when the water structure has water available for irrigation.

Intra-annual LULC methods, as described earlier, can help determine the first variable, and methods to detect surface water seasonality can determine the second variable. While identifying perennial water bodies is easier[23], the classification of seasonal water bodies has been challenging. Their turbidity, smaller size, shallow depth, and resemblance to highly irrigated areas makes the identification of seasonal water bodies using medium resolution satellite data complex, but the results are promising.[24]

Flood management

Summer monsoon rainfall prediction is crucial for decision-making in various sectors such as agriculture, energy, water resources, health, and flood management. The inter-annual variabilities of monsoon rainfall are mainly caused by factors such as the El Niño Southern Oscillation (ENSO) and Indian Ocean Dipole (IOD)[25], and the rainfall can also vary significantly over different spatial regions.

Machine learning–based models are likely to outperform traditional physical models used for seasonal rainfall prediction by modelling these spatial covariates more precisely. New methods such as graph neural networks (GNNs) are able to accomplish such "geometric learning" of spatiotemporal patterns in the underlying data sets[26] and are known to be able to find highly interpretable connections between variables.

GNNs are also likely to be useful for flood prediction. At the level of a basin, for instance, nodes can represent sub-basins and edges can represent channels connecting them, and this model can be used to predict stream flows on the complete graph.[27] Based on this, indices depicting flood severity, risk, and vulnerability can then be developed to plan flood adaptation strategies.

Tools for Communities

It is important that predictions and recommendations based on machine learning methods such as the above are not imposed in a top-down manner but are rather seen as assistive tools for communities to use in participatory planning processes.

This is essential, so that local knowledge and experience shapes decision-making, and the community does not lose control over decisions that directly affect their members. For example, methods used by indigenous communities to manage and conserve forests are known to yield better results than methods formulated with bureaucratic or professional assistance.[28]

We define community-based development as planning and implementation processes that are shaped by those local communities that have the required capability and commitment to take part in these processes.[29] We believe that non-participatory mechanisms stand the risk of missing out on local insights, which can even lead to harm, and also disempower communities by rendering them recipients without agency of top-down decision-making processes rather than making them democratic co-owners in a collaborative and decentralized governance process of planning and implementation. This draws upon Schumacher's notion of appropriate technology[30] and its current digital equivalent as technology that is designed in a user-centred manner and used and managed directly by the community itself.[31]

Keeping in mind that the trap of technology solutionism and technology determinism should be avoided, the various AI-based methods described in the earlier sections can be embedded in tools such as the following, operated through participatory processes.

Our research group at IIT Delhi is working on such tools and processes:

- GIS-based tools to enable communities to understand the historic trends of water stress in their geographies;
- a participatory decision-support tool to assist communities in site assessment to build water structures and to bring about changes in cropping patterns to tackle water stress;
- tools for forest communities to track rotational foraging practices and tree species biodiversity through satellite data, to understand forest health in different parts;
- GIS-based methods for water management in forest areas to improve forest rejuvenation; and
- tools for planning of agroforestry on private land, aided with site assessment, species selection, and monitoring of plantation health using remote sensing data.

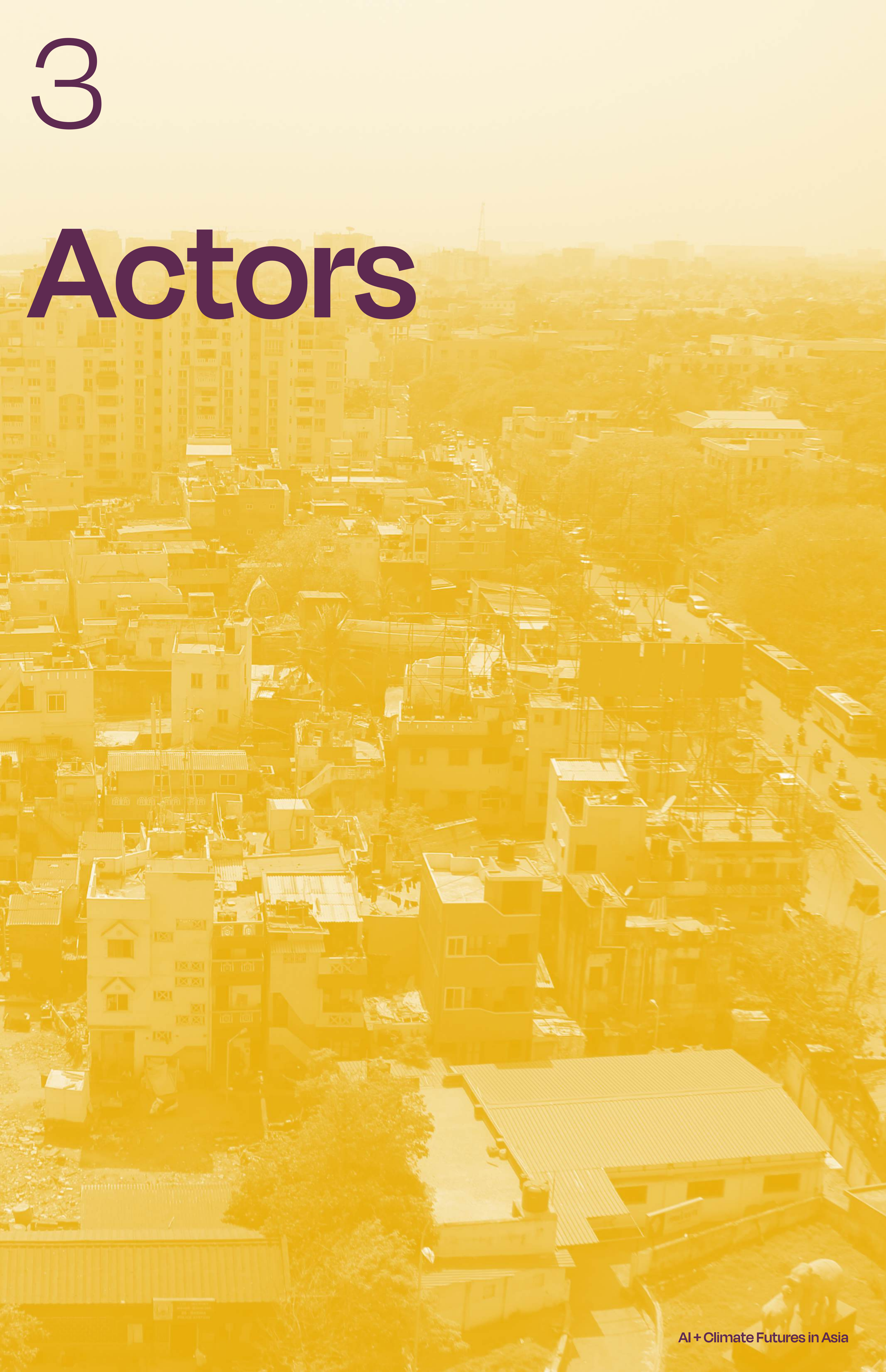
These tools are envisioned to be socialized through trained volunteers from the same communities because of their understanding of the local context.

The rationale of working through community volunteers, or rather *community stewards*, who are trained in various technological and developmental elements, instead of relying on external professional staff, for example, is further driven by the belief that nurturing an ethic of care and solidarity towards communities results in robust local community institutions.

Such institutions can serve to not only operate the envisioned AI-based tools in contextually appropriate ways, but will also encourage wider cooperation and cohesiveness in the community to cope with any future crises. They will enable marginalized groups to participate in local governance and decision-making processes. Going beyond community-based development, this is called the *commoning* approach[32], to emphasize the need for strong bottom-up structures of mutual support to sustain the communities during times of hardship and overcome entrenched unjust and oppressive structures that have resulted in negative impacts on these marginalized groups.

3

Actors



India has a rich set of welfare schemes such as Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA), *Pradhan Mantri Krishi Sichayee Yojana* (PMKSY) for irrigation, National Mission for Sustainable Agriculture (NMSA), and so on aimed at both generating livelihood and creating assets useful for the environment and local communities.[33]

MGNREGA works for rainwater harvesting, canal maintenance, check dams for watershed management, agroforestry, and land levelling to make fallow lands cultivable, among others.

These schemes have been observed to yield significant environmental benefits, such as reduced soil erosion, improved groundwater availability, and increased carbon sequestration.[34] Tools such as the ones suggested above, based on methods that use AI, can be useful for communities to plan new structures and put forth their demands for sanctioning of appropriate funds from the local government. Subsequent monitoring of the outcome of these structures, such as changes in cropping patterns or surface water availability, can lead to greater transparency and help track if vulnerable groups are indeed able to benefit from these government schemes.

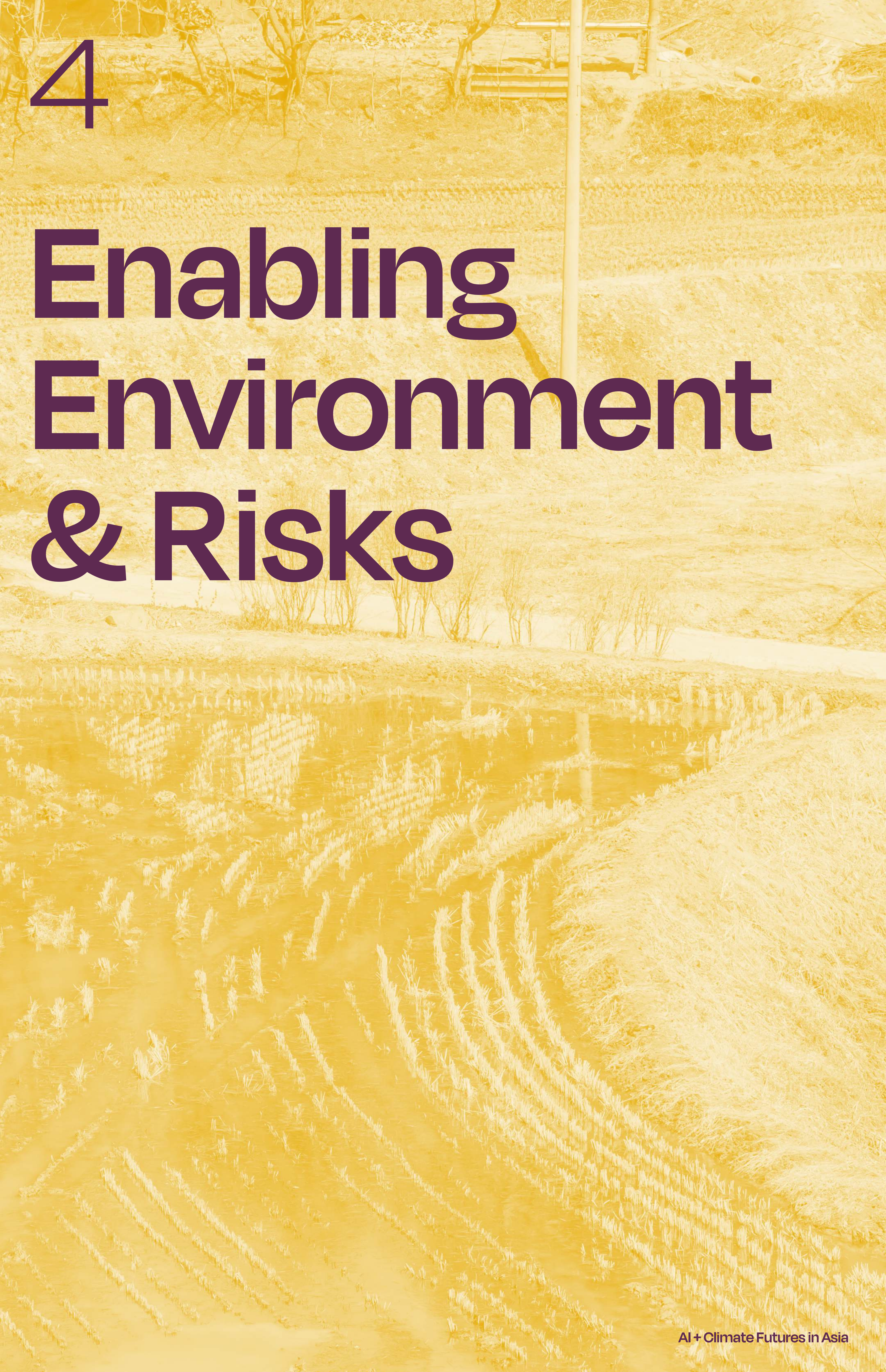
Similarly, for afforestation, where carbon credits are projected as being able to provide incentives to grow trees, tools such as the ones listed above can help monitor carbon initiatives and avoid exploitation of the poor when development initiatives do not go as planned but are continued nevertheless. This was noticed with a carbon offset project in the state of Haryana in India which aimed to compensate smallholder farmers for conversion of their lands to tree plantations but failed to provide timely and fair payments, which led to further impoverishment of poor farmers.[35]

Similar concerns of dispossession have surfaced in other carbon offset projects too[36], along with concerns that carbon credits are priced much lower than the actual social cost of carbon.[37] Such studies highlight the need to have strong local institutions to flag emergent problems as well as correct any mistakes arising from uncertainty in technology-driven recommendations and monitoring tools.[38]

Addressing over-crediting of carbon offsets is another problem that may benefit from more ground data and participatory processes to ensure that appropriate baselines or counter-factual assessments are used to measure additionality, permanence, and leakage in carbon offset projects.[39]

4

Enabling Environment & Risks



As has been argued, the technology to computationally model many natural processes is rapidly maturing and can aid climate action by helping with environmental monitoring and decision support.

The availability of good-quality data to train these models is a challenge but is seeing investment from both private donors (such as GIZ, Radiant Earth Foundation, Lacuna Fund) as well as public bodies. The policy environment to adopt such technologies is also positive – although not always for altruistic or democratic reasons, but rather for political and profit-making reasons. The risks at this moment, therefore, seem to be related to the following:

Over-promising the capability of the technology

Natural processes are complex, and their computational modelling accuracy depends on which variables are included, how well they are transformed into data and the corresponding availability of data to train the models. Agendas of economic or political benefit can over-promise the capabilities, and inadequate regulation for transparency and accountability can lead to a proliferation of cases where poor technology is deployed, which could create harm.[40]

Use of AI-based support in a top-down rather than paticipatory manner

If tools such as the ones described in this brief are adopted by the government to plan the implementation of forest rejuvenation or groundwater recharge, there is a risk of not only being inadequately informed of the local context to make up for technology errors, but also entrenching power in the hands of the bureaucrats.[41] Decades of progress made by social movements to strengthen decentralization and empower communities to engage with the state on their own terms can be compromised.

Technology solutionism and technology determinism

Technology solutionism – the idea that technology can solve a problem by itself – and technology determinism – that technology will lead to/determine specific outcomes[42] – are attractive narratives for technocrats because it validates their relevance and also helps them align with politicians and bureaucrats who stand to benefit from a similar centralization of power.

In the current context, big-tech, which benefitted prominently from the Internet economy (such as Google, Facebook, Amazon) and extensive computerization (such as Microsoft), is already very powerful in terms of computational capabilities and overreach with regulators and is actively co-opting the narrative of doing social good through their work.[43] As has been validated time and again, however, such technocratic approaches have a high failure rate and lead to the dispossession of nature and humanity while benefitting companies.

Increasing inequality

The AI-based innovations described in this brief were mostly community-centric – that is, at the level of landscapes rather than for individuals. The same techniques, however, are being actively adopted by agri-tech start-ups, which have a prominent business model of selling innovations to farmers who can afford these tools. When technology is sold to consumers – that is, to those who can pay and make their lives more efficient – it tends to increase inequality by forcing others to play perpetual catch-up.

The Green Revolution in India is a prominent example of how larger and more prosperous farmers benefitted significantly from improved yields because they could afford fertilizers required by the new seed varieties. Building technologies for consumers instead of citizens, thus, stands the risk of increasing inequality in society and further contributes to super-inequality by disproportionately benefitting technocrats, politicians, and bureaucrats.

Avoiding these risks requires stronger regulation, an alert civil society, a community-based and participatory approach to designing tools, and a commitment towards the democratic principles of equality and empowerment of the weak. We believe that such a transformation in an approach towards conceptualizing and designing technology in general, not just AI, requires the technologists themselves to be more aware of the societal risks related to technology and to adopt an ethos of working more closely with society.[44]

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Endnotes

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About the Project

Commissioned in early 2023 by The Rockefeller Foundation, this project explores the intersection of Artificial Intelligence and Climate Action in Asia. It examines opportunities, challenges and risks across three domains – agriculture and food systems, energy transitions, and disaster response in nine countries - Bangladesh, China, India, Indonesia, Malaysia, Singapore, Thailand, The Philippines and Vietnam.

We assembled a network of regional experts to help guide our investigation and provide context specific insights.

Aaditeshwar Seth (India)
ChengHe Guan (China)
Cindy Lin (Indonesia)
Elenita Daño (The Philippines)
Elina Noor (Malaysia)
Gaurav Sharma (India)
Md. Golam Rabbani (Bangladesh)
Pyrou Chung (Thailand)
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Digital Futures Lab is an interdisciplinary research collective that interrogates the complex interaction between technology and society in the global South. Through evidence-based research, public engagement and participatory foresight, we seek to realise pathways toward equitable, safe and just digital futures.

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