Smart Planet Governance

Analyzing the role of big data for monitoring the Sustainable Development Goals

Tim Bauer

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LUCSUS
Lund University Centre for Sustainability Studies

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Supervisor: Elina Andersson, LUCSUS, Lund University

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Abstract:

Achieving the 17 Sustainable Development Goals (SDGs) depends on timely and reliable information. However, standardized methodologies and regularly available data exist for only 40% of the 232 indicators. The “Data Revolution for Sustainable Development” is supposed to bridge these data gaps by harnessing ongoing developments in information technology, particularly big data. Currently existing pilots draw on sources such as satellite imagery, mobile phone data, and social media to calculate SDG indicators related to poverty, hunger, and health in real-time and disaggregated by demographic groups and locations. These approaches represent a new mode of knowing about people and planet whose consequences are yet to be understood. This work draws on the concept of cognitive assemblages to argue that representational technologies have knowledge and governance effects in terms of how problems are understood and addressed. It argues that inherent affordances of big data could exacerbate and obscure the knowledge and governance effects of the SDG indicator system and proposes six possible future trajectories. On this base, a combination of text mining and document analysis is used to identify and investigate 22 indicators that are currently supported by various big data approaches. It is shown that the uptake of big data in the SDGs is gradual and irregular rather than revolutionary. The inherent tendency of big data towards all-encompassing vision raises questions for the understanding of sustainability in the Anthropocene.

Keywords:
SDGs, indicator governance, big data, assemblage; text mining, document analysis

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Let me begin by acknowledging that it is in the middle of the night before the deadline that I am writing these final lines. This project has accompanied me for more than half a year and it feels strange letting it go now. According to plagiarism guidelines I am probably not supposed to say this, but I do not think that I could have written this work alone – I am speaking figuratively, ok?

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Tim, Malmö, 15.05.18

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1 Introduction

This is a study about the power of representations. More specifically about the power of technologically crafted representations in a time when our embodied perception can no longer comprehend the ecological, economic, and social dynamics that affect our lives. Climate change occurs too slow, economic crises stretch too far, and social transformation begins too small. Without help most of us would only notice disparate dots. The challenge of sustainability is that of connecting the dots to prevent harmful and promote desirable changes.

Such a vision is expressed in the 17 Sustainable Development Goals (SDGs), the global agenda for "transforming our world", adopted by the 193 United Nations member states in 2015. The SDGs address the most pressing ecological, economic, and social problems of our time, pledging to 'leave no one behind' in a united effort for a better world (United Nations, 2015). To effectively direct international efforts towards these problems, the SDGs need a global knowledge base. This is to be provided by a framework of 232 indicators that measure the "vital signs" of people and planet, highlight where action is needed most and inform which approaches produce best results. Without indicators, the SDGs are blind.

But this sensory apparatus currently suffers from visual impairments. Many countries do not yet have the capacities to provide regular and reliable basic statistics and many relevant data are not yet collected in standardized ways. That is why the SDGs have been accompanied by a campaign for a "data revolution". Ongoing developments in information technology are to be harnessed for innovative measuring approaches that close the data gaps of the SDG indicators. Central here is the promise of big data: when the increasing presence of sensors in our pockets, homes, and skies leaves ever more detailed data traces, one might be able to skip traditional methods and monitor life on earth directly and in real-time (Data Revolution Group, 2014).

But perception is never neutral and even machines can have biases. What would it mean for sustainability if we were able to realize Al Gore's (1998) vision of a "Digital Earth"? What can be included into such a representation and what is necessarily excluded? In this work I argue that indicators promote certain modes of knowledge and governance and that the use of big data is likely to exacerbate and obscure these effects. I investigate the indicator development process to assess the current role of big data in SDG monitoring. On these grounds I discusses four potential and two alternative trajectories for the use of big data in the SDGs.

1.1 A brief history of the data revolution for SDGs

The SDGs are replacing the previous global development agenda, the Millenium Development Goals (MDGs). In the wake of the transition from MDGs to SDGs it became increasingly clear that if the SDGs were to be successful, they had to move beyond their predecessor's shortcomings. A major limit of the MDGs has been a lack of reliable data, considered responsible for an uneven distribution of successes (UNDP, 2016). In 2013 a UN report on the Post-2015 Development Agenda described the need for "a data revolution for sustainable development, with a new international initiative to improve the quality of statistics and information available to people and governments" (High Level Panel, 2013, p. 21). This call was publicly echoed by the secretary general (Moon, 2015a, 2015b) who had appointed an expert group to assess the potentials of a data revolution for SDGs. Their report highlights the need for timely and high-quality data to inform the successful implementation of the SDGs. To ensure the availability of such data it proposes harnessing the ongoing developments in information technology, particularly big data (Data Revolution Group, 2014).

The SDGs consist of 17 goals, 169 targets, and 232 indicators. Their thematic vastness and desired disaggregation poses an unprecedented challenge that many national statistical systems are not prepared for (World Bank Group & UNDP, 2016). Indicators are ranked in a tier system that represents their current status. Tier I indicators are conceptually clear, have a standardized methodology, and have data produced for at least 50% of the countries were the indicator is relevant. Tier II indicators differ in that regular data production is currently lacking. For Tier III indicators a standardized methodology is yet to be developed. Currently only 93 indicators are considered Tier I. 71 are ranked Tier II and 70 Tier III. 6 indicators have a mixed classification due to their subcomponents (Figure 1).

A successful data revolution would improve this lack of data availability and standardized methodologies. A recent study by the Economic and Social Commission for Asia and the Pacific (ESCAP) estimates that big data approaches could be used to support the calculation of 42 indicators, more than half of them Tier II and Tier III (ESCAP, 2017). To contextualize what this work will be talking about, three examples of such approaches are provided in the following.

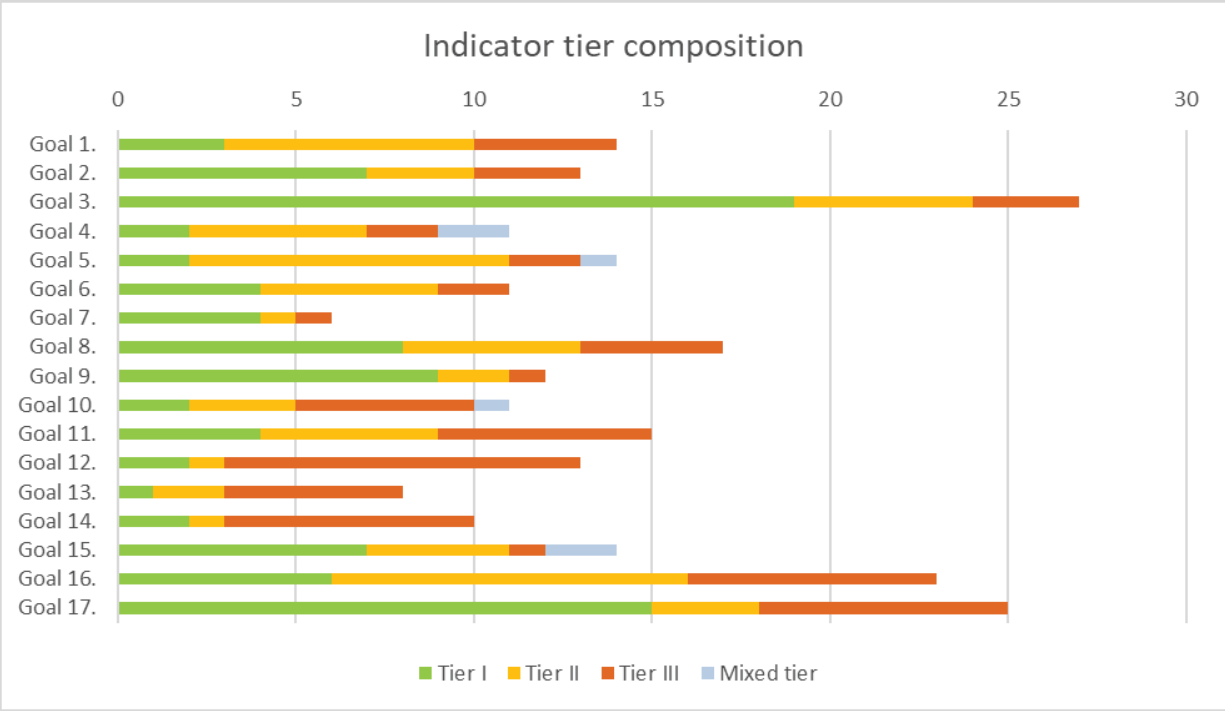

Figure 1. Shows the respective number of indicators per tier per goal for all 17 SDGs. Since several indicators are used repeatedly, the total number amounts to 244 uses of 232 individual indicators. Own illustration based on data from https://unstats.un.org/sdgs/iaeg-sdgs/tier-classification/

1. Measuring poverty through remotely sensing rooftop material

For many countries there are no reliable economic statistics on household level which makes the allocation of resources in combatting poverty difficult. The UN Global Pulse lab in Kampala has recently developed an approach that can reliably approximate household income from rooftop material. A remote sensing approach combined with image classification can distinguish between thatched, metal and tiled roofs, which correspond to household income (UN Global Pulse, 2018).

2. Mining tweets to detect food price anomalies

Fluctuations in food prices can severely affect the world's poorest and their effects on a household level are difficult to assess. Building on the observation that many Indonesians tweet about price changes on their local markets, researchers developed a tool that automatically screens Indonesian twitter for mentions of prices. Since tweets are often geolocated this allows insights into the household level consequences of food price changes that can inform SDG 2 'Zero Hunger' (UN Global Pulse, 2014).

3. Tracing diseases and drug use through web searches

Google Flu trends was an early application that allowed predicting flu outbreaks from the prevalence of thematically related search queries. Researchers have continued to develop such approaches and have

been able to predict rates for HIV infections, strokes, colorectal cancer, and marijuana use from google search trends (Ling & Lee, 2016).

2 Research strategy overview

The starting points for this work are the influence of indicators in global governance and the potential use of big data to calculate such indicators. I investigate how the use of big data for monitoring the SDGs might impact the ways in which indicators frame certain understandings of and responses to sustainability challenges. To do so I review recent theoretical and empirical works on indicators as a technology of governance and their use in the SDGs. I then combine this with a critique of the various developments that have been summarized under the term 'big data'. My goal here is to develop a tentative, critical theorization of the potential interactions between big data and indicators. I line out how indicators have a range of problematic effects on problem perception and governance and that inherent affordances of big data approaches are likely to exacerbate these effects while obscuring them at the same time. Based on this understanding, I investigate the actual role that big data plays in SDG monitoring. My approach combines quantitative and qualitative methods by using text mining and document analysis to review more than 420 openly accessible documents for 225 of the 232 SDG indicators.

2.1 Contribution to Sustainability Science

The story of the term sustainability is sometimes said to begin in 1713 when the head of the Saxonian Royal Mining Office, Hanns Carl von Carlowitz, developed a system to ensure sustained yields in forestry. Carlowitz' approach was to apply scientific principles to forestry, developing a systematic inventory of forest resources together with new management approaches which standardized forests, making extraction and calculation of expected yields easier (Grober, 2007, 2013). This approach ultimately failed. The synoptic view on timber yield bracketed interactions involving brushwood, soil, and habitats that sustained the forest system. Complexity haunts our dreams of perfect vision (Scott, 1998).

Sustainability science attempts to produce a more complete understanding of the dynamics within and between social and natural systems (Kates et al., 2001). Some of the biggest advances on this task have been accomplished by 'vast machines' – global networks of scientists, instruments, and models that have enabled us to understand for example the climate system (Edwards, 2013). But the complexity of social-ecological interactions puts limits to our understanding (Wells, 2013). As we cross more and more thresholds of the earth system, its behavior becomes increasingly hard to predict with possibly disastrous consequences (Steffen et al., 2015). At this point, even a radical reduction of human impact on the planetary

system is unlikely to reinstate balance in time. Humanity has to find ways forward that turn an extractive relation into one of stewardship – this is the challenge of the Anthropocene (Steffen et al., 2011).

Sustainability science contributes knowledge, goals, and strategies for navigating the Anthropocene (Jerneck et al., 2011). But it also includes the critical investigation of their production and their limits. To avoid reproducing unsustainability elsewhere, we need to critically reflect the approaches we take towards sustainability. This includes the underlying assumptions and discursive regimes that frame our understanding. And given the indispensable role of technology in enabling perception and action in complex systems it also involves understanding the role of such helpers. This work investigates how the use of big data for SDGs could impact perception of and response to global sustainability problems.

2.2 Existing research on a data revolution for SDGs

The data revolution for SDGs has generated considerable scholarly attention. However, only 10% of the scientific work on the topic has been coming from social sciences – a considerable research gap given the likely social implications of a data revolution (Di Bella, Leporatti, & Maggino, 2018). Yet a range of critical assessments have accompanied the data revolution from the beginning: Taylor and Schroeder (2015) argue that big data itself will not necessarily remedy existing knowledge gaps, comes with inherent risks for privacy, and might introduce new biases to development policy. Flyverbom and Rasche (2015) understand big data as a new governmentality in which visual representations becomes central. Ilcan and Lacey (2015) criticize technologies of calculation as instrumental to what they consider a neoliberal 'developmentality' in the SDGs. Gabay and Ilcan (2017) assess the role of affective politics in the SDGs and identify the data revolution discourse as one example where affective affirmations of god-like visibility can have problematic consequences for governance.

Scholars have also emphasized that data gaps pose a serious challenge to the SDGs and that a data revolution could provide needed support (Jacob, 2017). Hynes (2017) estimates that new technologies could bring down survey costs by 60% and allow for a more issue driven collection of data. Perera-Gomez and Lokanathan (2017) acknowledge the privacy risks associated with big data but argue for a multisource approach while developing governance frameworks to ensure ethical usage. Moorosi, Thinyane, and Marivate (2017) criticize the notion of data as panacea but maintain that responsible applications adapted to country contexts and regulated by international frameworks are much needed.

These works examine the interaction of data revolution and development policy but in doing so they do not engage explicitly with the mediating role of indicators. But the use of indicators in the SDGs has itself been criticized (Fukuda-Parr, 2016; Hák, Janoušková, & Moldan, 2016; Mair et al., 2018). This work

aims to reconceptualize the critique of a data revolution through an understanding of how big data might impact the SDG indicator framework.

2.3 Cognitive Assemblages

This work is going to apply assemblage theory (DeLanda, 2006, 2016) as its guiding ontological framework. Assemblage theory is a non-essentialist, process-oriented approach to thinking complex systems, based on the work of Deleuze and Guattari (1987). It proposes to understand reality as made up of nested and overlapping assemblages, meaning heterogenous entities with both social and material components and unique historical trajectories. It is a *flat* ontology in which generative processes are treated on the same ontological level as the produced phenomena themselves, understanding everything to be in continuous processes of *becoming.* This shifts the focus of research from abstracting general and universal edifices towards an empirical and ultimately intervention-oriented study of ongoing processes (Collier & Ong, 2005). Like critical realism (Bhaskar, 1978), assemblage theory allows maintaining a poststructuralist critique within a general commitment to realism. However, its rejection of essentialism and its embrace of post-humanism make it more suitable for conceiving of society and technology as mutually constitutive in an emergent process (Srnicek, 2010).

Recent applications of assemblage theory in international relations have shown how it can be particularly useful when studying systems of global environmental governance (Acuto & Curtis, 2014). One contribution has been Srnicek's (2013) use of *cognitive assemblages* to explain how new representational technologies influence the governance of climate change, financial markets, and disaster risk. The central argument is that without added representational technologies and organizational efforts, human cognition alone is not capable of mapping and responding to issues on global scales (Srnicek, 2013).

Cognitive assemblages can be defined as "hybrid systems comprised of individuals, institutions, norms and representational technologies which have as a primary goal the production of linguistic, numeric, and/or visual representations about some phenomenon in the world" (Srnicek, 2013, p. 14). As such the term builds on Foucault's notion of governmentality (Foucault & Senellart, 2008) and Latour's work on actor networks (Latour & Woolgar, 1986). From the former it takes an understanding of power as setting the conditions of possibility for knowledges and identities. From the latter it takes an awareness for how the material agency of instruments, tools, and procedures influences the production of knowledge. But cognitive assemblages move beyond the anthropocentric limits of governmentality and the prevalence of the semiotic in actor networks by emphasizing our constant entanglement with a non-human world (Srnicek, 2013). In that respect cognitive assemblages bridge the materialist/idealist divide that runs through the study of science and technology (Willcocks, Sauer, & Lacity, 2016). They emphasize that we

do construct the world we inhabit, but we do so using matter just as much as words, shaping and being shaped in the process.

The practical relevance of cognitive assemblages lies in highlighting how entanglements of discourse and technology obscure and highlight various aspects of the world, thus expanding and altering behavior and thought. The political focus lies on pointing out the seemingly neutral inclusions and exclusions that occur in the production of representations, especially on an international level (Srnicek, 2013). The SDG indicator framework is a cognitive assemblage that is to produce supreme visions of people and planet to guide the Agenda 2030. Now it is to be 'upgraded' with novel technology. This work is the product of an author-method assemblage tracing these developments and their potential consequences.

3 Theorizing big data and indicators

This chapter joins critical reflections on the use of indicators in governance with an understanding of the epistemological and practical affordances of big data. It first develops a critically informed perspective on indicators (3.1) and big data (3.2) and then combines them into a proposition of six possible trajectories for a big data-indicator assemblage (3.3). The main argument developed here is that the utilization of big data for measuring SDG indicators is likely to exacerbate problematic knowledge and governance effects. Next to these risks I point out latent potentials for putting a data revolution on alternative trajectories that are more inclusive of alternative knowledges.

3.1 Indicators and global governance

The SDGs differ from cases of global governance such as the MDGs, ozone protection, and biodiversity conservation in that they are at the same time not legally embedded, rely on weak institutional arrangements, emphasize global inclusion, and allow for flexibility in implementation. They constitute a new type of global governance in which goal setting has become the main strategy (Biermann, Kanie, & Kim, 2017). And goal setting crucially depends on indicators to be successful: once goals are defined and initial campaigns have raised awareness, setting clear benchmarks and tracking progress becomes the main instrument to direct action and ensure commitment (Young, 2017). In the case of the SDGs, their vast thematic scope makes reliable monitoring across all goals even more important. Pintér, Kok, and Almassy (2017) argue that monitoring has become a fundamental and crosscutting aspect of the SDGs, extending far beyond official state reporting, turning into a focal point for bringing together businesses, researchers, and civil society in partnerships for the goals. On these grounds it is possible to say that the 232 SDG indicators are a keystone of SDG governance.

3.1.1 Indicators and their benefits

Davis, Kingsbury, and Merry define an indicator as "a named collection of rank-ordered data that purports to represent the past or projected performance of different units" (2012, p. 6). Indicators are not "raw" statistics. They involve data from various sources that is filtered, extrapolated, recombined, and finally labeled. Indicators simplify complex phenomena and establish scales for measuring and comparing improvements (Davis et al., 2012). Prominent indicators include the Human Development Index (HDI), the Freedom House Rankings, as well as the OECD's Better Life Index. All these indicators provide condensed information on complex phenomena. But an indicator is always only one possible form of representation. Other options include textual summaries or a collection of videos. In a strict sense every form of representation simplifies the thing it represents. But not all representations do so in the same way. What characterizes indicators is that they systematically simplify information in such a way that it can be represented numerically and comparable across different cases (Davis et al., 2012).

Indicators are necessary and useful in governance because they enable informed decision making, provide baselines against which decision makers can be held accountable, and allow for effective communication and awareness raising (Mair et al., 2018). According to Donella Meadows (1998) the complexity of sustainable development makes the use of relevant indicators absolutely necessary. The SDGs constitute an unprecedented effort towards global sustainable development. Given the breadth of issues, simplification becomes central to global coordination. In the adoption of the Agenda 2030, the General Assembly declares that indicators are key to SDG implementation because "[q]uality, accessible, timely and reliable disaggregated data will be needed to help with the measurement of progress and to ensure that no one is left behind" (United Nations, 2015, p. 12). In this line, the indicator framework has been considered "a management tool to help countries and the global community develop implementation strategies and allocate resources accordingly" (UN SDSN, 2015, p. 7).

Indicators are generally considered to improve accountability because they provide an evidence base for decisions and constitute benchmarks against which political promises can be measured (Mair et al., 2018). Accountability is often divided into internal, external, and networked forms (Kuyper, Bäckstrand, & Schroeder, 2017). Within the SDGs, indicators can be said to enable internal accountability between citizens and their representatives, external accountability that allows NGOs to exert pressure on political shortcomings, and finally networked accountability between the member states themselves. This last form of mutual comparison and competition has been considered key to motivating action towards the otherwise non-binding goals (Biermann, Kanie, & Kim, 2017).

Finally, indicators are easily communicable and invaluable in raising awareness for specific issues. In recent times a range of previously neglected problems in the areas of gender equality, disability, education, and pollution have become politicized through indicators (Gray, 2015). This function is central to the SDGs which aim to communicate a globally shared vision for the future, addressing the most pressing economic, social, and ecological issues of our times in an integrative manner (United Nations, 2015). To the extent that the 17 SDGs have become representative of global sustainable development, their respective indicators are the most established lens through which one can assess, compare, and communicate this global challenge.

3.1.2 A critique of indicators

Given their increasing use in governance, it is important to ask a range of questions around indicators: How are they produced and how does that influence the provided knowledge? What are their consequences for decision making and power distribution? How can their power be contested or regulated? (Davis et al., 2012). Merry's (2011) genealogy of indicators provides starting points for critically examining these issues. The origins of current indicator use lie in corporate performance evaluation culture. Along with the dissemination of management principles into other social spheres, development policy and NGO work especially became transformed by what has been called the 'social indicators movement'. In this movement, indicators underpinned the shift towards evidence based funding and conditional cash transfers as main vectors of international development (Merry, 2011).

She then differentiates between two effects of indicators as a technology of governance. Indicators have a *knowledge effect* that prioritizes numbers as 'modern facts' over other forms of knowledge, emphasizing the benefits of generalized and universally comparable information. In addition to that the *governance effect* of indicators is to "replace judgments on the basis of values or politics with apparently more rational decision making on the basis of statistical information" (Merry, 2011, p. 85). The following parts review relevant studies to concretize the understanding of these effects within the SDGs.

3.1.2.1 Knowledge effects

It is a long standing observation that numbers are a specific form of representation with particular power in decision making (Porter, 1995; Rose, 1991). Quantified information has "distinctive properties of order, mobility, stability, combinability, and precision that each differs from words" (Hansen & Porter, 2012, p. 422). The "power of numbers" in sociological terms lies within their perceived robustness and the possibilities for precise comparison that they enable (Fukuda-Parr, Yamin, & Greenstein, 2014). The more

abstract an indicator is, the more cases it renders comparable.[1] Indicators as technology for governance employ this power and create "a knowledge system that privileges quantity over quality and equivalence over difference" (Merry, 2011, p. 89). Criticizing the use of indicators in the MDGs, Fukuda-Parr et al. (2014) point out that these properties are inherent to indicators, irrespectively of how well they are chosen. The use of indicators in governance inevitably promotes a specific reductive understanding of problems that precludes certain social and moral aspects (Merry, 2011).

A range of development scholars have picked up on this point to show how quantification in the SDGs is closely tied to a neoliberal conception of development (Halvorsen et al., 2017; Ilcan & Lacey, 2015; Weber, 2017). Neoliberalism in short is understood as a governmental rationality that deploys market values and mechanisms as the principle means for organizing conduct. Examples of neoliberal rationality in the SDGs include a conception of poverty that neglects inequality and favors individual entrepreneurialism and microfinance, a framing of hunger as lack of production rather than access, and an implementation framework that promotes the commercialization of key services (Weber, 2017). Ultimately though it expresses itself in the insistence that economic development and ecological sustainability are reconcilable and even synergic (Swain, 2017). Streamlining this neoliberal rationalities is partly achieved through "political technologies of calculation" which enable performance evaluation, benchmarking, and competition (Ilcan & Lacey, 2015, p. 616). Thus, the SDGs' propagation of global indicators can be said to entrench a highly contested understanding of international development.

The key problem here is that even though indicators favor certain understandings, they appear as neutral and objective because they hide the assumptions and uncertainties that went into their calculation. This is especially problematic when indicators represent contested issues (Mair et al., 2018, 2018). The SDGs have repeatedly been criticized for being a vaguely formulated collection of contested and partly contradictory targets (Biermann et al., 2017; Swain, 2017). This makes it ever more critical to pay attention to how indicators reduce the goals and targets to specific framings. What is eventually counted is key to how a target is implemented. For example, the SDGs conceptualize migration primarily through citizenship which precludes the rise of 'irregular' migration (Sexsmith & McMichael, 2015). Mair et al. (2018) point out that critical awareness of such shortcomings has been lacking in the SDG indicator process. Given that

[1] In that sense money is often understood as the universal indicator. The relevance of money as the central criterion for decision making is commonly explained with the necessity of economizing. However, Sen (1999) reminds us that at a deeper level the appeal of money is that it establishes a common and definite measure for comparing qualitatively different things and options to an independent third.

goals and targets are often vague and contested, they conclude that "the use of indicators in the SDGs should be approached with care" (Mair et al., 2018, p. 43).

3.1.2.2 Governance effects

The previous part has lined out how indicators are not a neutral tool but favor and entrench particular perceptions, obscuring normative contestation. This understanding is now expanded with a summary of related governance effects. Scholars have pointed out that the use of indicators in governance has effects on the making, implementing, and contesting of decisions (Davis et al., 2012). One particular consequence in this respect is an emphasis on 'responsibilization' (Merry, 2011). Under the absence of legally binding rules and mechanisms to ensure compliance, the SDGs depend on the self-governance of their subjects. Nation states, businesses, NGOs, and individuals are required to adjust their behavior responsibly in order to meet the SDGs. The unambiguity of numbers allows for direct identification and judgment of those who stay behind track records. In this way global indicators exert a decentralized power that is difficult to contest precisely because it appears as neutral and voluntary (Merry, 2011). The declared purpose of the SDGs is to ensure that no one is left behind – a credo that can also be read compulsory as Weber (2017) reminds us.

When indicators guide decisions, they can become identified with the issues they represent to the extent that action is directed solely towards what is measured. The creation of indicators excludes crucial parts of the problem understanding such as the reasons for concern in the first place. Eventually an indicator, itself a means for decision making, can replace the actual problem as the thing that is acted upon (Mair et al., 2018). But an improvement of the indicator might not always be an improvement of the problem itself. Additionally, an unintended consequence of adjusting behavior according to a score is that it creates incentive for 'gaming' the indicators, resulting in less reliable representations (Merry, 2011). Most of the SDG indicators are picked in such a way that improved metrics are necessary but not sufficient for achieving the respective targets. Given the extraordinary breadth of the concept of sustainable development as the purpose of the Agenda 2030, identifying it too closely with what is measured by the indicators as it is done by hyper-aggregates such as the SDG Index Dashboards (Sachs et al., 2017), comes with a continuous risk of diverting attention from ends to means.

Finally, approaching a problem through an indicator constitutes a technical framing of a political issue that diverts power from decision makers to expert statisticians. "[P]olitical struggles over what human rights or corporate social responsibility means and what constitutes compliance are submerged by technical questions of measurement, criteria, and data accessibility" (Merry, 2011, p. 88). On this topic it has been positively noted that the SDG indicator framework was based on a global consultation involving civil

society (Briant Carant, 2016). Yet decisions on the final framework were again taken by experts and inevitably led to the exclusion of many voices (Maistry & Eidsvik, 2017). Such reduction is inevitable, the problem is when the selection is biased. Unless processes of indicator generation occur in transparent, democratic and informed ways, they threaten to produce a "Tyranny of Benevolent Technocrats" (Moorosi et al., 2017, p. 235). Since the statistical capacities involved in the SDG indicator generation are generally concentrated in the global North, there are concerns that the indicator framework, despite being global, does not represent a global community (Chambers, 2017).

3.2 Big Data for SDGs: Opportunities and Risks

While the previous chapter has outlined the general function of indicators in governance together with a critique of their knowledge and governance effects, this chapter is going to prepare an understanding of big data in general and its affordances for knowledge production and development work.

3.2.1 Big Data and Small Helpers – an introduction to the technology

I follow Flyverbom and Rasche (2015) in conceptualizing 'big data' as the convergence of datafication and algorithmic developments. "To datafy a phenomenon is to put it in a quantified format so it can be tabulated and analyzed" (Mayer-Schönberger & Cukier, 2013, p. 57). Datafication can be analog or digital but the arrival of the latter has accelerated it substantially: Google Books is datafying the written history of humankind, Facebook is datafying our relationships, Amazon is datafying our consumer preferences. Most datafication now occurs passively and even before having a specific use in mind (think of the accelerometer in the first iPhone). IBM estimated in 2013 that 90% of all existing data were generated in the past two years (Jacobson, 2013). This kind of data is arguably "too big to store on a normal hard-drive, or to big to fit into an Excel spreadsheet" (Strom, 2012, p.1), but *volume* is only one of four V's that have been put forward to define the novelty of big data. *Velocity* relates to the speed of generation and use, *variety* to the different data types ranging from structured tables to texts and video recordings. *Veracity* highlights how noise and false entries are challenges for retrieving reliable insights from big data (Etzion & Aragon-Correa, 2016).

The four V's allow us to demarcate big data but there is a missing ingredient to understanding why big data is handled as the 'new oil' (The Economist, 2017). The value of big data is unlocked by algorithms, small helpers "without which the giant of big data would not be perceptible at all" (Amoore & Piotukh, 2015, p. 343). An algorithm is a step-by-step instruction for solving a problem that can be interpreted by a computer and thus performed faster than by human hand. Kitchin (2014a) describes four broad classes of algorithms, usually used in combination but associated with four main tasks of big data analytics: 1.)

data mining and pattern recognition are used to *describe* general features contained in a data set; 2.) data visualization and visual analytics are helpful to *explain* the relevance of findings; 3.) statistical analysis allows *predicting* trends; and 4.) simulation and optimization enable *prescription* of optimal courses of action. Underlying many of these algorithms is what has been called *machine learning*. "Machine learning seeks to iteratively evolve an understanding of a dataset; to automatically learn to recognise complex patterns and construct models that explain and predict such patterns and optimise outcomes" (Kitchin, 2014a, p. 140). The 'learning' part refers to the way in which the algorithm, through multiple iterations, builds a set of identifiers and assigns weights to them. [2] Taken together, these analytical tools enable the inductive generation of insights from large, unstructured datasets that could otherwise not be interpreted by humans.

3.2.2 A critique of Big Data

The public debate on big data, especially after the recent revelations on Cambridge Analytica (Cadwalladr, 2018), has almost exclusively focused on issues of privacy and security. These are highly relevant issues that have already been discussed in detail. What this work is particularly interested in is the extent to which big data constitutes a new episteme, a new way of knowing, and how it is being assembled with the SDG indicator framework under the 'data revolution'. The aim is to shed a light on the affordances of big data, that is the ways in which it enables certain understandings while constraining others, and to put them in relation to the features of the indicator system as discussed above. My general understanding is that big data and indicators align as technologies of calculation and that big data is likely to entrench and at the same time obscure the knowledge and governance effects of indicators.

3.2.2.1 Big Data Episteme

Everyday 'data doxa' tends to naturalize or fetishize those data applications that are convenient to us, ignoring their underlying features (Smith, 2018). But joining these reveals a new way of knowing. Ruppert, Law, and Savage (2013) offer nine tentative entry points: 1.) measurement has become a constant by-product of technologically mediated activity rather than being deliberately initiated by research; 2.) thus generated data does not anymore represent distinct entities but vast sets of heterogenous associations (transactions, movements, communication) which need to be homogenized by analysis; 3.) numerical and textual representation is increasingly augmented or replaced by visualization which is more useful at summarizing complex patterns; 4.) measurements are not anymore distinct snapshots in time (annual surveys)

[2] For an accessible account of how machine learning functions in spam filters and image classification, read Jenna Burrell's (2016) article on 'how the machine thinks'.

but continuous recordings; 5.) *n = all*, entire populations are captured and sampling becomes less important than identifying unique individuals; 6.) in the same vein analytic focus shifts from predetermined aggregates to unique identifiers and anomalies; 7.) a new type of experts, data scientists, is less concerned with data generation than with analysis; 8.) at the same time more people than ever are represented in, contribute to and have access to various repositories of data; and 9.) the distribution of information appears increasingly incoherent in what some call democratization and others erosion of knowledge. Many of these points have been echoed by others (Amoore & Piotukh, 2015; Chen, Mao, & Liu, 2014; Kitchin, 2014a, 2014b) and they are increasingly considered to constitute a new way of knowing.

"[B]ig data changes how knowledge is rationalized and hence creates a different ground upon which to evaluate 'truth'" (Flyverbom & Rasche, 2015, p. 21). A key proposition has been that big data heralds a new empiricism and the end of theory. The argument is that datasets have become so all-encompassing and analytics so independent, that there is no longer a need for a priori hypotheses that guide (and bias) research. Instead data can begin to speak for themselves, initiating an age of truly evidence-based (and eventually automated) decision making (Anderson, 2008; Chandler, 2015). Here the vast expansion of what can be datafied and monitored are shifting the grounds on which knowledge is considered to be warranted. Previously sample representativeness was key – now we are seeing knowledge claims that are founded increasingly on the size and timeliness of the involved data (Flyverbom & Rasche, 2015). Finally, the way in which data 'speak' is considered to be in correlation, a purer language untainted by the human assumptions that accompany causation (Mayer-Schönberger & Cukier, 2013). Critics have countered that data can never exhaustively capture reality, that algorithms tend to reproduce structural biases within datasets and that the use of findings inevitably involves interpretation and moral judgment (boyd & Crawford, 2012). Yet irrespective of such concerns, big data has already begun to change practices in research, security, and business. But how is big data going to influence our understanding of economic, social and ecological problems if used for the SDGs? The following paragraphs summarize a set of key concerns.

3.2.2.2 Fetishizing data

Advocates of the data revolution for SDGs have repeatedly argued that better data will lead to better decisions and that novel technologies are the way to gather that data (Data Revolution Group, 2014; UN SDSN, 2015). But development scholars writing on the topic have questioned this logic in several ways. First of all, better data alone does not ensure better decisions. Secondly, it is not clear whether big data can provide the information that is truly needed. Moorosi et al. (2017) observe a 'utilization problem' of data: more data does not lead to better decisions unless there exists a broader action plan, adapted to problem context and coordinated with stakeholders. Developing such plans should be primary focus but

"[t]he over-emphasis on the role of data and the presumed data revolution […] is not only a naive proposition, it is also a risky one that shifts the focus away for the ecosystem factors that need to be taken into consideration for effective development work" (Moorosi et al., 2017, pp. 234-235). It is generally agreed that the key to implementing the SDGs lies in adapting them to national and local contexts (United Nations, 2015). But in this respect, "[t]here are large gaps between change that is happening at the local level […] and the processes in place for monitoring progress" (Wheeler, López-Franco, & Howard, 2017, p. 1). Admittedly, the declared purpose of a data revolution is to close these gaps, but evidence regarding its true potential is lacking (Di Bella et al. , 2018). Given the uncertainties, a data revolution might only divert valuable resources from more substantial commitments (Weber, 2017).

Although big data generated insights are increasingly informing all types of enterprises, it is not clear whether the information they provide is immediately useful to craft informed policy solutions. This lies in the inherent features of big data analytics as described above. Successful policy requires an understanding of problem causes and contextual factors. The survey waves that traditionally inform development indicators are tailored to provide such additional insights (Norris, 2015). Big data is useful for detecting significant anomalies in large data sets, but it does not provide causal and contextual understanding (Di Bella et al., 2018). This has even led proponents of a data revolution to qualify their propositions: "a risk is that analyses based on big data will focus too much on correlation and prediction — at the expense of cause, diagnostics or inference, without which policy is essentially blind" (Letouzé, 2014, p. 16). Thus, big data solutions are for now unlikely to replace surveys. But even when using them to fill the data gaps they require alternative data sources for ground-truthing and might not always be reliable. This is because the majority of the proposed big data approaches for SDG indicators does not measure the indicator itself but a proxy (for example roof top material) that correlates with the indicator (household income) (Di Bella et al., 2018). Indicators already come with the limitation that they cannot entirely cover the construct they represent. A proxy indicator adds another layer of uncertainty that requires additional evaluation and interpretation of data validity (Di Bella et al., 2018). In that sense the all-encompassing scope of big data engenders a fallacy: instead of a gods-eye view, they create limited oligopticons (Kitchin, 2014a).

3.2.2.3 Skewed representations and digital divides

Big data offers to capture entire populations and to thus overcome the limits of sampling (Ruppert et al., 2013). But *n* never truly equals *all.* Some of the most promising data approaches for the SDGs make use of call detail records and social media data (ESCAP, 2017). But despite the fact that mobile phone possession and internet access have dramatically increased in the developing world, there are vast differences within and between countries (Poushter, 2016). The utility of big data for SDGs is often seen in the

possibility to disaggregate by demographic groups and locations. However, Cobham (2014, p. 326) demonstrates how what could be considered negligible undersampling on an aggregate level can turn into grave distortions when disaggregated. If we consider that the most marginalized, whom the SDGs promise to not leave behind, are underrepresented amongst internet and mobile phone users, then many big data generated insights likely do not apply to them. A truly inclusive data revolution would focus on capturing those voices from the margins through participatory appraisals, contend Wheeler et al. (2017).

Digital divides continue on a global scale. It has been pointed out that 'leapfrogging' might close them (Omland & Thapa, 2017) but this observation only holds for the consumption of information technology services and not for capacities for production and expert analysis. Most big data is generated in the global North, while the discussion is "very much at an embryonic stage in the global south" (Perera-Gomez & Lokanathan, 2017, p. 2). Similarly, there is an "enormous gap between the developing and developed worlds in the utilization of [big data]" (Kshetri, 2014, p. 2). The UN data revolution report acknowledges these divides (Data Revolution Group, 2014), however the extensive commitments to capacity building and knowledge transfers necessary for bridging them are currently not prioritized (Moorosi et al., 2017). In the data revolution discourse one can find instances of a belief that national statistical capacities are a thing of the past and that developing nations are better advised to leapfrog directly into a big data age (Letouzé, 2014). Yet unless respective questions of capacities and ownership are thoroughly discussed, developing nations are likely not to harvest all benefits in unequal partnerships with data giants, turning instead into real world data laboratories (Levy & Johns, 2016).

3.2.2.4 Citizenship and Accountability

Finally, the previously discussed issues of data access and literacy could have consequences for citizenship and accountability. Gabay and Ilcan (2017) argue that by approaching citizens needs and concerns through big data, a data revolution could undermine the understanding of citizens as active participants in democratic institutions, shifting it towards an understanding of citizens as users and producers of data. Instead of being rooted in a notion of inalienable rights, democratic participation could thus become increasingly mediated by access to and literacy of data. The SDGs themselves address these latter issues practically, with target 5.b calling for an expansion of "enabling technology", particularly for women (United Nations, 2015, p.18). Yet this emphasis can also be taken as evidence for the argument that the SDGs reframe citizens as digitally active agents. When thematizing the direct benefits citizens could gain from a data revolution, the official focus is on enabling them, along with governments and businesses, "to make better decisions for themselves" (Data Revolution Group, 2014, p. 19). According to Gabay and Ilcan this

is a form of responsibilization, producing “entrepreneurial citizens […] [who are] summoned, rather than responded to” (2017, p. 481).

When visibility in big data driven assessments becomes a main guarantor for ‘not being left behind’, this is likely to have implications for accountability. “At this point, not enough has been done […] to ensure the links between monitoring and collecting data and increasing accountability are made. […] Accountability requires shifts in relationships of power that ensure the answerability of government institutions is enforced” (Wheeler et al., 2017, p. 3). With digital capacities unevenly distributed and questions of data ownership left unanswered, a data revolution might exacerbate existing inequalities. To give an example: machine learning algorithms can produce certain biases (O'Neil, 2016), but in the case of some applications, fully comprehending an algorithmic decision is hardly possible anymore for humans (Burrell, 2016). Now these limits can again be countered with helping ‘audit’ algorithms, but the point is clear: for most citizens it would be impossible to comprehend and thus contest decisions based on big data.

3.3 Possible trajectories for a big data-indicator assemblage

The previous two chapters have conceptualized a set of key features of indicators and big data and criticized them in the context of problem understanding and decision making under the SDGs. It was pointed out how indicators come with a knowledge effect in which the ‘power of numbers’ naturalizes certain development conceptions and hides normative contestation of the SDGs. The related governance effect is that focus is shifted from the problem itself to its representation, means run a risk of being confused for ends and political issues increasingly turn into technical questions. On the side of big data it was noted how the technology is shifting our understanding of sound knowledge from sample representativeness to sheer size and timeliness, favoring correlation as a less biased form of understanding over causation. Yet fetishizing big data overestimates its usefulness for policy making and could direct attention away from needed action. Furthermore inequalities of access and capacity can result in skewed representations and entrenched digital divides. Lastly an SDG data revolution could produce citizens that are becoming more visible to decision makers while decision making itself becomes increasingly opaque to them.

Based on the work of Srnicek (2013) I treat the SDG indicator framework as a cognitive assemblage which is about to be upgraded with big data-based representational technologies. I have lined out a set of key features for both indicators and big data that allow me to hypothesize a range of possible trajectories for a joined big data-indicator assemblage. These are to be treated as tentative and pragmatic. They do not claim to predict but serve to highlight areas of interest. I propose four junctions between big data and indicators through which the knowledge and governance effects of indicators can be become intensified.

1. **Big data and knowledge effects:**
   1.1. *The big data episteme entrenches the 'power of numbers' by suggesting that data can speak for themselves in non-biased ways.*
   1.2. *Datafied citizens are responsibilized into entrepreneurial individuals as they become perceivable through comparative indexes.*

2. ***Big data and governance effects:***
   2.1. *Fetishizing big data draws attention from already known issues to improving means for measuring without a clear guarantee for applicability.*
   2.2. *Algorithmic opacity increases the power of technocrats and aggravates accountability and contestation of decision making.*

In other words, big data for SDGs comes with the risk of undermining the strengths of indicators and exacerbating their weaknesses. Yet in line with my understanding of assemblage theory, I do not take these trajectories to be necessary. This is not to suggest that the risks and opportunities of using indicators and big data solely depend on whether one puts them to 'good' or 'bad' uses. I believe to have shown that there are inherent features in both technologies that imbue them with 'material agency', behaviors that they exhibit independently of *how* we use them (Latour, 2005). Yet these agencies can be counterbalanced if one is aware of them. I understand big data to be a useful component of cognitive assemblages that might enable humankind to survive the Anthropocene. Without machinic help, we are simply not able to comprehend the non-linear system dynamics around us in time to react appropriately. However, we have to be aware that these technologies come with their specific affordances. I follow Moorosi et al. (2017) in that "[b]eyond the allure of fetishization of data, the tyrannical influence of the technocratic stakeholders, and the naive misuse of data analytics tools and instruments, lies a domain of effective utilization of data […] to support development action at the micro, meso and macro levels of society" (Moorosi et al., 2017, p. 240). In a big data-indicator assemblage, not only the indicator part will change. As big data is exposed to new social and ecological demands, it might be possible to shift the use of this technology onto new trajectories. Drawing on the deleuzoguattarian notion of 'lines of flight' (Deleuze & Guattari, 1987) meaning latent potentials for alternative becomings, I propose two alternative trajectories for future interventions:

3. ***Big Data and alternative trajectories:***
   3.1. Expanding what can be measured allows for introducing ecological and social concerns more effectively into decision making.
   3.2. Mobility of technology and accessibility of data enable counter-calculation and development of alternative indicators by activists and NGOs

The following study systematically analyzes the available documentation on the SDG indicator development regarding the role that big data related approaches are playing in the calculation of SDG indicators. It then discusses these findings and the light of the hypothesized trajectories for a big data-indicator assemblage.

4 Method

This work employs text mining and document analysis to assess more than 420 openly available documents from the indicator development process. Informed by general literature on text mining (Ignatow & Mihalcea, 2017) and document analysis (Bowen, 2009), I developed the following approach largely by myself and tailored it specifically to the task at hand.

4.1 Material Selection

Material was gathered from the website of the Inter-Agency Expert Group on SDG Indicators (IAEG-SDGs), the agency tasked by the General Assembly with developing and improving the indicator framework. The IAEG-SDGs has been meeting biannually since 2015 and recently held its 7th meeting. Ever since the 3rd meeting a tier system has been applied to classify indicators into three development stages (see chapter 1.1). Main UN bodies and international organizations have been appointed as custodian agencies for the indicators and were tasked with developing workplans for the remaining Tier III indicators. Upgrade requests were submitted for indicators that had seen progress. This entire process is well documented and openly accessible on the IAEG-SDGs webpage[3]. Since my main interest lies in methodological advances that evidently influence the SDG indicators, I prioritized these documents in my analysis over the plethora of data revolution visions statements and policy briefs by other stakeholders.

My main dataset is comprised of 420 metadata records and workplans covering 225 of the 232 SDG indicators. The seven indicators not included in my set are those for which no workplans were yet developed due to pending custodian agency (IAEG-SDGs, n.d.). The included documents span over the time between fall 2016 and spring 2018, including material from the 4th to the 7th IAEG-SDGs meeting. This allows tracing developments in updated workplan versions. Furthermore, I made use of available spreadsheets documenting the state of the tier classification system after each of those meetings. In addition to this I drew on available update requests submitted over the last two meetings. Guiding my understanding of the current state of big data approaches for SDGs is an extensive report compiled by ESCAP (2017) last

[3] https://unstats.un.org/sdgs/iaeg-sdgs/

year which reviews 140 currently existing big data approaches regarding their relevance for the SDGs. Having turned the reports dataset into a searchable table, one of my secondary interests was how many of the there mentioned approaches were actually discussed in the official process.

4.2 Text Mining

The sheer amount of gathered material and its various semi- to unstructured formats put my dataset itself in the vicinity of big data. It became clear early on that an analysis of all indicators would be tedious and prone to error even if conducted with conventionally available means for text search and spreadsheet summaries. Thus, I chose to build on my skills in using the programming language Python and wrote a series of scripts that allowed me to include all gathered metadata and workplans into an indexed and searchable database, combined with the spreadsheet information on the state of the tier classification over time. I then developed a set of thematic search strings to extract relevant text passages for each indicator. This approach can be considered a 'general inquirer' that does not make use of automated means of analysis (Ignatow & Mihalcea, 2017).

I developed three keyword groups, based on the big data taxonomy put forward in the recent ESCAP (2017) study, summarized in table 1. I adapted the terminology to singular or word stem and expanded it in several cases with related terms ('call detail records' for 'mobile phone'; 'uav' for 'drone'). Specifically for Digital Content I chose to include the names of several digital giants often discussed as data donors in the wider discourse. Finally, a general category was built around the usual suspects.

Table 1. ESCAP's (2017) original taxonomy of big data for SDGs for comparison

Exhaust data	Sensing data	Digital content
-mobile phone data	-satellite and drone imagery	-social media data
-financial transactions	-sensors in cities, transport and homes	-web scraping
-online search	-sensors in nature, agriculture and water	-participatory sensing and crowdsourcing
-access logs	-wearable technology	-health records
-administrative data	-biometric data	-radio content
-citizen cards		
-postal data		

Table 2. Keywords by group as used for searching the dataset

Exhaust Data	Sensing Data	Digital Content	General
administrative data	satellite image	google	algorithm
mobile phone	remote sensing	text mining	big data
call detail record	remotely sens	social media	automated data
financial transaction	sensor	web scraping	automated statistical
online search	uav	participatory sensing	machine learning
access log	drone	crowdsourc	statistical learning
citizen card	wearable	health record	
postal data	biometric	radio content	
		facebook	
		twitter	

The way the retrieval script functions is that it searches through all material available for every indicator and extracts relevant text segments for each keyword group if they contain *any* of the keywords from this group. It then outputs this material as a pdf grouped by indicator, keyword group, and source together with information on the tier development. I have shared my code on the open-source platform GitHub to allow others to cooperate, reproduce my results and use the script for further analysis.[4]

4.3 Document Analysis

Running the search script provided me with an initial selection of 40 indicators with the various big data types. After screening these findings in detail, I was able to exclude almost half of them as false positives which left me with 22 unique indicators. The available documents for these indicators where then studied in detail regarding the role that big data is playing for each of the methodologies. Following Bowen's (2009) recommendations for document analysis, specific attention was put on changes between older and newer documents and the communicated rationales and considerations for using big data. The findings were then grouped thematically depending on the associated SDG, the measured construct and the applied methodology. The results section discusses each of those findings individually.

4.4 Limitations

The most obvious limitations of my approach include the material selection and the search strings. It is possible that more detailed documentation of the indicator methodologies is available from the custodian agencies themselves. However, additional information might not have been available for all indicators in the same quality. Applying the text mining solely on metadata and workplans which follow predetermined structures allowed me to ensure that the information I gathered in the first round is comparable. The

[4] https://github.com/BaronKalle

document analysis then referred to additional online sources but only if they were explicitly cited in the initial material.

In developing my search string, I oriented myself on the terminology used by ESCAP (2017). Even though this publication belongs to the body of official UN documents on the data revolution, it is possible that terminology differs from that used by the IAEG-SDGs and the various custodian agencies and that it thus not captures all instances of big data related text segments. To ensure maximum capture I optimized the search string by including and comparing hits for different wordings. The search string yielded a substantial number of false positives which suggests that further optimization is possible. Given the easy replicability of my text mining approach, further studies could quickly expand on my findings if other wordings become apparent.

The document analysis proceeded qualitatively with the aim of gathering contextual information on the use of big data for the selected indicators. Given that the available material only represents summaries of highly technical methodologies the ability to draw definite conclusions is limited. Additional references were considered but only to contextualize formulations in the source material. Yet the reviewed indicator documents provide useful insights into a mosaic of approaches, rationales, and limitations for big data in the SDGs.

Finally, critical readers might be inclined to perceive a contradiction in using text mining to criticize the shortcomings of big data. Against this I hold that my approach involves none of the supposedly neutral automatic classifications associated with big data. Furthermore, I understand big data analytics to be a necessary tool for understanding a complex world. By drawing on machinic help I believe to engage myself in a simple form of algorithm audit which will become increasingly important in the future.

5 Results

Using the above described method I was able to identify 40 potentially relevant indicators through the search script which I then manually filtered for relevance, leaving me with 22 indicators for detailed analysis. I will first present the initial findings before moving on to describing the final selection in detail.

5.1 Initial retrieval

As mentioned above, I gathered four keyword groups, the first three adapted from ESCAP's (2017) taxonomy of big data, the fourth a series of generally relevant terms. Running the search script with these keywords found 65 associations of indicators with one of the keywords amounting to 50 unique associations for all four groups (Table 3). Excluding overlaps between the groups, those amount to 40 unique SDG

indicators associated with big data keywords. In each group, the highest yielding keyword was already able to match 75% or more of the overall findings, suggesting that a saturation point for findings was reached early on and that indicator officials are not yet using specific technical terminology such as 'call detail record', 'web scraping', and 'machine learning'. Overlap between keywords appears to be considerable for Sensing Data where from a total of 28 matches only 15 were unique. For other groups the keywords appear to be more diverse, yielding additional unique results.

Table 3. Number of indicators associated with each keyword and keyword group. Associations between keywords and between keyword groups overlap, thus the totals are smaller for each group and for all l involved indicators as a whole

Exhaust Data		**Sensing Data**		**Digital Content**		**General**		**Σ**
administrative data	19	remote sensing	14	google	3	algorithm	6	
mobile phone	5	satellite image	12	text mining	1	big data	1	
call detail record	0	remotely sens	1	social media	0	automated data	1	
financial transaction	0	sensor	1	web scraping	0	automated statistical	1	
online search	0	uav	0	participatory sensing	0	machine learning	0	
access log	0	drone	0	crowdsourc	0	statistical learning	0	
citizen card	0	wearable	0	health record	0			
postal data	0	biometric	0	radio content	0			
				facebook	0			
				twitter	0			
Total associations:	24	Total associations:	28	Total associations:	4	Total associations:	9	**65**
Unique associations:	23	Unique associations:	15	Unique associations:	4	Unique associations:	8	**50**
Unique indicators:								**40**

5.2 Filtering the findings

The intial retrieval identified 40 indicators with 50 connections to the four keyword groups. After a first screening, 23 of those connections were identified as false positives. The keyword 'administrative data' generated more than half of those false positives, being often used in contexts of survey methodologies. The keyword 'google' turned out to be solely associated with mentions of google maps already captured under Sensing Data. This manual filtering left me with 27 relevant instances of big data use for 22 unique indicators. 7 of those instances fell under Exhaust Data, 15 under Sensing Data, 2 under Digital Content and 3 were general instances (Table 4). Findings for Sensing data appeared to be most robust with only one false positive (but one reclassification from General). All other groups were at least halved in terms of associated indicators compared to table 3.

Table 4. Number of indicators associated with each keyword group after manual filtering

Exhaust Data		Sensing Data		Digital Content		General		Σ
Unique associations:	7	Unique associations:	15	Unique associations:	2	Unique associations:	3	**27**
Unique indicators:								**22**

The thus identified 22 indicators cover 11 of the 17 SDGs. When lining them all up (table 5), initial patterns become visible. Most indicators associated with Exhaust Data cover social SDGs such as 'No Poverty' (SDG 1), 'Zero Hunger' (SDG 2), and 'Quality Education' (SDG 4). Indicators that make use of Sensing Data approaches are predominantly covering environmental and infrastructure related SDGs. They include 'Life below Water' (SDG 14) and 'Life on Land' (SDG 15), as well as 'Clean Water' (SDG 6), 'Sustainable Infrastructure' (SDG 9), and 'Sustainable Cities' (SDG 11). Most indicators are only drawing on one of the three specific big data approaches. However, 1.4.1, 14.2 and 2.4.1 appear to be all associated with Exhaust Data as well as Sensing Data. Indicator 11.7.1, measuring available public space in cities, appears to draw on all three.

Additional information includes the tier classification in the following order: first as initially proposed (mixed tier in several cases), then as published after the 4th, 5th and 6th IAEG-SDGs meeting. For the most recent 7th meeting (April 2018) a new classification sheet is yet to be released as of this writing. 9 indicators are considered Tier III according to the latest classification and almost exclusively have been so since the beginning. 8 indicators currently rank as Tier II and 4 of them only acquired this status recently. 5 indicators are fully developed and have been so since the start, apart from 15.4.2 which was recently upgraded. For 8 indicators update requests have been submitted at either the 6th or the 7th IAEG-SDGs meeting. Decisions on the most recent update requests are still pending.

Table 5. Identified indicators with respective big data approaches, tier development, update requests, and mentions in ESCAP dataset

Indicator	Description	Exhaust Data	Sensing Data	Digital Content	General	Development	UR submitted	In ESCAP
1.4.1	Proportion of population living in households with access to basic services	x	x			3-3-3-3		
1.4.2	Proportion of total adult population with secure tenure rights to land, with legally recognized documentation and who perceive their rights to land as secure, by sex and by type of tenure	x	x			3-3-3-2	6th	
2.4.1	Proportion of agricultural area under productive and sustainable agriculture	x	x			3-3-3-3	6th	yes
3.3.3	Malaria incidence per 1,000 population		x			1-1-1-1		
3.7.2	Adolescent birth rate (aged 10-14 years; aged 15-19 years) per 1,000 women in that age group				x	1-2-2-2		
4.2.2	Participation rate in organized learning (one year before the official primary entry age), by sex	x				1-1-1-1		
4.a.1	Proportion of schools with access to: (a) electricity; (b) the Internet for pedagogical purposes; (c) computers for pedagogical purposes; (d) adapted infrastructure and materials for students with disabilities; (e) basic drinking water; (f) single-sex basic sanitation facilities; and (g) basic handwashing facilities (as per the WASH indicator definitions)	x				1/2-2-2-2		
4.c.1	Proportion of teachers in: (a) pre- primary; (b) primary; (c) lower secondary; and (d) upper secondary education who have received at least the minimum organized teacher training (e.g. pedagogical training) pre-service or in- service required for teaching at the relevant level in a given country	x				1-1-1-2		
6.3.2	Proportion of bodies of water with good ambient water quality		x			3-3-3-3	7th	yes
6.4.1	Change in water-use efficiency over time		x			3-3-3-2	6th	yes
6.6.1	Change in the extent of water- related ecosystems over time		x			3-3-3-3	7th	yes
9.1.1	Proportion of the rural population who live within 2 km of an all-season road		x			3-3-3-3		yes
11.3.1	Ratio of land consumption rate to population growth rate		x			2-2-2-2		yes
11.6.2	Annual mean levels of fine particulate matter (e.g. PM2.5 and PM10) in cities (population weighted)		x			1-1-1-1		yes
11.7.1	Average share of the built-up area of cities that is open space for public use for all, by sex, age and persons with disabilities	x	x	x		2-3-3-3	6th	
14.1.1	Index of coastal eutrophication and floating plastic debris density		x			3-3-3-3		yes
14.3.1	Average marine acidity (pH) measured at agreed suite of representative sampling stations				x	3-3-3-3		yes
15.1.1	Forest area as a proportion of total land area		x			1-1-1-1		yes
15.3.1	Proportion of land that is degraded over total land area		x			3-3-3-2	6th	yes
15.4.2	Mountain Green Cover Index		x			2-2-2-1		
16.1.2	Conflict-related deaths per 100,000 population, by sex, age and cause				x	2/3-3-3-3		
17.18.2	Number of countries that have national statistical legislation that complies with the Fundamental Principles of Official Statistics			x		3-3-3-2	6th	
22		**7**	**15**	**2**	**3**		**8**	**11**

4 of the 6 requests submitted for the 6th meeting appear to have been approved with indicators ranked up to Tier II. There appears to be no striking association between tier level and big data type. Finally, 11 of the 22 indicators are also mentioned in the recent ESCAP study on big data potentials for SDGs, which reviews big data projects that could assist the monitoring of 42 indicators in total (ESCAP, 2017). This last point suggests that the official indicator custodians apply a different judgment of the potential of big data for SDGs than the authors of the ESCAP study.

5.3 Document analysis

Depending on their associated SDG, the measured construct, and the applied methodology, the indicators can be separated into 6 thematic case groups that will guide the following reports. Citations refer to the official metadata and workplans which can be examined on the IAEG-SDGs website.[5] In several cases the official documents link to further webpages that provide useful context to the methodology. To distinguish them from other sources used in this work they were cited as footnotes when referred to.

5.3.1 Earth Observation

This is the largest group and includes 9 indicators covering 4 SDGs, all measuring different states of the earth system and human impact on it. All but one make use or consider the use of remote sensing. The group includes three water indicators (SDG 6), three land ecosystem indicators (SDG 15), two ocean indicators (SDG 14), and one urban indicator (SDG 11).

The three water indicators measure the extent of water ecosystems over time (6.6.1), water bodies with good ambient quality (6.3.2) and human impact in terms of water-use efficiency (6.4.1). The documentation reveals that methodologies for all SDG 6 indicators are developed by a Water Target Team including the European Space Agency. This target team is considering applying where possible, "[a] combination of Earth Observation and ground-based data" (6.6.1 workplan 6th, p. 3). Currently station data is central to these indicators but "globally technology and scientific development will show as to what level detailed water quality information can be supplemented over time by remote sensing information" (6.3.2 workplan 6th, p. 2). Indicator 6.4.1 is unclear as to how exactly it intends to make use of remote sensing data. While this option is mentioned in the workplan from the 5th meeting, the newest metadata sheet does not mention remote sensing anymore (6.4.1 metadata).

The land-related indicators measure land degradation (15.3.1), forestland in general (15.1.1) and in mountainous regions (15.4.2). Especially land degradation draws extensively on remote sensing products from land cover datasets. While the metadata state that data is ideally to be collected by national

[5] https://unstats.un.org/sdgs/metadata/

authorities, gaps in reliable data for a range of countries are thus to be bridged with remote sensing, ground-truthed through field surveys. This has already been done for mountain vegetation using the Collect Earth tool.[6] However, limitations to this approach are also discussed. Remote sensing is considered to be less reliable for observing forest regrowth and vegetation with low canopy cover (15.1.1 metadata).

Regarding oceans, 14.1.1 measures coastal eutrophication and floating plastic debris while 14.3.1 assesses marine acidity. Both indicators are currently calculated on the base of data provided by respective national authorities and NGOs. Marine litter is approximated by sampling beach litter. However, a cooperation with NASA aims to develop a remote sensing approach by 2020 (14.1.1 workplan 6th). 14.3.1 is the only indicator in this group not directly associated with remote sensing. It is stated that one intends to apply "automated data harvesting" of online accessible data sources to create more timely data series (14.3.1 workplan 6th, p. 3).

Finally, 11.6.2 measures city air quality. An annual mean concentration of particulate matter is available for the entire planet using a modelling approach that combines aerosol remote sensing with ground measurements where available (11.6.2 metadata).

5.3.2 Data modelling

Health related indicators are largely based on survey data and official records, however I considered two of them (3.3.3 and 3.7.2) in my final results since they highlight the importance of various analytical tools for coping with disparate and missing data. 3.7.2 counts birth rates for females aged 10-14 or 15-19. In many countries civil registries are considered not reliable enough to provide this information. Different surveys exist, however for different time ranges and regions, with different methodologies and large variations. To include this disparate data in the calculation of global estimates it is common to draw on "expert-based opinion reviewing […] or, in more recent years, using automated statistical methods" (3.7.2 metadata, p. 3-4).

3.3.3 draws on remotely sensed information. The indicator measures malaria incidents but has to make up for incomplete reports with estimates. Using a geostatistical model from the Malaria Atlas Project[7] it is possible to predict parasite prevalence in risk regions at high spatial resolution for every year. Based on this model expected malaria cases can be predicted for 5 x 5 km grids which allows taking targeted precautions (3.3.3 metadata).

[6] http://www.openforis.org/tools/collect-earth.html
[7] https://map.ox.ac.uk/making-maps/

5.3.3 Data validation

This group contains the three education indicators 4.2.2, 4.a.1, and 4.c.1. All of them draw on administrative data from schools in different respects and combine it with means to account for irregularities. For all three it is identically stated in the metadata that "[t]he data received are validated using electronic error detection systems that check for arithmetic errors and inconsistencies and trend analysis for implausible results. Queries are taken up with the country representatives reporting the data so that corrections can be made (of errors) or explanations given (of implausible but correct results)" (4.2.2 metadata, p. 4). Error detection through checksums is itself not surprising, however the application of "trend analysis" to spot significant outliers is also a typical application of big data analytics. It is unclear from the metadata itself to what an extent such an application is truly used here, but the finding itself speaks of the efforts that go into ensuring globally comparable and valid data.

5.3.4 Experimental approaches

This group contains two indicators for which big data approaches were mentioned as potential support in the workplans. Indicator 16.1.2 measures conflict related deaths, disaggregated by sex, age, and cause. According to its workplan it draws on a multi-method approach, making use of questionnaires, surveys, and official records. In this context it is also mentioned that "[i]n addition, data made available by civil society organizations carrying out media and other global monitoring (e.g. big data) will also have to be assessed for their usefulness in compiling components of the indicator" (16.1.2 workplan 6th, p. 3). This methodology is not yet finished as of now, so it is unclear whether and how such data will be incorporated. However, this finding underlines that indicator officials are actively considering new data sources.

17.18.2 on the other hand is part of the overarching 'Partnership for the Goals' (SDG 17), which is to coordinate overall SDG implementation. The indicator measures the number of countries with statistical systems that comply with the UN resolution on Principles of Official Statistics[8] through surveying officials. An earlier workplan states that to assure data quality one is to "employ text mining for each country's statistics law to assess compliance" (17.18.2 workplan 5th, p.3). The indicator was recently upgraded; the new metadata document does not mention "text mining" anymore and instead describes a methodology entirely based on surveying national statistics officials. Text mining was used in an earlier publication on statistical systems by the indicator custodian, PARIS 21[9]. It appears to have been considered as an experimental approach but got discarded now.

[8] https://unstats.un.org/unsd/dnss/gp/fundprinciples.aspx
[9] http://www.paris21.org/sites/default/files/2017-09/BoardDocument2017.pdf

5.3.5 Mixed methods

This group consists of 3 indicators, 2 of them associated with 'Sustainable Cities' (SDG 11) and one with 'Sustainable Infrastructure' (SDG 9). 9.1.1 measures the so called Rural Access Index, the share of people who live in 2km distance from an all seasoned road. The workplan states that the World Bank, which is the custodian for this indicator, has recently developed a new calculation approach that makes use of administrative spatial data and remote sensing and that is expected to be operational by 2020 (9.1.1 workplan 6th). This approach is documented in an additional report. Here the potential of remote sensing is qualified: it is considered to be costly at the moment, but the option of crowdsourcing information on road conditions through Smartphone applications is being discussed.[10]

The indicators covering SDG 11 are all being developed by UN Habitat which appears to consider big data approaches for 2 of them. 11.3.1 measures the ratio of land consumption rate to population growth rate. It is considered under Tier II, meaning it is conceptually clear but data points are lacking for a majority of countries worldwide. Land consumption is here defined as the change of the extent in urban agglomeration over time. The challenge is to ensure a consistent application of this definition given the vastly differing types of settlements worldwide and the lack of official documentation for certain countries. To cover for data gaps, the metadata record proposes using the Global Human Settlement Layer, a spatial data product containing both information on population and built-up area as a future option as soon as its coverage has been extended sufficiently (11.3.1 metadata).

11.7.1 assesses the share of open space in cities that is available for public use. This indicator is supposed to be disaggregated by sex, age, and persons with disabilities. Here streets are considered part of public space, so a more fine-grained approach than 11.3.1 is needed to distinguish them from other built up area. Since reliable spatial data are not globally available, a remote sensing based sampling method is proposed: randomly selecting 10-hectare sized circles over a city area and then classifying those according to street areas, open spaces and built-up areas can provide representative samples for the estimated share of open space for entire cities. A limitation to this approach is seen in the fact that it does not cover quality and accessibility of open spaces (11.7.1 metadata). For this purpose, a community mapping tool is suggested. The update request from the 6th meeting contains a mobile application dummy where one can enter information regarding type, usage, accessibility, and perceived safety for a public space.[11] As of now these methodological proposals do not seem to have led to a tier upgrade.

[10] http://documents.worldbank.org/curated/en/367391472117815229/pdf/107996-REVISED-PUBLICMeasuringRuralAccessweb.pdf
[11] Available under https://unstats.un.org/sdgs/meetings/iaeg-sdgs-meeting-06/

5.3.6 Abandoned for now

Finally, three indicators covering the goals 'No Poverty' (SDG 1) and 'Zero Hunger' (SDG 2) are a group of social indicators with low data availability for which alternative sources have been explored. 2.4.1 measures the proportion of agriculture under sustainable and productive agriculture. This information is to be gathered through integrated farm surveys but the earliest available workplan for this indicator also mentions the possibility of using remote sensing to gather relevant information (2.4.1 workplan 4th). This part was then dropped in subsequent versions and seems to have been replaced by a mention that the data "can be supplemented with data from other sources, including data from monitoring systems" (2.4.1 workplan 6th, p. 2). No further elaborations are given, and farm surveys remain the key data source for this indicator.

Indicator 1.4.1 which measures the proportion of population living in households with access to basic services has also mentioned remote sensing as a potential source in its workplan. Here this possibility is expanded towards discussing the option of making use of UN-habitats global network of urban observatories and to invite additional stakeholders to contribute data and expertise. Apart from this, household surveys remain the primary data source for the indicator.

Finally 1.4.2 measures the proportion of adult population with secure tenure rights to land, with legally recognized documentation and who perceive their rights to land as secure. This is to be disaggregated by sex and tenure type. The specific qualifications of this indicator make the availability of administrative records and reliable surveys central. However, an earlier workplan also seems to consider remote sensing as an option, yet without explaining how (1.4.2 workplan 5th). While respective surveys are considered to be in place, a challenge for assessing tenure rights is that many countries continue to have paper-based land information systems. In the newest workplan the reference to remote sensing appears to have been excluded again (1.4.2 workplan 6th).

5.4 Summary

The here described indicators constitute a mosaic of a wide range of actual and potential applications of big data sources and analytics for calculating the SDG indicators. Rather than a 'revolutionary' shift, one can see a gradual dispersion of big data that might often simply be a continuation of established approaches with slightly improved means. Indicator custodians evidently respond to the SDGs' data demand by considering new opportunities, but in many cases those are not yet implemented. The indicators for which most novel approaches are being developed are those covering cities. Here we see how concentrations of technology use and administrative capacity are potentially interlocking into new paradigms for monitoring and planning, elsewhere discussed under the buzzword "Smart Cities". The most conceptually clear approaches involve remote sensing – itself hardly a recent technology – that offers new opportunities when combined with automatic image classification and additional data

sources. In general, one can observe a tendency towards greater integration of disparate sources that becomes more robust to missing values and measurement errors. Here automated approaches enable gathering, validating, and combining data more effectively on global scales. Limited availability of digital records remains a barrier but the SDGs themselves set a course for global datafication (Target 17.18). The purpose of the SDGs indicator framework is to produce global vision for a global vision. Though not yet fully developed in all cases, this purpose aligns well with the knowledge production enabled by big data.

6 Discussion

Based on the previous accounts, the following part is going to relate the findings back to the initially proposed six trajectories along which a big data-indicator assemblage could develop. These are not to be taken as predictions that this work aims to support but as tentative tools for highlighting areas of specific interest. Two of those relate to the knowledge effects of indicators, two are relevant for the governance effects and finally two can be considered alternative potentials that are promising for future interventions.

6.1 Big data and the knowledge effects of indicators

1.1. *The big data episteme entrenches the 'power of numbers' by suggesting that data can speak for themselves in non-biased ways.*

In several cases of the considered material, indicator custodians explicitly state their awareness of methodological limits. This is for example done in the material for 15.1.1 and 11.7.1 which highlight limits of remote sensing in capturing both certain environmental but also social factors. 1.4.2 highlights shortcomings of established survey waves to reliably represent the most marginalized. Here the experts seem to be aware of the 'power' of the numbers they eventually deliver to policy makers and express concern about making them both as reliable as possible while communicating limitations. This suggests that the danger of perceiving indicators as robust facts rather than as the complex constructs that they are lies much less in their production but likely in a communication deficit between statistical experts and policy makers and a wider public. Indicators are delivered as 'packages' containing upmost a set of shiny numbers. Metadata are provided to contextualize these numbers and highlight their limits. But always contextualizing indicator use with these reflections contradicts the very appeal of indicators: being simple and directly comparable for different regions and times. Unexamined belief in the 'power of numbers' is likely less of an issue in the process of knowledge production – it might only become an issue because knowledge products necessarily disguise their circumstances of production.

1.2. *Datafied citizens are responsiblized into entrepreneurial individuals as they become perceivable through comparative indexes.*

Within the here described cases there is little evidence for the direct datafication of citizens lives. What they highlight instead is an additional necessity to responsiblize data providers into providing accurate numbers in standardized formats. Challenges to datafication are discussed in relation to paper-based records, missing data and disparate measurements. In order to enable a globally coherent monitoring system it is necessary to standardize statistical operations as addressed by indicator 17.18.1. This is for example expressed in the consideration of using text mining to automatically examine whether the information provided by national statistical officials on indicator 17.18.1 is in fact reliable. But this approach appears to have been dropped in favor of direct consultation in cases of doubt. The value of machinic data validation is however discussed for the mentioned education indicators. Here the emphasis is on spotting implausible outliers by using trend analysis. This finding can be understood in light of the incentive to game indicators, especially when tied to reputation and funding. It is probable that the utility of big data analytics for spotting anomalies will be used increasingly to examine the examiners themselves, responsiblizing data providers to ensure that reliable data in turn responsiblizes decision makers and citizens.

6.2 Big data and the governance effects of indicators

2.1. *Fetishizing big data draws attention from already known issues to improving means for measuring without a clear guarantee for applicability.*

As described earlier, proponents of a data revolution for SDGs have been criticized for making many unwarranted claims regarding the potential of big data. But as noted in the discrepancy between the use of big data terminology in the ESCAP (2017) study and in this sample, indicator officials seem to apply different judgment when it comes to assessing such potentials. In the cases of the indicators 16.1.2 and 17.18.2 which are not considered as suitable for big data by ESCAP (2017), indicator custodians have entertained the ideas of using “text mining” and “big data”, however with unclear implications. In the former case this possibility was eventually dropped. In the latter it is yet unclear how such an approach would function. Similarly, several indicators appear to have vaguely considered the option of using remote sensing at some stage in their development but then discarded it (1.4.1, 1.4.2, 2.4.1, 6.4.1). These cases together suggest that indicator experts are not immune to the allures of the big data discourse and invest time in considering them even though they might turn out as not applicable.

2.2. *Algorithmic opacity increases the power of technocrats and aggravates accountability and contestation of decision making.*

It is inherent to the function of indicators to veil the inconsistencies and uncertainties that have to be overcome in their production. The challenges posed by missing and disparate values and the resulting in limits to indicator validity constitute issues that statistical officials are likely to be more aware of than the users of indicators as discussed above. When combining many disparate data sources into

one measure, the approach for health indicator 3.3.3 appears to make use of automated statistical tools to generate weights for each source that inform the computation of a single measure. With the limited information available here it is impossible to judge functionality, extent, and potential shortcomings of such methods. It is thus premature to pass a judgment on potential consequences for accountability and contestation. However, it should be noted that such applications need to be considered in detail in the future. (Burrell, 2016) reminds us that processes of automated weighting might be comprehensive for humans if they operate on a small set of factors, however as the amount of data that is collected into a single measure grows, they become increasingly opaque. So far, no cases were this could evidently have harmful consequences were observed in this selection.

6.3 Big Data and alternative trajectories

3.1. Expanding what can be measured allows for introducing ecological and social concerns more effectively into decision making.

A broad concept like sustainability contains many components that are hard to quantify including complex ecosystem dynamics and human concerns. Sustainability scientists often emphasize that such aspects are best considered directly in the local contexts where they arise (Lang et al., 2012). Forms of global governance that enhance rather than potentially aggravate context dependent implementation might not require full knowledge of local specificities but need to be aware that they exist. In this respect a big data enabled expansion of what is measurable could be positive for integrating local and global levels of decision making. An ecological example of this could be 14.1.1 which enables better understanding the pressing issue plastic debris in oceans. A more interesting case though is indicator 11.7.1 which makes use of a multi-method approach, including potentially participatory sensing to include context specific considerations into the indicator. A measurement that indiscriminately represents streets and open surface as public space with the ability to “enhance community cohesion” (11.7.1 metadata, p. 1) could provide a skewed picture and set wrong incentives. Here the use of big data could enable the assessment of a complex construct such as ‘public space’ in more reliable ways for the entire planet.

3.2. Mobility of technology and accessibility of data enables counter-calculation and development of alternative indicators by activists and NGOs

This final potentiality is difficult to assess with the available material since it directly refers to activities outside of the UN-mandated monitoring framework. What is possible to highlight in several cases though is that indicator custodians appear to be aware that they are not the only ones who measure. 11.7.1 and 17.18.2 mention the consultation with NGOs and independent scholars as central steps in methodology development and data sourcing. Recognition by official statisticians does not amount to counter-calculation but it shows that there are possibilities for independent investigators to generate highly valuable information. Wheeler et al. (2017) have argued that a true data revolution would have

to come from the margins. The relevance of knowledge from the margins does not exhaust itself the possibility of becoming officially recognized: it can itself become a basis for alternative visions which are much needed given the insistence of the SDGs on the reconcilability of ecological sustainability and economic growth. The results have illustrated the efforts that are put into creating an all-encompassing knowledge system that supports this vision. Given the concerns on knowledge and governance effects, this tendency itself warrants the need for alternative indicators and calculations.

7 Conclusion

In this work I have identified 22 relevant SDG indicators from a body of 420 documents and analyzed their use of big data in the light of six proposed trajectories for big data in the SDGs. It was argued that big data is likely to exacerbate and obscure the knowledge and governance effects of indicators and that alternative trajectories need to be supported. But contrary to the high expectations of a data revolution discourse, the use of big data for SDGs is still in its early stages. My findings show that where such developments are happening, they do not constitute a revolutionary break with previous statistics but proceed stepwise and irregularly accross the indicators. The general critcism of the indicator framework's weaknesses holds irrespectively of big data. The results have shown that if big data is to strengthen a dangerous belief in the neutrality of numbers, that is likely not due to a lack of awareness on the side of indicator custodians but due to the circumstances and public discourses in which indicators are used. Big data's impact on indicator governance is likely subtle and gradual. Through easing the integration of disparate data sources it first and foremost simplifies statistical work. But this automated smoothing of differences and merging of patches is what might constitute a newly emerging global mode of knowledge and governance.

Global visibility is a precondition for implementing the SDGs' global vision. For now, big data produce particular spotlights, harmful in some and useful in other cases. But inherent to the technology is a tendency towards greater standardization that already now discursively culminates in allusions to a gods-eye view (Kitchin, 2014a). If the Anthropocene calls on us to turn from exploiters into stewards does that require us to become all-seeing? Or would true stewardship be rooted in the nurturing of difference and acceptance of incompleteness? 300 years after von Carlowitz attempted to instate sustainable forestry, complexity haunts us more than ever.

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