Global Models and Local Knowledges

On machine learning and politics in flood forecasting

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Global models & local knowledges

On machine learning and politics in flood forecasting

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Introduction

On September 5th, a storm in Greece released more rain than what is normally seen in an entire year. Streets turned into deadly rivers and whole villages were submerged. The storm continued on a trajectory across the Mediterranean, where it gained in strength before reaching the northeast coast of Libya. Intense precipitation caused the collapse of two dams, generating a seven-meter high wave that wiped out entire neighborhoods and swept homes into the ocean. Within the first two weeks of my inquiry into technologies that intend to alert people to the risk of flooding, such hazardous events abruptly ended the lives of tens of thousands of people.[1]

Climate change is expected to increase the frequency and intensity with which flooding occurs.[2] Framed as an invading force (Brooks 2005), both public and private organizations seek weapons to fight this harmful phenomena back. Regularly proposed in contemporary discourse as a potent weapon in this battle is artificial intelligence.[3]

The urgency and scale of the climate crisis calls for solutions with speed and reach. However, what is often obscured in grand visions of a sustainable future for all, is how we imagine and act to get there.

With this project, I inquire into the politics of flood forecasting with machine learning. I study visions of the global with climate disasters, how these visions are operationalised with machine learning, and how such projects form together with identities, norms, and practices in specific localities. To understand how flood forecasting models are political, I ask what is being optimized, for whom, and who gets to decide.

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[1] Yeung, J. "Ten countries and territories saw severe flooding in just 12 days. Is this the future of climate change?" 2023, September 17. *CNN World*.
https://edition.cnn.com/2023/09/16/world/global-rain-flooding-climate-crisis-intl-hnk/index.html
[2] UNEP. (2020, March 3). How climate change is making record-breaking floods the new normal.
https://www.unep.org/news-and-stories/story/how-climate-change-making-record-breaking-floods-new-normal
[3] See, for example;
Minevich, M. (2022, June 8). How To Fight Climate Change Using AI. *Forbes*.
https://www.forbes.com/sites/markminevich/2022/07/08/how-to-fight-climate-change-using-ai/
The Atlantic & IBM (2022). The Secret Weapon for Sustainable Business? AI. - Sponsor Content - IBM. *The Atlantic*.
https://www.theatlantic.com/sponsored/ibm-2022/the-secret-weapon-for-sustainable-business-ai/3741/

Methods

I study relationships between machine learning and climate disasters with models used for flood forecasting. In this context, I inquire into how models are manufactured, envisioned, scaled, and used. How are models produced, by whom, and with what knowledge? How do modelers envision the utility of their forecasts? How are models scaled to make forecasts in new localities and jurisdictions? How are forecasts used, and how do they influence the social and political lives of people in specific localities? Who does manufacture, envision, scale, and use flood forecasting models?

My objective is to provide thick, descriptive answers to these questions, and to advance understanding and theorisation of the politics of machine learning models in climate disasters like flooding. In doing so, I contribute to conceptual frameworks in political and social studies of technology in society, which may be applicable across academic and public policy domains.

In this project, I use iterative-inductive, qualitative methods of case study research, semi-structured interviews, and document analysis. Case study research emphasizes the study of a small number of cases (Becker and Ragin 1992). It allows an in-depth analysis and engagement with intertwined social and political elements embedded with the construction of science and technology. Further, it supports epistemological inquiries into knowledge and meaning making in the production of machine learning models. Google's flood forecasting model serves as a focal case study in this project.

Semi-structured interviews help me develop a deep understanding of the main issues in machine learning and flood forecasting (Becker and Geer 1957). My interviews, with interlocutors in Switzerland, Germany, Austria, Denmark, the United States, Uganda, and India, are inspired by multi-sit(uat)ed ethnographic practices (Sunder Rajan 2021), and involve encounters with people who manufacture, envision, scale, and/or use flood forecasting models. Semi-structured interviews allow study participants to in their own words express their views, interpretations, understandings, experiences, and opinions, and so shape my investigation of what is at stake in contexts of flood forecasting models (Byrne 2018). Through open-ended and collaborative dialogue, I together with interlocutors co-create the themes that guide the narrative of this thesis.

Document analysis is a systematic study of text, image, and video records (Prior 2004). It inquires into the production, sharing, and use of documents in social contexts. In this project, documents include books, illustrations, graphics, sketches, websites, policy documents, presentations, newspaper and academic articles.

If my conversation partner consents, I create anonymised data from interviews with audio and/or video recordings and software-aided transcriptions (Trint). In advance of a scheduled meeting, participants receive a consent form with information about the objectives of the study, their rights, and how data from the interview will be stored and used.[4] I analyze and thematically code transcriptions and documents, and cluster them with qualitative data analysis software (Obsidian). With a grounded theory approach (Strauss and Corbin 1994), I combine deductive and inductive coding of my research data. Practically, this means that I update and change codes and clusters as I iteratively engage with new theoretical frameworks, materials, and interlocutors. This method is particularly useful as a mode of qualitative research for theory development.

I analyze my empirical material with key concepts and theory from Science and Technology Studies (STS), including co-production (Jasanoff 2004), thinking globally (Edwards 2010), situated knowledges (Haraway 1988), politics of scaling (Pfotenhauer et al. 2022), and non-scalability theory (Tsing 2012). Research in and with STS enables me to inquire into social, political, and cultural issues of flood forecasting models. With this framing, I study the consequences of these models and the forms of institutions and life that they promote.

Outline

Guided by topics emerging in my analysis, I divide this work into three main chapters. In the first chapter, I turn to visions of the global with climate disasters. I offer a brief social, political, and cultural history of the science of water until the emergence of the Early Warnings for All initiative. I historise through the lens of co-production (Jasanoff 2004) to show how we know and represent the world with flood forecasting, and how this is inseparable from the way we choose to live in it. I read Paul Edwards (2010), Donna Haraway (1988), and James Scott (1998) together to unpack what visions of the global make legible. Finally, I draw on Matthew H. Edney (2009) and Saptarishi Bandopadhyay (2022) and argue that what is at stake in maps that arrange the global with climate disasters are mutually constitutive identities of “developed” and “developing” countries.

[4] Interview data and recordings are collected and stored in anonymised form in accordance with ETH Law Art. 36d. This study was examined by the ETH Zurich Ethics Commission and can be found as proposal EK-2023-N-232.

In the second chapter, I shed light on how flood forecasting models scale. I use the case of Google's flood forecasting model to build upon and expand the concept of politics of scaling by Pfotenhauer and colleagues (2022). I do so by reading my empirical material with Kate Crawford's (2021) data infrastructures and Anna Lowenhaupt Tsing's (2012) non-scalability theory. With logics from development economics, presented in the first chapter, I show how a way of scaling, which I term "piloting," raises issues of human dignity and power distribution.

Projects of scalability never fulfill their promise; they are always linked with the non-scalable. In the third chapter, Tsing's (2012) non-scalability theory and Haraway's (1988) thinking on situated knowledges, objectivity, and the privilege of partial perspectives, help me draw attention to other locations and modes of knowing and living with floods. Together with Andreas Greiner's (2022) (re)writing of infrastructure development, I highlight the resilience of community structures and practices in flood forecasting, while providing a critical reflection on what it means to engage in a just transition for all.

Finally, I conclude by arguing that it is *through* practices of vision and map-making that developing (and developed) countries are made developing (and developed) countries. Early Warnings for All, and flood forecasting models, increase the dependency on corporations and institutions in developing countries. They erode the social, environmental, and political authority of the state and diminish the very possibility for democracy to flourish in developing societies. Rather than forcing all states into one frame for (sustainable) development, I argue, we can only achieve a just transition with spaces and public institutions that take seriously the generative and transformative potential of meaningful diversity.

1
Visions of the global with flood disasters

Human attempts to master flood disasters are produced together with social norms and hierarchies. The knowledge that goes into the makings and representations of flood forecasts are simultaneously results of social work and constitutive of forms of social life. A similar proposition is introduced by Sheila Jasanoff (2004) in *States of Knowledge: The co-production of science and social order*. She argues that to understand past and present sociotechnical formations, we need to consider natural and social orders as being produced together.

In this chapter, I offer a brief history of hydrology read through this lens of co-production. Building on Jasanoff (2004), I argue that the way we know and represent the world with flood forecasting is inseparable from how we choose to live in it. Flood forecasting, and the scientific field of hydrology in which it originates, is not a reflection of "reality." It both embeds and is embedded in the social with its practices, norms, discourses, instruments, and institutions. To fully appreciate its past and present, I analyze with this chapter a selection of inseparable cultural and political formations that are historically woven together with flood forecasting.

In the following, I discuss how theories of water are visualized as interlinked and closed systems best studied by excluding humans. I shed light on visions of water as a resource to consume and control, and how access to more data for decades have been portrayed by hydrology modelers as the key to unlock financial gains. I trace how the importance of water (data) for modern, stable societies is reinforced both by intergovernmental organizations and hydrologists, and how machine learning is introduced in hydrology together with desires to make predictions in places perceived as lacking water data. Furthermore, I surface concurrent practices in development economics, and how visions of (sustainable) development are formed in economic theory, hydrology, and international institutions. I convene at a contemporary moment in which "Big Tech" is rallied by international organizations to predict and alert developing countries of climate disasters.

Visions of the global with climate disasters form at once a steady view of the whole and a directed gaze towards some of its parts. I suggest that visions of the globe produced throughout the history of hydrology encompass an arrangement of the world; one which is at once globular and horizontally sliced in two, with developed countries on the top and developing countries below. At stake in these visions, I argue, are identities of "developed" and "developing" nations and states.

A brief history

Humans have pondered on the movement of water and its vital implications for our lives since the beginning of civilisations. For thousands of years, people have studied and tried to manage water on Earth. Today, this is often called hydrology.

Hydrology is the study of temporal and spatial water phenomena on and in the Earth and its atmosphere. Despite our dependency on water, how knowledge about it is made has neither received much attention among scholars in science and technology studies (STS) nor in history of science.[5] In the following, I offer a brief history of hydrology, and the development of its subdiscipline flood forecasting, with the help of works in engineering and hydrology sciences by Asit K. Biswas (1970), Wilfried Brutsaert (2005), Dan Rosbjerg and John Rodda (2019).

Biswas (1970), Brutsaert (2005), Rosbjerg and Rodda (2019) all trace the first records of hydrology to the Greek antiquity 500–600 B.C. From this very beginning, theories of water circulation have been explained in vertical dimensions. For example, in early seawater filtration theory, water is assumed to come upward through the Earth from below and so be the source for springs and streams and other surface waters. In rainfall percolation theory, still the essence of hydrologists' understanding, water on land is replenished from above through precipitation.

Hydrology is distinct from other geosciences, like oceanology, meteorology, and climatology, with its focus on what Brutsaert (2005) calls "continental water processes;" the transport of water above, on, and below the Earth's land surfaces. Simultaneously, it links other geosciences through its focus on global balances and transfers of water. The movement of water is understood by hydrologists to occur in a closed system called the hydrologic cycle. Based on Brutsaert's (2005: 3) sketch

[5] To my knowledge, a few studies in *Earth Sciences History* discuss the history of hydrology. For example, Francesco Luzzini (2015) traces the development of water cycle concepts from the mid-sixteenth to the early eighteenth century, and Martina Johnson (1983) studies how geologists, chemists, and engineers were united in the study of groundwater in the United States in the eighteenth and nineteenth century. More recently, Debjani Bhattacharyya has studied the history of rivers through a conceptual framing of hydrosociality (2021).

below, water is considered mainly to move vertically between landmass and the clouds or, at times, down a hill into a stream, lake, or sea.

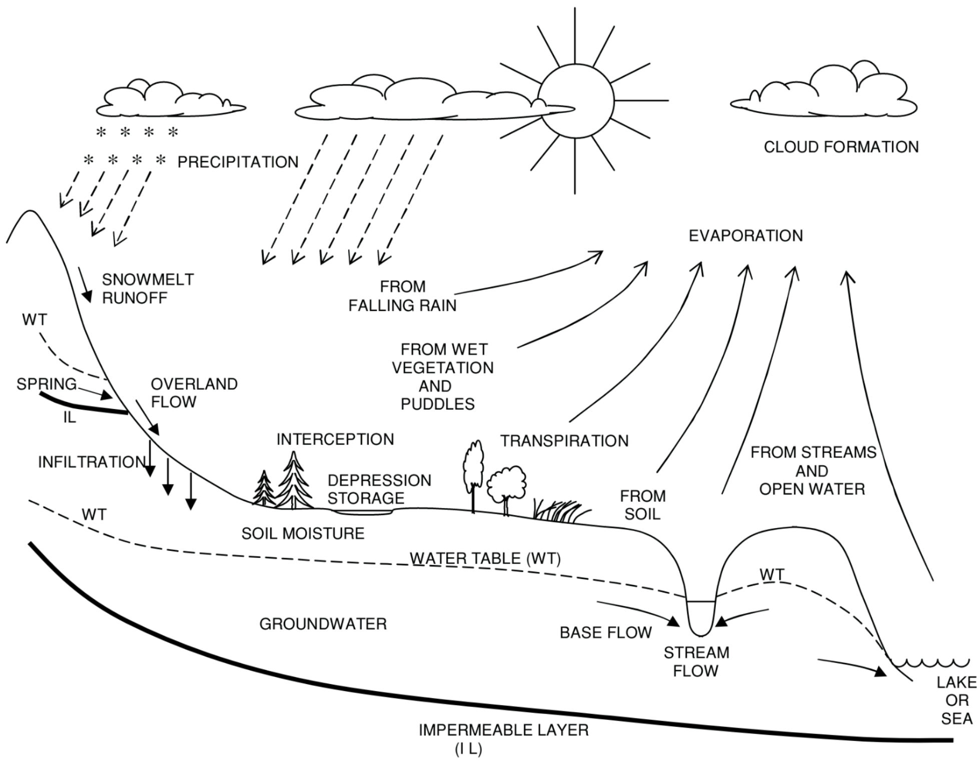

Figure 1. "Sketch of some of the main processes in the land phase of the water cycle" (Brutsaert 2005: 3).

The practical promise of hydrology is the "determination of the amount and/or flow rate of water at a given location at a given time under natural conditions, without direct human control or intervention" (Brutsaert 2005: 2). The last piece, "without human control," is an important element for hydrologists, which distinguishes the field of hydrology from that of hydraulics. This might explain the omission of people in Brutsaert's sketch.

The study of water on Earth is global in its mission. Cross-border collaboration among scientists in hydrology was institutionalized in the beginning of the 20th century, coordinated through the International Association of Scientific Hydrology (IASH). By the end of World War II, hydrology suddenly received increased public attention, after being recognised as a science with significance for economic development (Rosbjerg and Rodda 2019). Plans for economic growth were built on efficient utilization and control of the Earth's resources. This included reducing the risk of flood through methods of forecasting and prevention, and led to the building of dams, reservoirs, canals, and embankments.[6]

The design of hydrological structures required historical data for hydrologists to precisely manage and control water and, with it, to help fulfill promises of economic welfare (Rosbjerg and Rodda 2019). When projects did not meet financial expectations, hydrologists argued, not too dissimilar from today, that this was due to a lack of data.

In addition to desires to manage its resources for economic expansion, visions of the Earth in the aftermath of World War II were characterized by what Paul Edwards (2010) refers to as "thinking globally." In *A Vast Machine: Computer Models, Climate Data, and the Politics of Global Warming*, Edwards argues that "thinking globally" meant seeing the world as a knowable entity; as an interconnected and evolving dynamic system, but also as fragile and vulnerable. This new vision of life on Earth led to the "One World" movement and the establishment of international organizations such as the United Nations (UN) and the World Meteorological Organization (WMO), which since 1950 considers hydrology as one of its main responsibilities (Rosbjerg and Rodda 2019).

Physics to artificial neural networks

In 1995, Kuo-lin Hsu, Hoshin Vijai Gupta, and Soroosh Sorooshian published a demonstration of how to apply machine learning, or artificial neural networks (ANNs), in the field of hydrology. Traditional, physics-based models, the authors argue, are impractical. They require data that is often not available and calibration, which takes unnecessary time and effort. Whereas physics-based models may help scientists to understand hydrological processes, they also require sophisticated mathematical tools and experience with the model. Hsu and colleagues claim that in many "practical situations," such as forecasting, accurate predictions are more important than understanding processes and mechanisms of hydrology. With ANNs, they suggest a new way to make knowledge about phenomena like floods. Instead of methods that grapple with the interconnected nature of dynamic systems like precipitation, soil moisture, and stream flows, they advocate for a "practical" approach that provides answers without demanding explanations. Now, they assert,

[6] This was not the case for countries defeated in the war. For example, Yutaka Takahasi (2009) discusses how Japan in the decades after World War II suffered from a combination of economic depression and the most severe flood disasters in its history.

"explicit knowledge of the internal hydrologic subprocess is not required" (Hsu et al. 1995: 2518).

This simultaneous technical and cultural shift, towards valuing outcome over process, did not emerge in isolation. It was produced in historical, social contexts together with political and cultural formations.

Development economics

Around the same time as artificial neural networks were first introduced in hydrology in the mid-90s, economists started to notice and raise concerns about unequal distributions of economic welfare. The increasingly international trade of products and services since the end of World War II turned out not to benefit everyone equally. This gave rise to the field of development economics, which supports projects of intervention in states perceived as obstacles to an ideal, globally expanding economy.

The economist Debraj Ray (2013) describes countries of interest to development economics as having "fundamental economic inadequacies in a wide range of indicators," and goes on to list a number of "levels" that are below "developed-country benchmarks," such as low levels of capital per person, education, and safe water (Ray 2013: 3). He maintains that "[o]ne could expand this list indefinitely." He views these "inadequacies" of underdeveloped countries as "chicken-and-egg problems" that will not be solved by themselves. To correct for historical accidents that lead to these problems, Ray concludes, underdeveloped countries need a "push;" a one-time or temporary policy intervention that incentivises inhabitants to contribute to economic growth.

Ray builds upon the economic theories by Paul Rosenstein-Rodan (1943), which explain the motivation behind such policy interventions.[7] Policy interventions for economic growth, Rosenstein-Rodan argues, are not in the interest only of underdeveloped countries, but in the interest of the world as a whole. The high share of unemployment in undeveloped countries, he continues, is a "waste of labor" that hinders the maximization of world income (Rosenstein-Rodan 1943: 202). To enable maximization of income, labor must either be transported towards capital, or capital must be transported towards labor. Rosenstein-Rodan discards the first as too costly

[7] In their account of the history of development economics, Michele Alacevich and Mauro Boianovsky (2018) consider the publication of Rosenstein-Rodan in 1943 as "the birth of the postwar development discourse." See their "Writing the History of Development Economics" in *History of Political Economy* for a more thorough discussion of the debates in development economics at this time.

and concludes that maximization of world income "will have to be solved by industrialisation" of underdeveloped countries.

Similar to hydrology sketches of flows of water on Earth, the world is in these accounts at once envisioned as interconnected and divided. One part consists of countries in a position more advanced and the other is further below; underdeveloped. To maximize world income, developed countries need to "push" underdeveloped countries out of their "chicken-and-egg problems." This should remove obstacles to what is presumed to be a globally shared objective of worldwide economic expansion.

Such "push" has, since introduced in the 1990s, dominantly been operationalised with randomized controlled trials (RCTs).[8] In *Foreign Policy*, the economist Sanjay Reddy (2019) argues that the RCT trend reflects a collapse of faith in the ability of public policies to change economic futures, which has led to a surge of market-oriented policy reforms. Perceptions of governments in developing countries as particularly ill-equipped to contribute to global economic expansion were formed together with RCTs; interventions designed in union by non-governmental organizations, private organizations, investment funds, and foreign governments, Reddy explains. Scientific interventions delivered through these constellations, it was argued, would better help individuals in developing countries make the "right" choices. Rather than inviting people into an open-ended exploration of how to improve the institutions they are part of, the behaviors of millions of individuals in some of the world's poorest countries are with RCTs envisioned as variables to calculate and alter.[9]

Ungauged basins

The formation of global visions with a firm gaze towards developing countries manifested in hydrology through the decade of Predictions in Ungauged Basins (PUB). The International Association of Hydrological Sciences (IAHS) initiated PUB in 2003 with the objective to coordinate its scientific community towards "major advances in the capacity to make hydrological predictions in ungauged basins"

[8] After awarding the three pioneers of the method with the Nobel Prize in 2019, the Royal Swedish Academy of Sciences' declared that RCTs had come to "entirely dominate development economics." The Committee for the Prize in Economic Sciences in Memory of Alfred Nobel states that the method is suitable to identify "workable policies, for which one can make causal claims of impact" (2019: 3).

[9] Abhijit Vinayak Banerjee, Esther Duflo, and Michael Kremer (2020) state that "[p]olicy innovations that have been tested with RCTs have reached millions of people" and that the method has "if not revolutionized, at least profoundly altered, the practice of development economics" (2020: 440).

(Hrachowitz et al. 2013: 1201). Ungauged basins are rivers and watersheds, often found in developing countries, which do not have installations, called stream gauges, that make measurements of the water's level, movement, and quality.[10]

Hrachowitz and colleagues (2013) state in review of the PUB initiative that its approach, to extrapolate knowledge from locations with gauged basins to those without, diverted from traditions of empirical, on-site observation in hydrology. They conclude that despite the initiative's title, work during the decade of PUB mainly advanced research on water in gauged basins, not in ungauged basins. Grand aspirations to help poor, developing countries turned out to mainly benefit more wealthy and developed countries.

Similar to after World War II, hydrologists argued that the reason for why projects did not quite live up to their (economic) expectations was a lack of data. Some went further and implied that the issue was due to institutions in developing countries. "Hydrological data collection and analysis worldwide are not keeping pace with actual water development and management needs," the hydrologist Zbigniew Kundzewicz (2007) argued during a meeting in Brazil. Hydrological observation networks are particularly inadequate in tropical Africa, he affirms in his conference proceeding. He calls for more investment in global research, monitoring, and experiments by organizations operating across jurisdictional lines. Coordination, which Kundzewicz describes as "very limited to non-existent" (2007: 41), between agencies involved in activities related to data collection make national institutions in his view less suitable for the task of water management. Rather than involving national institutions, Kundzewicz calls for global hydrological data with remote sensing. As we will see, remote sensing has indeed evolved into a prominent theme in hydrology and its models.

Early warning systems

In 2022, the UN Secretary-General António Guterres launched what he named the "Early Warnings for All" initiative.[11] With his opening remarks, he called

[10] Nearing and colleagues (2023) use data from the World Bank and the Global Runoff Data Center to visualize the correlation between Gross Domestic Product (GDP) and years of daily streamflow data. With this, they communicate that the poorer the country, the fewer publicly available records of historical data.

[11] UN. (2022, November 7). Secretary-General's remarks at the launch of the Early Warnings for All Executive Action Plan.
https://www.un.org/sg/en/content/sg/speeches/2022-11-07/secretary-generals-remarks-the-launch-of-the-early-warnings-for-all-executive-action-plan%C2%A0

attention to the increasing frequency of climate disasters. To help those most at risk, he expressed his aspiration to ensure that every person on Earth is protected with early warning systems within five years. “Universal early warning coverage can save lives and deliver huge financial benefits,” Guterres said. The UN Secretary-General then committed to an investment of $3.1 billion dollars in the initiative, and outlined four areas of focus for early warning systems; understanding disaster risk, monitoring and forecasting, rapid communication, and preparedness and response capacity. To ensure effective implementation, Guterres made the World Meteorological Organization (WMO) and the United Nations Office for Disaster Risk Reduction (UNDRR) co-chair the initiative. They, he said, should guide countries with existing early warning systems and help establish systems in vulnerable countries.

The four areas of focus for early warning systems are visually interpreted by WMO in what they call a “value chain diagram.” This diagram illustrates the four areas of focus, as dictated by Guterres, in confined spaces on a thick outline of a circle. Enclosed in the middle of the circle are illustrations of people, accompanied by the label “people-centered.”

The connecting ends of dotted pipelines attach to the area in which people are contained in the middle of a circle, as if the four areas of early warning systems interact with them through remote sensing, stethoscopic analysis, or an envisioned combination of the two.

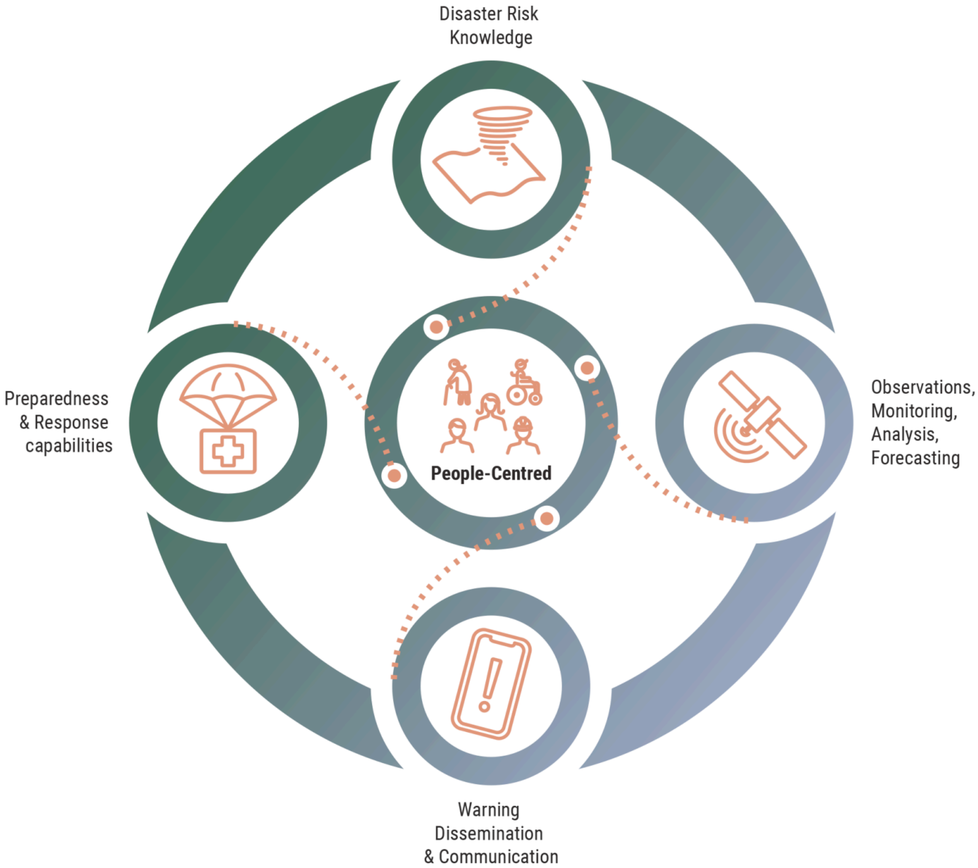

Figure 2. Value chain diagram of Early Warnings for All by WMO.[12]

Shortly after being appointed to co-lead the initiative, the WMO and UNDRR recruited a number of implementation partners. Together, they embrace an approach of "global upward reporting" of data, which is envisioned to be freely exchanged between all countries and ingested into highly advanced supercomputing modeling centers. Predictions from these centers should then cascade "back down from global to regional and national levels." According to their website, modern weather and hydrology forecasts would not be possible without this "complex, global effort enabled by WMO."

[12] WMO and the Early Warnings for All Initiative.
https://wmo.int/site/wmo-and-early-warnings-all-initiative

Figure 3. On the WMO website, global activities are pictured at the top, followed by "last-mile," local responsibilities at the bottom.[13]

In their vision of activities involved in early warning systems, the WMO depicts the global management of infrastructure as unlocatable and elevated. Observations from the globe are pictured with numerous satellites orbiting the Earth in space, international exchange is monitored with a map from afar, and fluid, colorful regions cover the planet in global weather prediction. Although explained as carried out locally, forecasts and warnings are illustrated with a terrestrial body draped in mesh. First after steps of global observation, exchange, prediction, and forecasting, the WMO anticipates the involvement of people and pictures a woman in hijab with a megaphone. Activities from the global to the local are imagined to lead to "effective decision-making and action," visualized with the Sustainable Development Goals (SDGs).

Seven months after UN Secretary-General António Guterres announced his vision of early warning systems, the collective responsible for the implementation of Early Warnings for All included "Big Tech."[14] Alibaba, Google, IBM, and Microsoft all committed to support Early Warnings for All. As the collective gathered, WMO framed extreme weather events as an opportunity to save lives and reap a tenfold

[13] WMO and the Early Warnings for All Initiative. https://wmo.int/site/wmo-and-early-warnings-all-initiative
[14] WMO. (2022, October 25). Private sector – and Big Tech - rally behind Early Warnings for All. https://wmo.int/media/news/private-sector-and-big-tech-rally-behind-early-warnings-all

return on investment.[15] Thereafter, they explained the problem as financial, leading to "hundreds of billions of dollars in economic losses," caused by "gaps" in developing countries. WMO diagnosed a "global incapacity" to "translate early warnings [to] early action."[16] The WMO envisioned Big Tech to fill gaps of "last mile" systems nationally, regionally, and locally, and posed artificial intelligence as a particularly promising solution.[17]

Identities in visions of the global with climate disasters

Visions of the global with climate disasters form at once a steady view of the whole and a directed gaze towards some of its parts. Water is portrayed as a risk and an investment to be controlled and capitalized upon with practices of centralized monitoring and management. When doing so, international organizations and private corporations narrate that they fill national, regional, and local gaps of incompetence and incoordination. These imaginations, I argue, figure people in developing countries as victims not only of climate disasters, but also of flawed institutions.

In the 1990s, views of developing states and their institutions as flawed gave rise to so-called "neotrusteeships." In *All is Well: Catastrophe and the Making of the Normal State*, Saptarishi Bandopadhyay (2022) argues that disaster management is conceptualized as a problem for the entire international system. It is rooted in fear that political, social, and environmental catastrophes in decolonised nations would affect "normal," modern, previously colonizing states. Since the global character of disasters seemed too profound for a single authority to manage, command was assigned to a collective of national and international organizations, together with one or more powerful states with an interest in the political welfare of the region. Similar to Early Warnings for All, authorities in these neotrusteeships developed systems to detect disruptions of environmental, as well as social, character. With appropriate interventions, neotrusteeship governance removed natural anomalies, corrected irrational subjects, and taught societies to choose the "right" future. Such

[15] The IPCC, similarly, states that "there is a rapidly closing window of opportunity to secure a liveable and sustainable future for all (*very high confidence*)" (53).
IPCC. (2023). Synthesis Report of the IPCC Sixth Assessment Report.
https://www.ipcc.ch/report/ar6/syr/downloads/report/IPCC_AR6_SYR_LongerReport.pdf

[16] WMO. (2022, October 25). Private sector – and Big Tech - rally behind Early Warnings for All.
https://wmo.int/media/news/private-sector-and-big-tech-rally-behind-early-warnings-all

[17] WMO. (2023, May 31). Big Tech and Artificial Intelligence can support Early Warnings for All.
https://wmo.int/media/news/big-tech-and-artificial-intelligence-can-support-early-warnings-all

systems and interventions, Bandopadhyay argues, embody core themes of contemporary global governance; neoliberal political economy, risk modeling, and "peace" through free trade. At the same time, they produce dependence on developed countries while maintaining a clear separation between them and developing states.

Claims to see everything through disaster management systems, without itself being seen, and to represent everything, while escaping representation, is what Donna Haraway (1988) refers to as "the god trick." By presenting the Early Warnings for All initiative as a universal solution, international constellations of public and private organizations claim that they can (fore)see climate disasters across time and space. Yet these actors care not to make themselves visible to communities in specific localities affected by climate catastrophes. Early Warnings for All claim to represent everyone, to build systems that protect every person on Earth. Yet the WMO, UNDRR, and Big Tech escape representation.

During the launch of the "action plan" for the Early Warnings for All initiative, Selwin Hart at the UN promised that "even if we fail [...] we will still save potentially tens to hundreds of millions of lives."[18] He then turned to the room with the noble words; "we are all making history." It seems not to matter to him how many lives they "save," Early Warnings for All is primarily an opportunity to "make history."

Early Warnings for All is proposed as a remedy to institutional malfunctioning, which is envisaged as uniform and shared among developing countries. This reductionist myth is circulated by international organizations and their partners when they forecast and communicate catastrophes from a position illustrated as above and detached, inhabited while dodging accountability to the people whose lives are impacted by climate disasters. But as Haraway (1988) eloquently argues, an objective, disembodied "view from nowhere" is a myth.

That the knowing subject in the history of science is "distanced from everyone and everything," as Haraway (1988) explains it, is not new. What is new, I argue, is how knowing, or capable, subjects are distanced from unknowing, or incapable, objects in emerging views of the global with climate disasters. Edwards (2010) describes visions of the Earth in the context of climate change as a knowable entity; an interconnected, evolving dynamic system which simultaneously is fragile and vulnerable. I suggest that visions of the globe formed throughout history with hydrology additionally comprise an arrangement of the world entity; one which is at

[18] UN. (2022, November 7). Launch of the Action Plan on Early Warning Systems. https://unfccc.int/event/launch-of-the-action-plan-on-early-warning-systems-0

once globular and horizontally sliced in two, with developed countries at the top and developing countries below. The knowing, “developed” subject is unlocatable yet constantly found above.

James Scott shows how a narrowing of vision, in this case directional and hemispherical, is required for certain forms of knowledge and control. In *Seeing like a State: How Certain Schemes to Improve the Human Condition Have Failed*, Scott (1998) suggests legibility as a central problem in modern statecraft. To govern with central recording and monitoring, states have for centuries manufactured simplified, legible measures of populations and natures. Projects of legibility, Scott suggests, are like fragments of maps. They do not represent the actual activity of the society it records, nor do they intend to. They only render a selected part of society that the observer is interested in. As Scott shows, maps are not just maps. When paired with power, they remake the images that they selectively depict.

The geographer Matthew H. Edney (2009) studies maps by removing boundaries between cartographic and other (oral, gestural, performative, written, graphic) representations that likewise serve as maps. In his chapter, “The Irony of Imperial Mapping,” he describes mapping as an activity that both depicts and constructs places. Depictions of physical and cultural landscapes, he argues, are made in modern times in distinction to other places. Hence, categories of polity neither emerge from self-evident geographies nor do they exist in isolation. Polities are made, Edney argues, through deployment in discourses of cultural, highly partial, and ideological artifacts that make distinctions between places with what we might call a map. Drawing on Edney, I argue that this is what is at stake in the oral, written, and graphic maps that arrange the global with climate disasters; mutually constitutive identities of “developed” and “developing” countries.

Bandopadhyay (2022) diagnoses sustainable development and risk management as the premises for the survival and prosperity of a “normal” (self-governing) state. Combined with Edney (2009), it is by allocating sustainable development and risk management to developed countries that their identities as “normal” states is (re)made. Hence, the project underway with Early Warnings for All is not, I argue, primarily to help developing countries. It is to reinforce what it means to be “normal,” modern, and developed.

2
Piloting flood forecasts

With the Early Warnings for All initiative, WMO, UNDRR, and "Big Tech" use artificial intelligence to implement a system that promises to predict climate disasters anywhere, determine who is at danger, and subsequently warn anyone on Earth. The previous chapter discussed political, economic, and cultural conditions embedded with the formation of this initiative.

This chapter focuses on projects intertwined with the Early Warnings for All program that attempt to make flood forecasts and alerts globally available. First, I discuss how machine learning models are produced for flood forecasting and bring attention to the material conditions of their making; (open source) data and computing power. Second, I shed light on a process with which one of these models attempts to scale to eventually reach every person on Earth. Finally, I turn to issues of dignity and concentrated power in the combination of flood forecasting and RCTs.

This chapter builds and expands on the politics of scaling, as introduced by Sebastian Pfotenhauer, Brice Laurent, Kyriaki Papageorgiu, and Jack Stilgoe (2022). Scalability thinking, they demonstrate, is pervasive not only in narratives of innovation but also in contemporary public policy initiatives. Scale is used, similar to in the arenas of entrepreneurship and venture capital, as a framing device which prescribes problem definitions, the desirability of solutions, and who is authorized to bring about societal change. Ultimately, the authors argue, scale is used to identify what is worth doing in public policy.

The fixation on scalability reconfigures political and economic power by introducing a normative understanding of societal change in policy initiatives and public research programs. Pfotenhauer and colleagues (2022) show how in the pursuit of impact at scale, social disruption is accepted while details about the envisioned transformation, and who gets to shape it, are obscured. What's at stake in what they call a "scalability zeitgeist," in imaginaries of scalability as a desirable end in itself, is control over the future.

With the case of flood forecasting, I illustrate the politics in a process of scaling that I call "piloting." Piloting is, in the case of flood forecasting, the work of "evidence-based" experiments and randomized controlled trials (RCTs) that are conducted on people in developing countries and designed by Big Tech and NGOs.

Through piloting, experiments with flood forecasting are not simply geographically expanded from its initial location. With a vision from above, pilots steer towards a specific locality, where they land to pair experimental development economics with flood forecasts, before taking off to run the next experiment elsewhere. Through my inquiry into normative, material, and social configurations, I build on Pfotenhauer et al. (2022) with a complementary understanding of experimentalism and the politics of scaling in and around experimental sites.

Machine learning

Machine learning is a subfield of artificial intelligence, which Stuart Russel and Peter Norvig describe as a field which attempts "not just to understand" human intelligence, but to build intelligent entities (2010: 1). In their view, "intelligence is concerned mainly with rational action." As Kate Crawford notes in her *Atlas of AI: Power, Politics, and the Planetary Costs of Artificial Intelligence* (2021), depending on who you ask, you may receive different definitions of artificial intelligence. She insists that artificial intelligence is neither artificial nor intelligent, but embodied and material, and entirely dependent on political and social structures. In her book, Crawford refers to artificial intelligence as "the massive industrial formation that includes politics, labor, culture, and capital."

Machine learning encompasses approaches in which a machine learns a function that predicts the output for new, unfamiliar inputs (Russel and Norvig 2010). It learns this function based on a phase of training on a collection of input-output pairs. In flood forecasting, machine learning models, for example, use historical data that describe how rainfall runs off in gauged rivers, and learn a function that predicts how rainfall would run off in ungauged rivers, which do not have historical records of data.[19] To produce such predictions, modelers need access to large amounts of historical data.

According to Russel and Norvig (2010), learning algorithms are better than the best programmers at recognising patterns. They demonstrate their argument by stating that "most people are good at recognizing the faces of family members, but even the best programmers are unable to program a computer to accomplish that task, except by using learning algorithms" (2010: 693). In this description, as well as in Crawford's (2021) account, faces (of family members) are presented as data points;

[19] See, for example, Kratzert et al. (2019).

not as means of identification, but as tools to manufacture an automated form of vision. Crawford argues that the imagined neutralization of personal, social, and political meanings of pictures, that are used to train machine learning systems, reflects what she calls "a shift from image to infrastructure." (2021: 93). Infrastructures assembled with historical data are in this sense used daily in the manufacturing of machine learning models.

Machine learning models are made with data taken from the internet or from state institutions without context and without consent. These globally distributed internet sources are, according to Crawford (2021), often envisioned to be endless; to persistently offer more data for modelers to capture. In their paper titled "AI Increases Global Access to Reliable Flood Forecasts," Nearing and colleagues express their desire for more data by concluding that "[w]e believe that the best way to improve flood forecasts [...] is to increase access to data" (2021: 13). Over the last decade, mass collection of digital material for training of machine learning models has become so commonplace that it is now largely unquestioned.

Data and open source

In conversation with forecasters, I learn that data commonly used to predict floods originate from two main sources; The National Aeronautics and Space Administration (NASA), a part of the federal government in the United States (US), and the European Space Agency (ESA). These data often take the form of satellite images. Figure 4 shows samples from a frequently used dataset by ESA.

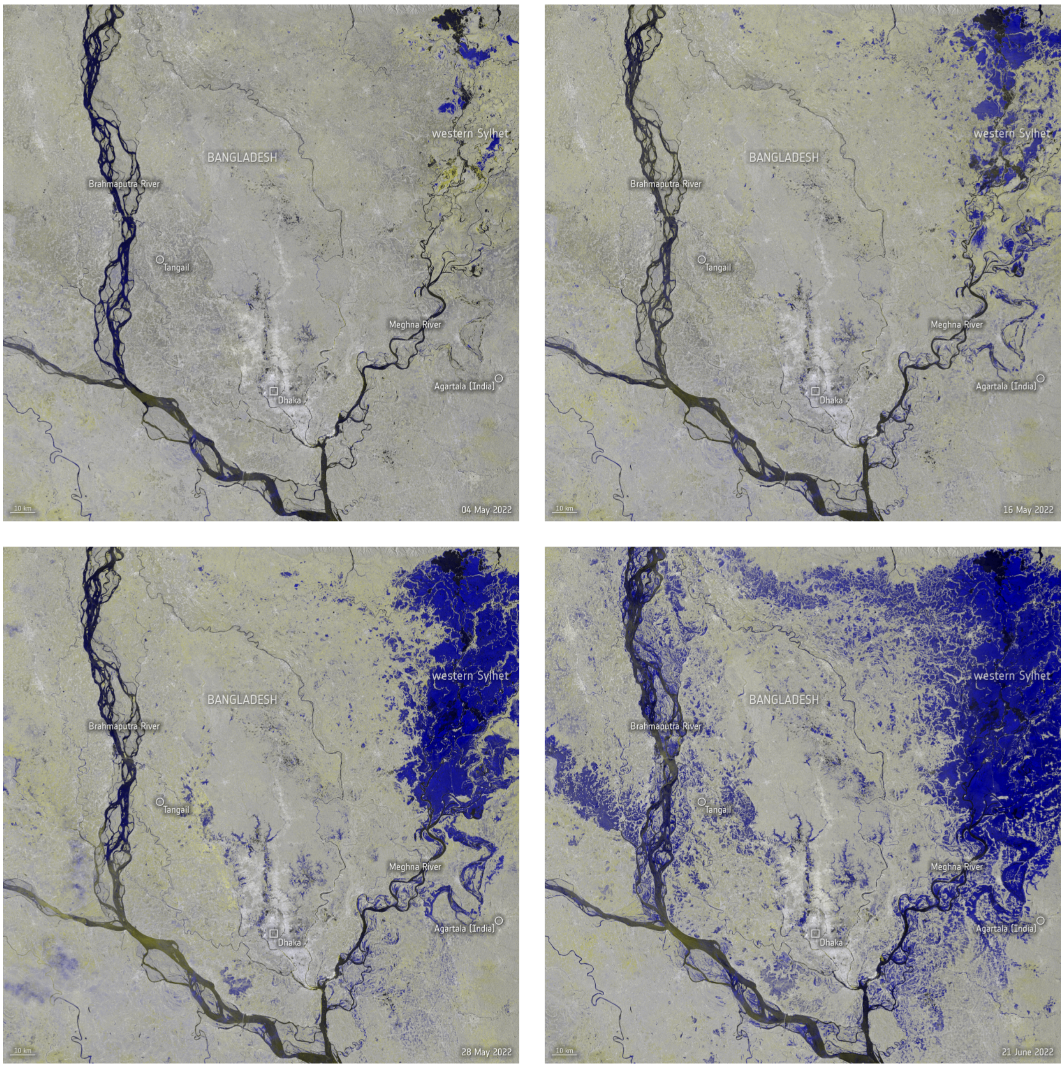

Figure 4. Satellite images, made with ESA's two-satellite constellation called Copernicus Sentinel, picturing floods in Bangladesh in 2022.[20]

Additionally, modelers use data produced by river gauges that measure stream flows. Only around one percent of the world's watersheds have gauges that make these measurements.[21] When training a machine learning model to make predictions for approximately one million watersheds in the world, modelers rely on historical, "publicly available clean data" from around 10'000 stream flow gauges, which are most likely to be found in countries with a relatively high Gross Domestic Product (GDP) such as the United States, Canada, Germany, and the United Kingdom. These locations are marked with dots in yellow and green in Figure 5. With these data,

[20] ESA. (2022, June 30). Copernicus Sentinel-1 maps Bangladesh flood. https://www.esa.int/ESA_Multimedia/Images/2022/06/Copernicus_Sentinel-1_maps_Bangladesh_flood
[21] AI for Good. (2023, March 15). AI for flood forecasting | Grey Nearing at Google. https://www.youtube.com/watch?v=P06Mb-3GYMM

machine learning models are used in flood forecasting to make predictions in ungauged basins, which are most likely to be found in countries with a relatively low GDP, such as India, Bangladesh, and Mozambique, countries which also tend to have higher risks of flooding. These locations are marked with purple, or remain white, in Figure 5.

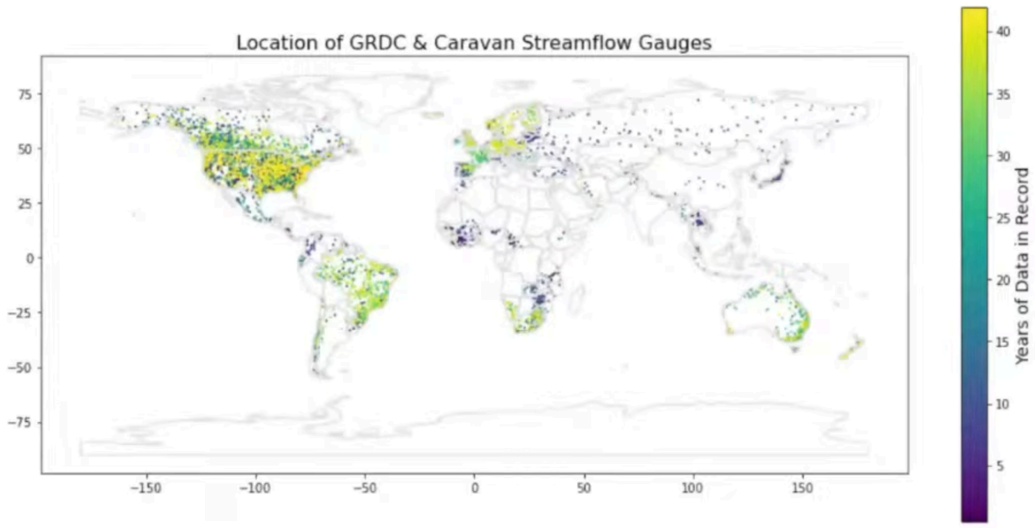

Figure 5. Regions with many years of historical hydrology data are indicated in yellow and green. This is where Google mainly "took" data from, as one modeler explained it, when training flood forecasting models. Regions with few years of historical data are indicated in purple. Regions without data remain white.[22]

Data in themselves, however, are not sufficient to produce machine learning models. To process vast amounts of data and to train machines to "learn," modelers need computing power.

Computing power

For decades, open source data has been used both in academia and in industry to manufacture machine learning models. However, as Nur Ahmed, Muntasir Wahed, and Neil C. Thompson note in *Science* (2023), computing power, one of the key ingredients for artificial intelligence research, is increasingly dominated by technology corporations. Computing power materializes in data centers, which have been incurred by Big Tech over the past decades to support their businesses of

[22] AI for Good. (2023, March 15). AI for flood forecasting | Grey Nearing at Google. https://www.youtube.com/watch?v=P06Mb-3GYMM

making (user) data. Today, most large data centers are owned and operated by a few large corporations.

With ownership of vast physical space, capable of housing infrastructure for creating, running, and deploying data applications and services, actors in industry have access to significantly more computing power than academia. To show the difference in computing available to the two groups, Ahmed, Wahed, and Thompson (2023) estimate that industry models on average are 29 times bigger than academic models. They insist that policymakers should be worried about the implications of this systemic shift, and caution that artificial intelligence research might be pursued in a direction misaligned with public interests.[23]

Google, Microsoft, and IBM all use machine learning to forecast floods. Google uses flood forecasts to send push alerts to people through personal smartphones and provide a visual overview of flood disasters around the globe on what they call the Flood Hub.[24] Microsoft uses machine learning in subseasonal forecasting, and forecast floods as part of their "Planetary Computer."[25] IBM builds flood forecasts together with other weather and climate applications for research and commercial uses.[26] Recently, IBM announced their geospatial foundation model, developed in collaboration with NASA, which they envision scientists to use to estimate the extent of floods and wildfires.[27] In their blog post, they confidently claim that "[t]he emergence of pre-trained AI models means that the field of weather and climate modeling has effectively been democratized."

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[23] This is a growing concern also among legal and policy scholars. See, for example, Veale, Matus, and Gorwa (2023).

[24] Google. (2023). Flood Forecasting. https://sites.research.google/floodforecasting/
Also, see Nearing et al. (2023).

[25] Sanchez-Andrade Nuño, B. (2023, January 24). Using Microsoft Planetary Computer to calculate the extent of the Pakistan floods. https://www.youtube.com/watch?v=kqkpE8l_bSc
Microsoft's Planetary Computer. https://planetarycomputer.microsoft.com/
Mackey, L., Mouatadid, S., Flaspohler, G. and Cohen, J. (2023, June 16).
Improving Subseasonal Forecasting with Machine Learning. *Microsoft Research Blog*.
https://www.microsoft.com/en-us/research/blog/improving-subseasonal-forecasting-with-machine-learning/

[26] More on IBM's approach to artificial intelligence in "climate change applications" in "AI for climate impacts: applications in flood risk" by Jones et al. (2023).

[27] See, for example, Jones et al. (2023), and IBM. (2023, November 30). IBM and NASA are building an AI foundation model for weather and climate.
https://research.ibm.com/blog/weather-climate-foundation-model
The press release was timed with and linked to IBM's involvement during COP28.
IBM. (2023, November 30). IBM Advances Geospatial AI to Address Climate Challenges.
https://newsroom.ibm.com/2023-11-30-IBM-Advances-Geospatial-AI-to-Address-Climate-Challenges

Through my encounters and conversations, I learn that the models that technology corporations share openly through public software repositories are in fact not the same as they use internally. Hence, the model labeled open source is not the model used by the corporation to predict floods. Further, through direct and indirect partnerships with governments, large technology corporations access and use data for their models that are not available to the public. Even if, say, a national meteorological department would have access to the actual flood forecasting model and its data, only officials who can write and run code in Python are able to use the model. Finally, and most importantly, even if models were manufactured in a way that would challenge the three previous arguments, the computing power needed to freely use, modify, and share flood forecasting models is not currently available to all. Governments would need access to a supercomputer, or pay for a cloud service subscription, to create models similar to those developed by Google, Microsoft, and IBM. Only a few departments in high-income countries, like the National Oceanic and Atmospheric Administration (NOAA) in the United States, have access to supercomputers. Governments in low- and middle-income, in particular, are unlikely to have the required computing resources to run or modify machine learning models. This disproportionate computational power relation risks making low- and middle-income countries more dependent on (private) actors in high-income countries.

Unless we refer to the publicly funded data and infrastructure that provide supply for flood forecasting models, the label "open source," I contend, does not seem appropriate for these models' exclusive use, modification, and sharing. To democratize the field of weather and climate modeling with artificial intelligence, as seems to be the inspiration of IBM, we ought to seriously reconsider to whom their manufacturing, use, and distribution is available.

Piloting

At the "AI for Good Global Summit 2023," Grey Nearing presents Google's flood forecasting initiative in a presentation titled "Global Models for Local Information."[28] He explains how the model "runs over the whole world" but that they push forecasts to the public only in regions where the government allows them to, and where they feel confident in the model's predictions.

[28] AI for Good. (2023, March 15) AI for flood forecasting | Grey Nearing at Google. https://www.youtube.com/watch?v=P06Mb-3GYMM

The most effective way for them to communicate with local communities, Nearing explains in the presentation, is by partnering with NGOs. He shares how Google recently partnered with GiveDirectly to conduct a "pilot study" for which they enrolled 6'000 people in several villages in Mozambique in randomized controlled trials (RCTs).

According to their website, GiveDirectly sends money from donors to "the world's poorest households."[29] "We use rigorous experimental research (randomized controlled trials) to measure our impact and answer public policy questions," GiveDirectly asserts, and lists how the "impact" of direct cash transfers is measured with individuals' subsequent increase in earnings, in assets, and in nutrition spend.

In the pilot study, GiveDirectly used Google's flood forecasts to determine the "impact" of sending cash to poor households before versus after a flood.[30] Conducted as an RCT, I conclude that the partnership involved enrolling 6'000 people that Google predicted would be affected by flooding, then sending cash transfers to a third of them before the flood, a third of them after the flood, and to deny the last third of any cash transfer, since they would be considered by experimenters as part of a "control group."

When I speak with a project member in this pilot study, I learn that the location in which they experiment with disaster relief is based on risk analyses from firms that focus on insurance payouts. Combined with satellite images, these firms combine historical frequencies of disasters with fund risk, to create a map with what they consider to be suitable villages to include in an experiment. Experiment designers combine this information with additional data sets, such as the Relative Wealth Index, described to me as a "geospatial tool for poverty mapping."[31] Thereafter, employees of the NGO travel from village to village to speak with

[29] GiveDirectly. (2023) About GiveDirectly. Available on: https://www.givedirectly.org/about/
GiveDirectly. (2023). Research at GiveDirectly. https://www.givedirectly.org/research-at-give-directly/
[30] AI for Good. (2023, March 15) AI for flood forecasting | Grey Nearing at Google.
https://www.youtube.com/watch?v=P06Mb-3GYMM
In the presentation, Nearing mentions "training videos" that Google uses to help a variety of NGOs to understand and disseminate Google's tools. These videos explain how to "use" and "interpret" the information that modelers produce about flood forecasts. For an example of such a video, see Google. (2021, May 20). Flood Forecasting Alert - Training Video.
https://www.youtube.com/watch?v=OWIXVest4ss
[31] Later, I learned that the Relative Wealth Index is created by Meta, formerly Facebook. For more, see Chi, G. et al. (2022, January 12). Micro-estimates of wealth for all low- and middle-income countries. *Meta Research Blog.*
https://research.facebook.com/blog/2022/1/microestimates-of-wealth-for-all-low-and-middle-income-countries/

community leaders, and finally make a decision about which communities that are most appropriate to experiment on.

When I inquire into how the specific locality for an RCT is determined, I learn how, despite considering the initial experiment unsuccessful, the project team has decided to launch replicated experiments in two additional countries in Africa and South Asia. The decision on where to do "piloting," I understand, is ultimately determined by donors. Large donors indicate which countries they consider to be "priority countries," and which countries that are not. In the case of GiveDirectly, large disaster relief donors include Google.org and the Google CEO Sundar Pichai.[32]

Power and politics in (non)scalability

Whereas data infrastructure is considered necessary to train machine learning models, it is computing power that is the main material ingredient. Today, computing power is possessed almost exclusively by a small number of large technology corporations. As a result, research and development of machine learning models, in and outside of hydrology, are mainly done in "Big Tech." Hence, when WMO "emphasizes the use of technology like AI to support the attainment of the objectives of the [Early Warnings for All] initiative,"[33] they state their preference for Big Tech to disseminate warnings of climate disasters to every person on Earth. At the same time, the WMO obscures details about the transformation to a global warning system, and who gets to shape how these systems increasingly warn more people. All that seems to matter is to reach the objective uttered by the UN Secretary-General.

In this chapter, I unveil how one of the systems produced under the umbrella Early Warnings for All leverage what I call "piloting" to scale. In this process, technology corporations partner with NGOs to marry machine learning models with "evidence-based" methods from development economics. People in some of the world's poorest countries are experimented upon before, during, and after climate disasters, so that NGOs can "answer public policy questions." As suggested in my encounters, it is ultimately not quantification of impact, but donors with deep pockets, who determine at what sites to continue piloting flood forecasts through experiments with villages and communities.

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[32] GiveDirectly. (2020, April 14). New funding from Google CEO, Google.org, and Flourish Ventures. https://www.givedirectly.org/new-funding-covid-19/

[33] WMO. (2023, December 1). Early Warnings for All: Artificial Intelligence to unlock the potential of Early Warning Systems. https://wmo.int/events/cop28/ew4all-ai-unlock-potential-EWS

The case of flood forecasting raises issues of politics in scaling. It draws attention to a form of scaling that is distinct from a vertical, gradual "scaling up," and instead characterized by a two-dimensional dynamic; as if using satellite images of the planet to navigate sideways and zoom in and out of specific locations. With what I call "piloting," this scaling dynamic operationalises visions of the global through incremental, spatially dispersed experiments that pair development economics with flood forecasts. Expanding on the work by Pfotenhauer and colleagues (2022), whether flood forecasting is worth experimenting with in a specific locality, I suggest, is not determined with rhetoric of scale, but by the will of obscured donors who channel their funds through NGOs. In the case of GiveDirectly, some of the largest donations come from executive officers and departments in "Big Tech."

At stake in piloting is dignity and power. My concern is how piloting mirrors the imagined process of neutralization, as Crawford (2021) describes, where images are made into data infrastructures. In piloting, people are stripped of their virtues and conceptualized as experimental objects. Experiments like RCTs, I argue, reduce human subjects to data points. Their vulnerability at times of disasters is exploited to make "evidence-based" predictions and claims about the future. The overlapping material and financial forces of Big Tech in both flood forecasting and through donations entitle a few wealthy individuals to dictate which poor communities should next be turned into experimental objects. This treatment of humans in times of crises, I argue, raises questions of human rights. Early Warnings for All should not only propagate their objectives to technology corporations, but also examine whether their objectives are achieved with "act[s] towards one another in a spirit of brotherhood."[34]

Anna Lowenhaupt Tsing (2012) calls with her non-scalability theory attention to the ruins that scalability leaves behind as it spreads and is abandoned. With efforts to conceptualize and make the world through "expansion," Tsing describes how biological and cultural diversity are conceived of as enemies of universal progress. She uses examples from sugarcane plantations, and the supply chain capitalism surrounding matsutake mushrooms, to show that only if elements remain the same, project expansion is equalized with progress. Elements, Tsing argues, can only persist as unchanged if they do not form transformative relationships, which are the medium for diversity and potential change. However, despite grand ambitions, Tsing

[34] UN. Universal Declaration of Human Rights. https://www.un.org/en/about-us/universal-declaration-of-human-rights

shows how projects of scalability fail to meet their own expectations. Scalability is never complete, she argues: “[i]f the world is still diverse and dynamic, it is because scalability never fulfills its own promises” (2012: 510).

Thinking with non-scalability theory, I suggest that piloting is designed to avoid transformative relationships by isolating experiments in spatially dispersed localities. The division of people into treatment and control groups further fosters alienation and enhances control. Individuals in these experiments are considered to be interchangeable design elements, engineered for the purpose of piloting. But, as we will see in the next chapter, scalability is always linked with the non-scalable. “Design elements” are never fully under control.

3

Knowing floods

Piloting, I argue in the previous chapter, is a project of scalability that operationalises visions of the global with climate disasters. As Tsing (2012) shows, scalability is inevitably linked with non-scalability. Throughout this chapter, I think with her non-scalability theory to illuminate how projects with disembodied visions of the global, that aspire to expand through piloting, form together with non-scalable elements and situated knowledges.

In this chapter, I bring machine learning models together with perspectives on climate disasters and flooding in India and Uganda. First, I describe how machine learning modelers envision the utility of their forecasts in Africa and Asia, and how they communicate flood risk. Second, I decentralize the manufacturing of flood forecasts by attending to how they are alternatively produced and used in Telangana, India. Third, I contrast visions of the global by surfacing perceptions on climate disasters in Uganda. To do so, I read my encounters and empirical material through Donna Haraway's (1988) concept of situated knowledges.

Inquiring into the meaning of "objectivity," Haraway (1988) suggests a move distinguished from both the dichotomy that she perceives feminist critical empiricists trapped in, and from radical social constructionist arguments for all forms of knowledge claims. It is not enough, she argues, to deconstruct truth claims of science by showing "historical specificity, and so contestability, of *every* layer of scientific and technological constructions" (1988: 578). Feminists have to insist on a better and richer account of the world that enables us to "live in it well and in critical, reflexive relation to our own as well as others' practices of domination and the unequal parts of privilege and oppression that make up all positions" (1988: 579).

In "Situated Knowledges: The Science Question in Feminism and the Privilege of Partial Perspective," Haraway (1988) insists on embodiment of all vision, organic and technologically mediated, and on situated knowledges as a doctrine of feminist objectivity. Only then, she argues, may we resist myths of a conquering technological gaze from nowhere that attempts to split subject and object. Objectivity is about embodiment that is particular and specific, not about transcending, disembodied vision. Haraway insists that it is only partial perspectives that promise objective vision, and argues for situated knowledges that are locatable, responsible, and able to be called into account.

Seeing from locations of periphery and depth, Haraway (1988) cautions, is not to be romanticized. It is neither easy nor unproblematic. Subjugated positions are not innocent. They are preferred because they are the least likely to deny the inherently critical and interpretive of all knowledge.

The value of locations

Over the past years, hydrology modelers have increasingly used machine learning to forecast floods. Whereas government departments traditionally have been responsible for forecasting and alerting their population of floods, now corporations like Google, Microsoft, and IBM are encouraged by non-governmental organizations to "upgrade" flood warning systems, especially in developing countries in Africa and Asia.[35] With data produced by gauged rivers in the United States and Europe, machine learning is used to make forecasts in ungauged rivers in Africa and Asia.

Google communicates their flood forecast through push notifications to people in India and Bangladesh.[36] Through a website called Flood Hub, they visualize flood forecasts in eighty different countries. Polygons in teal green illustrate whether the water level at the location is below what modelers have defined as a "warning level." Yellow polygons signal that a "warning level" has been reached, and a "danger level" when the polygon turns red. These levels are based on a maximum value that is expected on average every two years in a river, excluding where humans and buildings are, and regardless of whether the water overflows the river bank or not. In a regional television broadcast in Mexico, a Google representative in Chile, Alejandra Bonati, presents the Flood Hub as a tool for emergency response teams and for the general public.[37]

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[35] In their first section, titled "Flood forecasting is limited by data," researchers at Google frame the current problem by referring to the World Bank; "upgrading flood early warning systems in developing countries to the standards of developed countries would save an average of 23,000 lives per year," on page 2 in Nearing et al. "AI Increases Global Access to Reliable Flood Forecasts." 2023. *eprint arXiv:2307.16104*. https://doi.org/10.48550/arXiv.2307.16104.

[36] Matias, Y. (2020, September 1). A big step for flood forecasts in India and Bangladesh. *Google Research Blog*. https://blog.google/technology/ai/flood-forecasts-india-bangladesh/

[37] T13. (2023, August 21). Flood Hub: Inteligencia artificial anticipa inundaciones. https://www.youtube.com/watch?v=dpVeLFMm0-Q#ddg-play

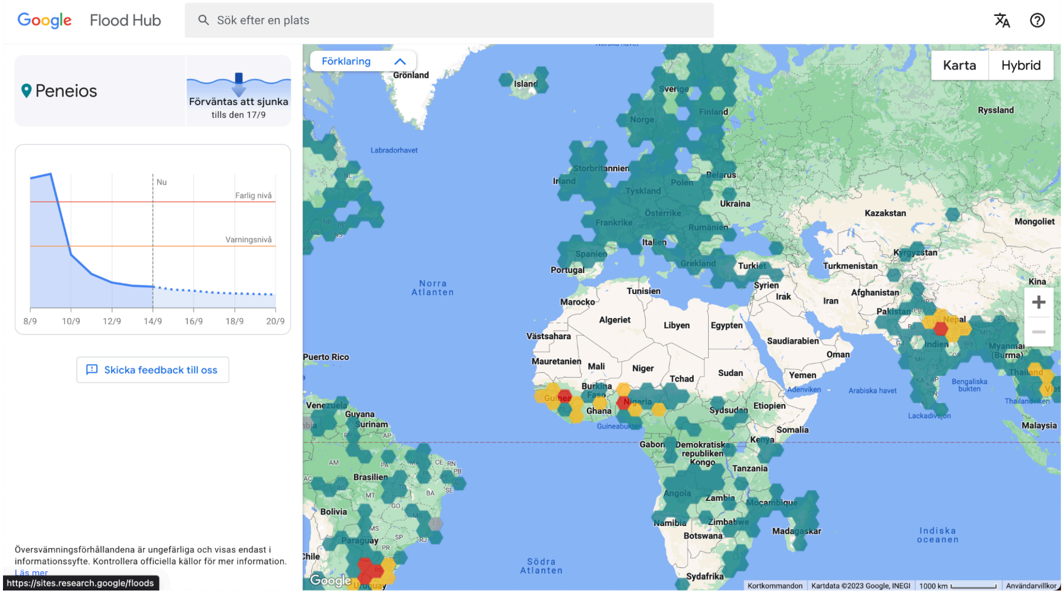

Figure 6. Google's Flood Hub.[38]

Even though estimates for warning and danger levels do not consider where humans are, Google portrays flood risk on mobile devices with a black-filled illustration of a person who seems to be standing in yellow water. I assume that this depiction of water would reach above the illustrated human's waist, and turn red, when her location is predicted to reach a "danger level."

[38] This screenshot was taken on September 14th, 2023.
Google's Flood Hub. https://sites.research.google/floods

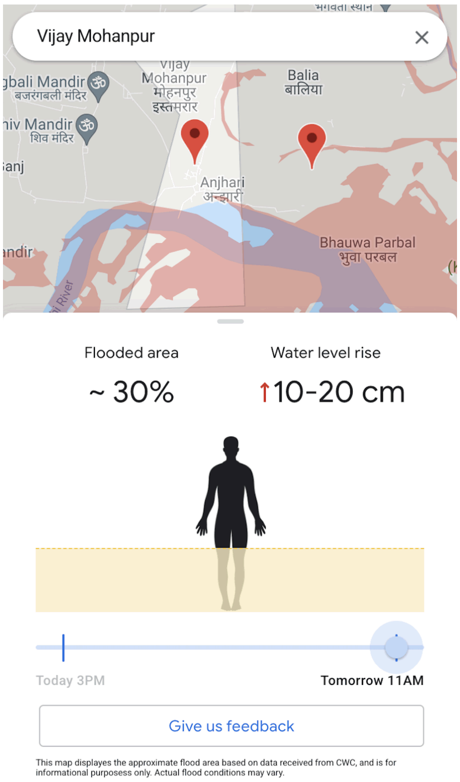

Figure 7. Google's Flood Hub on a mobile device.[39]

Over the past years, Google asserts that the corporation has sent out dozens of millions "potentially life-saving alerts" to notify people in India and Bangladesh of predicted flooding.[40] Importantly, it is communicated in a training video for NGOs, individuals need to "turn on location" on their phones, so that apps and services can access the phone's (and its owner's) location.

[39] Matias, Y. (2021, November 9) Expanding our ML-based flood forecasting. *Google Blog.* https://blog.google/technology/ai/expanding-our-ml-based-flood-forecasting/
[40] Matias, Y. (2021, November 9) Expanding our ML-based flood forecasting. *Google Blog.* https://blog.google/technology/ai/expanding-our-ml-based-flood-forecasting/

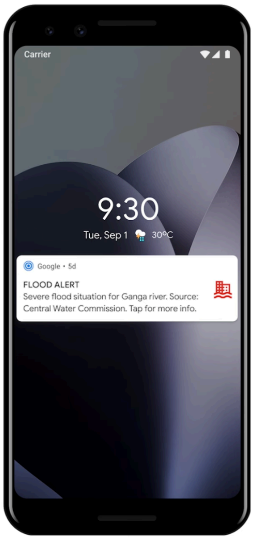

Figure 8. Example flood alert as shown in a video used to train NGOs.

"Turning on location" does not only enable flood alerts to be sent to mobile devices. Based on descriptions of location-based services on Android devices, turning on location also allows other applications to show location-based information, services, or advertisements.[41] When "turned on," phone location is among other things used to send flood alerts and to make applications like Google Search and Maps display (ads for) shops and restaurants in the individual's proximity. While doing so, applications collect data to improve their location-based services.

Hyperlocal forecasting

When I speak with what journalists have called a "hyperlocal weather forecaster" in Telangana, India,[42] I learn that he considers his forecasts, which are followed by hundreds of thousands of people on social media and occasionally broadcasted on local television, as a hobby. It started, I am told, when he was a child and experienced heavy, pouring rain from his balcony during the monsoon season in

[41] Google. (2023). Manage your Android device's location settings. https://support.google.com/accounts/answer/3467281?hl=en#zippy=%2Cwhen-location-is-on%2Cwhen-location-is-off
Google. (2023). Understand & manage your location when you search on Google. https://support.google.com/websearch/answer/179386
[42] I first came across hyperlocal weather forecasters through the nonprofit publication *Rest of the World*. Kumar, R. (2023, September 11). Hyperlocal weather forecasters are now influencers in India. *Rest of the World.* https://restofworld.org/2023/india-weather-influencers/

India. As of this first experience with a thunderstorm, which he vividly describes as full of lightning, thunder, wind, and rain, he is fascinated with how the afternoon can be sunny and warm, and then suddenly turned into an evening filled with heavy downpour.

He emphasizes that he is not a professional. He is not interested in joining any corporation or government department, or receiving financial compensation for his work. A combination of anxiety and curiosity about weather phenomena is his motivation to create and share forecasts on social media, which he does in parallel with university studies in civil engineering.

The forecaster in Telangana explains how he shares his prognosis for how the weather will change through social media; Twitter, Instagram, Facebook, and WhatsApp. On these platforms, he virtually meets with other enthusiasts, and together they discuss how to interpret the weather situation. For example, when he notices that another forecaster describes rainfall up north in Hyderabad, he reaches out to learn more and discuss how it might evolve.

The most important aspect in forecasting, he explains to me, is so-called "ground analysis." An analysis of clouds, their different kinds, colors, positions, and movements, should inform the local weather forecast. This, he calls "cloud gazing." Through cloud gazing, he estimates the instability and potentiality of clouds, and whether they hold water. A ground analysis, including cloud gazing, observations of how the rain falls, and of current conditions on the ground, is blended by local forecasters together with charts, maps, and models from open source datasets. He explains to me how he might start with a chart, and if it indicates that it is cloudy in his specific locality, he asks "is it really?" and lets his gaze shift to the sky.

In the event of a forecasted flood, the forecaster I meet explains three phases of analysis; past, present, and future. Before the event, he studies the terrain around the river expected to flood. As water slowly accumulates, he continues to study how the river frame is affected, and how and where water enters into villages and communities. On social media, he together with other forecasters broadcast which roads to avoid, or recommend in which areas people should consider staying inside. After the event, he studies trails of destruction in the area and communicates on social media which dams or roads that might benefit from reconstruction, and which communities that are in need of more relief measures.

Together, forecasters build what he refers to as a "strong community" in his state. When I ask about the eligibility to become part of the community, I learn that it is open. Anyone interested in the local weather in the region, and who uses large social media platforms, can join, interact with one another, and with forecasters.

The forecaster in Telangana is aware of forecasts by companies like Google. For his analysis, however, he prefers to rely on other sources. "If you want to modify their forecasts, you have to go to the Google people and tell them to change them," he explains to me. "This all takes time, and in that time water might be going up." In his opinion, variations of unpredictable weather in Telangana are better captured by communities of (hyper)local forecasters. Finally, he adds, whether other people want to rely on forecasts from Google, the Indian Meteorological Department, hyperlocal forecasters, or another source, is something that they ought to choose for themselves.

When I speak with one of the followers of locally produced Telangana forecasts, I learn that she chooses to set up her mobile device to receive notifications on her screen as soon as these forecasts are published on Twitter. After seemingly randomly coming across them in her Twitter feed, she started to notice how these forecasts in most cases turned out to accurately predict the weather in her part of Telangana. Especially during the monsoon season, she finds these forecasts helpful. When she receives a notification, she reads the forecast together with related comments from the Twitter community, and uses the information to organize her day. Most flood and weather forecasts do not primarily save her life or that of others, as they are envisioned in blog posts by Google, but rather help her plan which roads to take with the two-wheeler during her hour-long commute to and back from work.

She has received cyclone alerts from the Indian Meteorological Department (IMD), but is not aware of any flood or disaster alerts from corporations. When I discuss it with her, she assumes that the interests in operation at scale of employees and shareholders would probably not allow for a privatized company to gain the necessary understanding of specific surroundings and seasonal change. Such knowledge, in her view, is needed to provide timely and trustworthy flood and weather forecasts in Telangana. It would not be advisable, she concludes, for a company to do this work.

The community of (hyper)local producers and users of flood and weather forecasts exemplifies practices alternative to those by technology corporations. In their view, embodied knowledge and temporal specificity are key ingredients to weather forecasts in Telangana.

Social media platforms support alternative forms of weather and flood communication. At the same time, many of these platforms are produced and managed by the very same corporations now broadcasting warnings of climate disasters. While virtual communities may contribute to a sense of agency, and help us imagine alternative futures for flood forecasting, the social and political context in which they are built is marked by systemic power imbalance. In the following section, I shed light on action which seeks to counter some of this imbalance.

Climate activism

To be a climate activist means to take "an initiative to risk your life or risk everything that you have to fight for people who are facing injustice," I am told in conversation with a climate activist and student in Uganda. His aspiration is to amplify the voices of people in his community. "There are so many people who would like to say something, who would like to talk about these issues that are happening, but they are not able to speak up," he tells me. As someone awarded with a scholarship to attend university, and who is able to speak English, he considers it his responsibility to advocate for those who cannot speak up.

By speaking with people in his community, he collects stories to share in international arenas such as the UN Climate Change Conference, COP, or during demonstrations. He focuses his activism in Europe and on internet platforms. Demonstrations on the streets in Uganda would risk the lives of activists, or that they get arrested. Compared to in Europe, he says, it is not easy to get out of prison. You do not know whether or when you will be able to get out, and if you will still be healthy.

He started his activism journey in 2021, after a serious drought which caused suffering and death in his community. During this period, his family witnessed how crops dried up, how their livestock were left with no grass to gaze or water to drink. They had to walk long distances for water and pasture. During a workshop at his university, organized by climate activists, he suddenly related climate change to what was happening in his village. Thereafter, he increasingly became more involved with activism. After a successful initiative at COP27, during which he together with a group of activists "pushed for the Loss and Damage Fund to be put on the agenda," he knows that "people are actually listening to us" and that "the people are giving us a voice to speak up."

The climate activist and student explains how his activism is a fight against fossil fuel lobbies, companies, and Global North leaders. He fights against leaders who accept fossil fuel exports, transitions to renewable technologies, and cobalt mining for electric vehicles and devices in Congo, that exploit and displace communities. The objective of his activism, he insists, is not only the phasing out of fossil fuels. It is about defending people's rights and wellbeing, especially for those in vulnerable countries, who are being exploited even in processes referred to as "just transitions."

His objective is to let the whole world know about what is happening to people in his community. He wants the world to "feel like we feel," he tells me, "the way we feel when we face a flood, the way we feel when it's an extreme drought." He wishes for people to put themselves in their situation and ask themselves what they would do.

People from the Global South, he argues, are able to tell the world what is happening. "We know what we are facing," he tells me, "and we know that for us it's a matter of life. It's not a matter of having a second chance to live, but it's a matter of having half chances. You either die, or you don't die. You have to just keep fighting."

When I ask him who can be an activist, he answers that anyone can, and it does not mean having to hold a placard in the street. It is about speaking with people about climate change, he explains, about different people working together, and about creating policies that are inclusive and sustainable for everyone. This is how he envisions a just transition.

Agency and justice with flood forecasting

Matsutake mushrooms in the Pacific Northwest are collected by people that work for themselves (Tsing 2012). They pick mushrooms because they enjoy the freedom of the forest, independent searching, and because of the money which they use to support themselves. In contrast to capitalist labor, they neither receive regular wages nor have standardized work practices. These "work units," Tsing argues, are examples of non-scalability. Projects only qualify for scalability when they enlarge without alterations. But since mushroom foragers pick for their own, unique reason, their work cannot possibly be expanded without transforming it.

In a similar way, the work by hyperlocal weather forecasters, like the engineering student in Telangana, are examples of non-scalability. He does not want financial compensation or to make forecasts for any corporation or government department. He makes them for his own reason; to learn about weather phenomena that fascinate him, and to share and discuss analyses with his online community.

With his approach, this forecaster offers a view alternative to a conquering gaze from nowhere. I consider it a response to Haraway's call for images of worlds that do not alienate distance, but that are made with "elaborate specificity and difference and the loving care people might take to learn how to see faithfully from another's point of view, even when the other is our own machine" (1988: 583). This forecaster uses globally distributed open source data while critically questioning the maps and graphs that render his surroundings on a computing machine. He blends these data with a situated, ground analysis; his distinct way of making meaning with vision. By operating in a specific locality and across temporalities, he acknowledges the importance of historical contingencies in the formation of social and natural conditions in the present and in the future. Without ambitions to scale, he recognises the specificity of his and other contexts, and inquires into situations in different localities through conversation with people situated there. By no means does he attempt to "upgrade" systems in his locality, and certainly not in other regions, with his forecasts. His hobby is not a move towards domination or power. Rather, it should be up to the people to decide, from a multitude of options, which forecast they trust.

In contrast, machine learning models that attempt to "upgrade" warning systems in developing countries seek what Haraway calls a "conquering gaze from nowhere" (1988: 581). They reduce (flood) conditions in specific localities to colorful polygons, which shows the reader of a world map, with normative codes in red, where to find dangerous locations. Looking at the map, both its maker and reader may get a sense of total control and monitoring of problematic areas all over the globe.

The boundaries created for conditions of warning and danger are made with exclusions of villages and people. Places and lives are imagined as interchangeable in the Flood Hub, which reduces individual specificity and difference to an illustration of an anonymous human body filled in black. Behind a veil of altruistic marketing, I suggest, lie calculated expectations on location data, which fuel businesses of digital applications and advertisements. Only when people agree to continuously transmit to some obscure computing infrastructure where they are may they receive flood alerts. With this, I question what Nearing and colleagues claim to be "dissemination of [...] warnings to individuals and organizations in a timely manner [...] without cost or barriers to access" (2023: 13). Whereas not everyone may try to quantify it in monetary terms,[43] one's location, and to influence what those absent know of it, certainly has value. In this sense, the cost to flood alerts is privacy.

[43] In 2017, the European Commission decided to put a price tag on personalized data. They then estimated that by 2020, the value of personalized data would be 1 trillion euros, almost 8% of the EU's GDP. World Economic Forum. (2017, September 22). The value of data. https://www.weforum.org/agenda/2017/09/the-value-of-data/

Networks of and around hyperlocal forecasting share similarities with what Andreas Greiner (2022) calls "vernacular infrastructure" in *The Journal of African History*. Similar to Tsing (2012), Greiner argues for a more nuanced interpretation of dominant systems. In his study of road infrastructure in East Africa under German colonial rule in the 1890s, he demonstrates how newly imposed highways did not have power in themselves. Although roads reconstructed space, Africans responded to European interventions by continuing to travel through precolonial networks of vernacular pathways. By drawing attention to the persistent use of spatial practices, Greiner effectively highlights the resilience of communal structures and their producers under colonial rule.

Communities of forecast producers and users similarly may resist attempts to "upgrade" pre-existent systems through practices of collective sharing and elaborating on forecasts. Despite heroic claims and half a decade of flood forecasting in India,[44] people I meet benefit from alert systems different from that by Google. Yet, I argue, we need to scrutinize interventions that even in the slightest sense resemble dynamics of infrastructure development from times of colonial rule.

In this chapter, I surface climate activism in Uganda and demands for spaces in which we, as Haraway puts it, "learn how to see faithfully from another's point of view" (1988: 583). Thinking my encounters with climate activists with Haraway, I argue that what we need is both a reclaimed sense of vision and renewed spaces for speech. We need to realize practices and inhabit spaces in and through which we embrace a plurality of voices, carefully including peoples historically prevented from speaking. Projects under the umbrella Early Warnings for All make silent people in Asia and Africa by rendering them as objects for experimentation. Meanwhile, they give voice to and fuel businesses headquartered in Silicon Valley. This, I argue, is not a "just transition" for all.[45] Rather, it is a political move that promotes exclusive representation in stark contrast to both practices and demands in climate activism and hyperlocal forecasting communities. Ultimately, what is at stake in climate disaster forecasts and alerts with machine learning is justice.

[44] Matias, Y. (2018, September 24). Keeping people safe with AI-enabled flood forecasting. *Google Blog*. https://blog.google/products/search/helping-keep-people-safe-ai-enabled-flood-forecasting/

[45] UNDP. (2022, August 26). Issue Brief: Just Transition. https://www.undp.org/publications/issue-brief-just-transition

Conclusion

Visions of the global with climate disasters figure people in developing countries as victims not only of hazards like floods, but also of flawed institutions. This is expressed, I argue, in and around the initiative Early Warnings for All. It promises systems that protect every person on Earth with support from "Big Tech" and artificial intelligence. By pairing estimated numbers of lives and dollars that the initiative promises to save, the project is communicated similar to an entrepreneurial pitch; as an opportunity.

A global community with climate disasters is envisioned as split in two; capable subjects on one end, and incapable objects on the other. This framing, I argue, contributes to formation of institutional and societal identities. By intentionally picturing one as opposite of the other, two mutually constitutive identities are produced. Initiators of Early Warnings for All gather what they consider to be capable subjects, and opportunistically use artificial intelligence to intervene and, once and for all, develop the incapable objects. To centralize recording and monitoring in some supranational union of international organizations and "Big Tech," warning systems produce and maintain maps which selectively render societies as more or less successful in the defeat of climate disasters. As if in a digitized version of a panopticon, map readers may study how localities turn from green to yellow to red, and decide when and how to heroically intervene. It is when such maps are paired with power, that they risk remaking the images that they depict.

Increasingly exclusive access to computing power, together with publicly sponsored open source data, is reshaping power dynamics between public and private actors. Whereas WMO, UNDRR, and Big Tech cryptically describe, if at all, how to jointly reach a future with all-encompassing climate warning systems, I unveil one of the methods currently in use, which I call piloting. Through piloting, NGOs and Big Tech partner up to provide numerical answers to environmental, social, and political issues. They do so by flying in and out of specific localities to measure and experiment with the behaviors of people and communities before, during, and after climate disasters. Piloting is linked with visions of the global, and together, I insist, they are reason for serious concern. This cocktail of machine learning and development economics entrench polarizing identities and *make* people in developing countries vulnerable.

People and their wildly colorful diversity are reduced to uniform, black "objects" in experiments and in communication of flood forecasts with machine learning. Yet the world is still diverse and dynamic. It holds at once global models and local knowledges of weather conditions and climate disasters. Vernacular systems offer paths on which to navigate around the visualizing tricks and conquering gaze of "Big Tech." Hyperlocal forecast communities show how partial perspectives, embodied knowledge, and shared conversations help people maneuver climate disasters like flooding. It is by nurturing diverse, human ingenuity, and acknowledging at once the value of agency and mutual connection, that we may collectively embrace just transitions.

Climate activism in Uganda brings the focal point of this thesis from agency (back) to power and justice. I argue, with Haraway (1988), that we need to recognise historical contingencies for all knowledge claims and to seriously commit to faithful accounts of the world. People living with and in climate disasters confirm contemporary, vertically polarized ideas of the globe by calling for ways to speak "up." A just transition, in, around, and through any crisis, requires us to start speaking and seeing *with* each other, rather than up and down "onto" one another. To see together from positions in the periphery requires effort that is both less artificial and more intelligent than machine learning. We need spaces and public institutions that take seriously the generative and transformative potential of meaningful diversity. This, I argue, is how we might live well together in and through times of crises.

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