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Enacting the Pandemic: Analyzing Agency, Opacity, and Power in Algorithmic Assemblages

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Abstract

This article has two objectives: First, the article seeks to make a methodological intervention in the social study of algorithms. Second, the article traces ethnographically how an algorithm was used to enact a pandemic, and how the power to construct this disease outbreak was moved around through an algorithmic assemblage. The article argues that there is a worrying trend to analytically reduce algorithms to coherent and stable objects whose computational logic can be audited for biases to create fairness, accountability, and transparency (FAcCT). To counter this reductionist and determinist tendency, the article proposes three methodological rules that allows an analysis of algorithmic power in practice. Empirically, the article traces the assembling of a recent epidemic at the European Centre for Disease Control and Prevention—the Zika outbreak starting in 2015—and shows how an epidemic was put together using an array of computational resources, with very different spaces for intervening. A key argument is that we, as analysts of algorithms, need to attend to how multiple spaces for agency, opacity, and power open and close in different parts of algorithmic assemblages. The crux of the matter is that actors experience different degrees of agency and opacity in different parts of any algorithmic assemblage. Consequently, rather than auditing algorithms for biased logic, the article shows the usefulness of examining algorithmic power as enacted and situated in practice.

Keywords: algorithm, assemblage, situated opacity, power, pandemic



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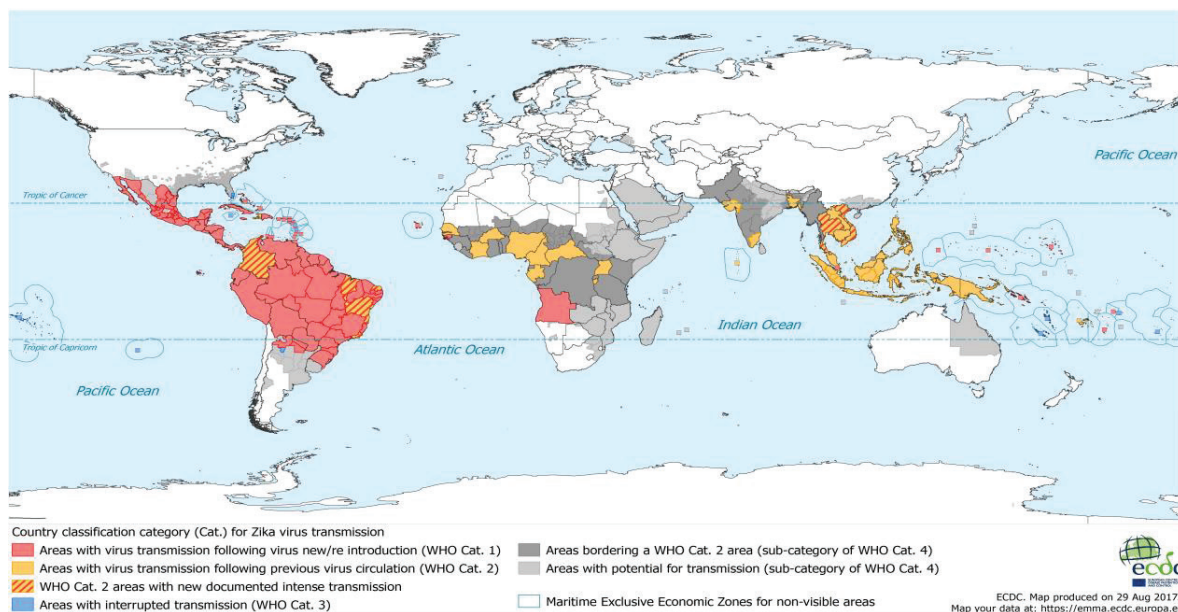


Figure 1. The Current Zika State as published on the website of the European Center for Disease Control and Prevention on 29 Aug 2017

The aim of this article twofold: to make an empirical contribution to our understanding of how pandemics are put together with algorithms, and a methodological intervention in the social analysis of algorithms. As multiple epidemics and pandemics sweep our interconnected and globalized world—not least the COVID-19 pandemic which is holding society in a vice as I write this—it is becoming crucial to understand how a pandemic comes about through various infrastructures, algorithms, models, sensors, practices, and decisions.

The empirical focus of the article is the algorithmic making of the Zika pandemic which emerged in close proximity to the Olympics in Rio de Janeiro in 2015–2016, and started spreading around the world, raising concerns that the disease would spread globally.¹ The article traces the work of assembling a particular version of this epidemic, called the Current Zika State—a map of the spread and intensity of the Zika pandemic (see Figure 1). The Current Zika State was the official version of the Zika pandemic that the European Center for Disease Control and Prevention, the ECDC, published. The Current Zika State was generated by what my informants called the Zika Algorithm.

The empirical aim of the article is to shine light on how this algorithm enacted the Zika pandemic.

That is, how the social and natural orders of Zika were assembled at the ECDC and how various quantifications, models and classifications—from faraway times and places—were folded into the Zika Algorithm with consequences for different actors’ space for agency, opacity, and power (cf. Lee et al., 2019). For my informants, the Zika Algorithm promised automation, simplicity, and orderliness—an unambiguous and automated map of the Zika pandemic.

This means that we are dealing here with a particular kind of assemblage that my informants and I refer to as an algorithm.² In practice, an algorithm is a multifaceted object that can be many different things and is interpreted and used differently in different settings. But, rather than defining it along the lines of computer scientists or health professionals (who call different things algorithms) this article approaches algorithms in an emic manner (cf. Dourish, 2016; Seaver, 2017). This means that I follow my informants in their various makings of what they call the Zika Algorithm. In essence, I follow the work of my informants of assembling, stabilizing, and interpreting the Current Zika State with the Zika Algorithm, and how agency, opacity and power were distributed in this assemblage.³

Using this case as a springboard, I argue that much social analysis of algorithms risks falling in

an epistemic trap by importing a stabilized and delineated notion of algorithms from computer science (cf. Muniesa, 2019). I argue that this epistemic trap underpins much of today's algorithmic critique which focuses on the power of the black-boxed algorithm (Pasquale, 2016), different degrees or types of opacity (Burrell, 2016; Diakopoulos, 2020; Larsson and Heintz, 2020), biased search results (Sandvig et al., 2016), algorithmic oppression (Noble, 2018; O'Neil, 2016), or quantitative auditing (Sandvig et al., 2014).

This argument is political to the highest degree. What is at stake is how we understand and analyze power in an algorithmic society. The crux of the matter is that arguments about automated, black-boxed, biased/objective, opaque/transparent algorithms perform a punctualization of agency and politics, which risks transferring the politics of technoscience to the realm of the technical artefact, rather than how power is distributed in assemblages. As one of my interlocutors humorously put it: "Well, isn't it useful to point the finger at the algorithm!"—when we should be having discussions about the use and broader effects that algorithms have on society.⁴ Instead of analyzing the racist algorithm we should be looking at racist assemblages—and where the possibility for agency, choice, and power reside in these assemblages.

By following the algorithmic enactment of the Current Zika State, the article demonstrates the usefulness of three methodological rules in the study of algorithms: 1) Don't punctualize agency to the algorithm; *instead attend to how agency and choice are assembled.* 2) Abandon the opaque/transparent binary; *instead attend to multiple and situated translucencies.* 3) And last, dispense with the algorithm as the prime mover; *instead attend to how power clusters and disperses in assemblages.* The argument is that we need to analyze the effects that different algorithmic assemblages have in the *multiple practices* where they are made, tinkered with, and used, rather than focusing on the inherent politics of the black boxed algorithm.⁵

Algorithms, the very idea: on the epistemic trap of the black boxed algorithm

Social studies of algorithms have since the outset acknowledged the fluidity and assembled nature of algorithms, at the same time as the field has lamented the inscrutability and power of the algorithm. Goffey (2008) for instance describes the nature of algorithms as part of long chains of actions upon actions, at the same time as he argues that "Algorithms do things, and their syntax embodies a command structure to enable this to happen" (Goffey, 2008: 17). While Gillespie concludes that the "there may be something, in the end, impenetrable about algorithms." (Gillespie, 2014: 192).⁶ Powerful black boxes indeed.

Thus, in debates about the theory and methods of social studies of algorithms, there exists an oscillation—often in the same papers—between on the one hand acknowledging the fluidity, complexity and assembled characteristics of algorithms (Seaver, 2017, 2018), and on the other hand a notion of algorithms as stable and delineated objects, existing out there, that can be unfair, unaccountable, opaque, and biased, and in the need of auditing in order to rectify said biases (Diakopoulos, 2016; Pasquale, 2011; Sandvig et al., 2014).⁷

My argument is that this oscillation in how algorithms are understood analytically—on the one hand as fluid and assembled, and on the other as delineated objects that can be made fair, accountable, and transparent (the famous FAT movement, now FAcCT) makes for a precarious analytical vantage point for the social sciences.⁸

One reason for this precariousness is that we social scientists, as Muniesa has argued, have taken over a "vocabulary of information in the analysis of social realities" (Muniesa, 2019: 200). That is, by taking on the vocabulary of our informants—that we indeed analyze an object called *algorithm*—we have fallen into an epistemic trap that delineates, stabilizes, and delimits our objects of study as well as our analytical problems.

My point is that we—along with our informants, computer science, and the media—perform *algorithms* as clearly delineated and pre-existing objects that can be analyzed in themselves. By falling into this epistemic trap we perform algo-

rithms as *punctualized* (Callon, 1991). That is, by treating algorithms as stable objects “out there” we—social scientists—ascibe agency and power to this performed object, instead of paying attention to the assembling of agency in practice and the performative effects that the assemblage has (cf. Callon and Law, 1995).

Consequently, when we talk about the “power of the black boxed algorithm” or “auditing the algorithm,” we start thinking about this performed object as being the object for our own studies—with concomitant forms of problematizing algorithms in society. In this way the algorithm becomes a seemingly naturalized object for social analysis, which leads to particular forms of political and analytical action: *Analyze and audit the powerful black boxed algorithm!*⁹

The two cultures of algorithm studies

These different analytical approaches to algorithms—one where they are understood as delineated and stabilized objects and the other as fluid and assembled—create very different understandings of the politics of algorithms. And also very different problematizations of how to analyze the currently unfolding algorithmic society (cf. Lee and Björklund Larsen, 2019).

The stabilized notion of algorithms seems to treat algorithms as having political qualities “under the hood.” In this view, the algorithm—as an object for us to audit and investigate—is treated as having stable qualities that shape society in particular ways, which makes the “politics of the artefact” the natural analytical focus (cf. Winner, 1980). Consequently, we take on the epistemic objects of computer science as our own—and become auditors of the stabilized algorithm. (Auditing is of course an important function in a world run by algorithms. No disagreement there!) But, I argue, nonetheless this epistemic trap leads to simplified understandings of how algorithmic power works in society.¹⁰

In my view, the central problem with the stabilized and punctualized understanding of algorithms is that we take on a reductionist and determinist view of the politics of algorithmic assemblages. For sure, algorithmic assemblages *do have power*. But it is seldom an autonomous

power, where algorithms act on their own to oppresses the poor, but rather as Goffey (2008) and others have acknowledged, it is a rhizomatic and capillary power that works by actions upon actions.

This article suggests that to understand the politics of algorithms we need to be wary of importing this punctualized view of the “black boxed algorithm,” and keep our awareness of how algorithmic assemblages structure power in multiple and dispersed practices. Don’t let social science become the algorithmic auditors that computer science might imagine it needs.

In sum, my argument isn’t that algorithmic assemblages are powerless—quite the contrary they are very powerful—but rather that we as social analysts need to be aware of when we are taking over the object definitions of computer scientists, politicians, or auditors as they risk leading to impoverished understandings of how our world is enacted with algorithmic assemblages. Below, I will show the futility of attending to the punctualized version of algorithms and, in conclusion, suggest three methodological rules to break out this epistemic trap.

Let us now return to the issue at hand, the enactment of the Zika Algorithm and the Current Zika State—and how spaces for agency, transparency, and power are configured in these assemblages.

Assembling pandemics

In disease surveillance today, the knowledge of disease outbreaks is increasingly produced through an abundance of technical, political, and animal infrastructures.¹¹ These infrastructures are constantly working in organizations across the globe. In the west, the US Center for Disease Control (CDC), the WHO, and the ECDC are endlessly monitoring their screens, attempting to detect the next big outbreak of disease; in the South and East the Chinese and Brazilian CDCs are important hubs.¹² Currently, these information infrastructures are reshaping our knowledge about epidemics: new disease patterns and outbreaks becoming visible through the development of new infrastructures (Caduff, 2014; Kelly, 2018; Lee, 2020; Mackenzie, 2014; Sanches and Brown, 2018).

At the ECDC outbreaks are continually being assembled, updated, displayed, and debated about. A host of methods are used to classify and value disease intensities, disease threats, and disease risks, which can lead to conflicts between different actors about the understanding of an outbreak (Keck, 2008; Lee, 2020). One visualization, which has been part of disease control for hundreds of years, involves enumerating cases in time and space. Others involve making risk calculations based on environmental models, tracing food stuffs through distribution networks, tracking genetic relations between pathogens, or using social media to find likely places of contagion.

To visualize these classifications and valuations of disease intensities, risks, and predictions there are a number of well-established visualizations that are harnessed in order to establish where in time and space the outbreak is at the moment. For example: There is the infamous epidemic curve, or epicurve, which enacts a disease as the number of cases on a timeline. The epicurve is an iconic part of disease surveillance highlighting the disease intensity over time, producing images of the development of a disease outbreak, COVID-19, different strains of Flu, Ebola, and Zika are all visualized in time series showing the severity of disease (cf. Kelly, 2018; Mackenzie, 2014). There is the contact-tracing chart, which exhibits a network of potential disease pathways between patients.

Last, and most importantly for the assembling of the Current Zika State, there are an abundance of maps produced visualizing where disease risk and disease intensities are highest. The production of maps lies at the heart of disease control. Maps are produced of most outbreaks on different scales and with different purposes. COVID-19 maps, influenza maps, yellow fever maps, Zika maps, Ebola maps. For the surveillance of disease, maps are tools to determine the source of disease, tools for tracking how a disease spreads, or a tool for making recommendations for action.

The visualizations that are produced at the ECDC make political waves. Disease is tied to lock-downs, tourism, food supplies, and work. The presence of disease is a delicate matter: COVID-19 maps reshape our whole lives, Zika created headlines around the world, Salmonella

can cause the closure of industrial egg handling facilities, and so on. This puts knowledge production of pandemics in a position where disease, international trade, national economies, international relations, tourism, and national politics can become implicated at any moment.¹³

At the ECDC these visualizations are crucial tools for understanding, discussing, and communicating with disease professionals, decision-making politicians, and the public. Below we follow the assembling of a particular visualization, a map that classifies the world into different intensities of disease, and different areas of disease risk. The Current Zika State is a vehicle for enacting a classification of society and nature. It produces the social and natural orders of a Zika pandemic.¹⁴

An ethnography of the Zika Algorithm

Empirically, the article draws on fieldwork in a larger project that examines how new information infrastructures shape disease surveillance. The project commenced in 2015 with a preliminary study that inquired into the rise of so-called infodemiology, that is, the harnessing of new types of data in disease surveillance (cf. Fearnley, 2008). These new types of data can for example entail genetic data, web searches, tweets, sales data, or travel information.

The material for this article used a strategy of multi-sited ethnography to follow the assembling of the Current Zika State inside and outside the ECDC (cf. Marcus, 1995). The article draws on a multitude of different materials and strategies of data collection: situated fieldwork, document analysis, and interviews done during 2016, 2017, and 2018. Hence, in this engagement with the Zika Algorithm, I followed the assemblage through a variety of places, situations, and materials.

The fieldwork at the ECDC consisted of three weeks of participant observation in the epidemic intelligence team in early 2017, as well as weekly follow up observations with other teams during the following spring. During the first round of fieldwork I worked in the so-called epidemic intelligence team, where I performed routine disease surveillance. This team is tasked with trawling social media, news media, and a constant flow of email to find and assess new disease threats.

During fieldwork, I attended meetings, participated in staff training, and interviewed my informants formally and informally in the epidemic intelligence team and other teams.

This situated fieldwork served as a springboard for a wider investigation into the making of the Zika Algorithm, where I complemented the initial period of participant observation with interviews and extensive document analysis following where the algorithmic assemblage led. Thus, the current article draws on participant observation, informal conversations, interviews, working documents, flowcharts, official ECDC publications, as well as other scientific publications.

Accordingly, this paper takes its starting point in the observation of a meeting about the Zika Algorithm at the ECDC, and branches out into interviews, observations from other meetings, document studies, and interviews. In short, I have followed the Zika Algorithm to the many sites where it was assembled.

The Zika Algorithm

Me and my informants Thomas, and Bertrand are in the Emergency Operations Centre—a situation room for disease control—at the ECDC after the daily roundtable meeting. At this daily meeting, disease experts from across the ECDC gather to assess today’s disease threats against the European population. Thomas and Bertrand are gearing up to have a meeting on an algorithm that produces the Current Zika State.

Bertrand has worked for months to produce this new algorithm for classifying the world into zones of Zika risk. The goal is to construct an algorithm that will help to automate the work of putting together a snapshot of the Zika epidemic. This particular meeting is to start translating the Zika Algorithm (in the form of a logical flowchart) into layers of code, visualizations, and software. The resulting map, titled the Current Zika State, is published online, and included in regularly recurring reports about the state of the Zika epidemic.

At the meeting, the visual focus has become a flowchart (Figure 2) as well as a bewildering array of database tables. They are all projected on the

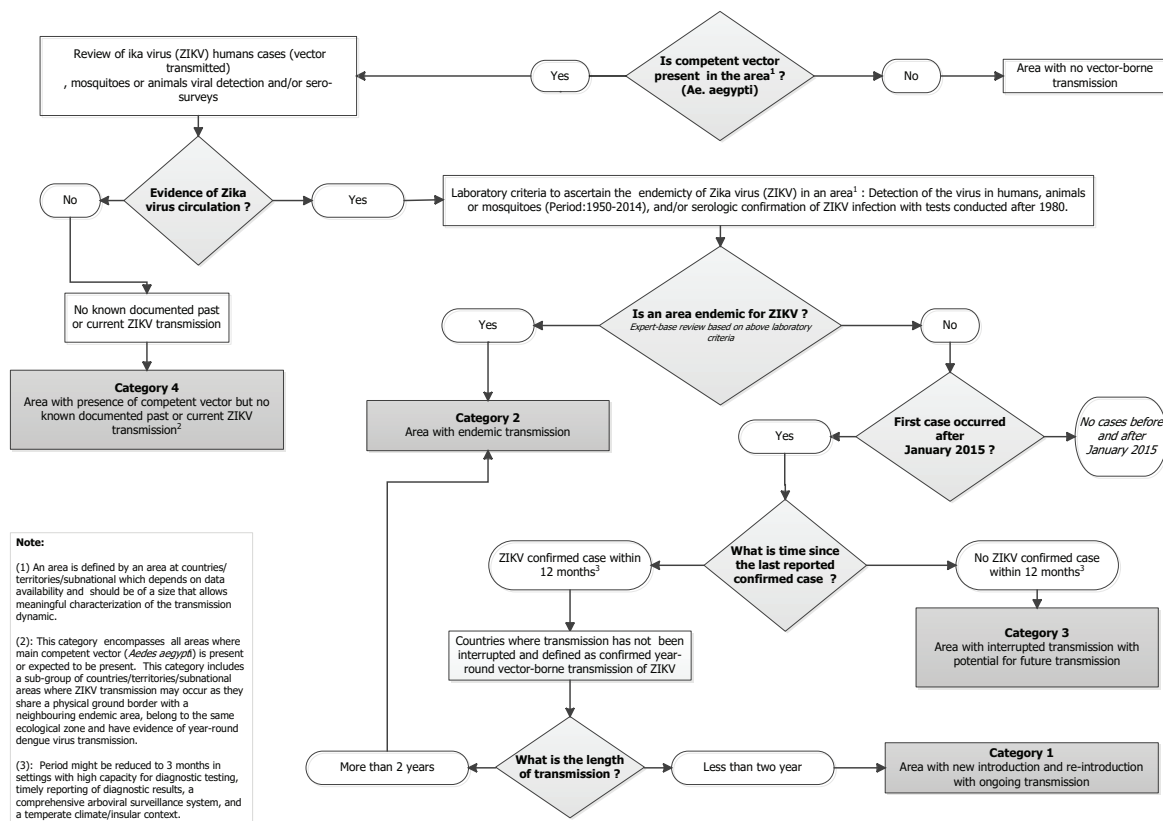


Figure 2. Bertrand’s provisional Zika algorithm

huge screen that fills one wall of the Emergency Operations Centre. The flowchart visually outlines the Zika-algorithm that is used to classify a country's Zika risk.

After quickly running through the flowchart version of the algorithm, Bertrand clicks between different columns and datasets in the database to show what data is needed to produce the color-coded Zika map. Bertrand keeps saying that it is easy, and Thomas keeps nodding his head in agreement.

—“The classification is based on dates. Basta!” says Bertrand

The classification of geographical regions according to when the date of the last case was reported is treated as unproblematic. Everyone agrees—the classification based on dates is unproblematic. The question “where is Zika?” has become phrased as “where and when are Zika cases reported?” (Fieldnotes)

At the most basic level, the Zika Algorithm is assembled as a series of questions that aim to produce a Zika classification of the world:

- ◇ Is the mosquito that transmits Zika, *Aedes aegypti*, in the area?
- ◇ Is there evidence of Zika virus circulation?
- ◇ Is an area endemic for the Zika virus?
- ◇ When did the first Zika case occur?
- ◇ What is the time since last confirmed case?
- ◇ What is the temporal length of transmission?

These questions, which are also articulated in the flowchart version of the Zika Algorithm have been translated into computational form by Thomas and Bertrand—layering, as we will see below, several computations, databases and models and transforming them into a series of classifications that are then shown on a world map—the Current Zika State. However, things are not simple and straightforward. As we will see below, Bertrand's statement “The classification is based on dates. Basta!” is full of caveats, nooks, and crannies. At every turn, the production of the algorithm is folded with different datasets, different manners of judgment, and different tools for counting and classifying. And all these folds configure algorithmic power differently (cf. Mackenzie, 2014).

ECDC: situated translucencies | situated agencies

Back to Thomas and Bertrand's meeting: the quality of disease surveillance in different countries has come up. The meeting has paused for a moment. After clicking through a myriad of tabs on the database, Bertrand stops his clicking and highlights a yellow-tinted column of data on the wall-screen of the Emergency Operations Centre. He explains that the database column he has highlighted details the quality of disease surveillance in different countries. Bertrand zooms in on the column and shows that it classifies the surveillance capabilities of different countries as better or worse: “good,” “medium,” or “bad.” Bertrand and Thomas seem to take this classification for granted and nod their heads in agreement. Thomas turns to me and tells me:

—“The Brazilian CDC is very good!”
(Fieldnotes)

Thomas' point is simple. Not every country on the globe has the same infrastructure for disease surveillance. And the ECDC wants to take this into account in producing the Current Zika State. What Bertrand is showing on the screen—good, medium, bad—is that the Zika Algorithm is also inscribed with an assessment of the quality of different countries' disease surveillance systems. What my informants are concerned with is: should each Zika case be counted in the same way?¹⁵

The Zika Algorithm is inscribed with several questions about the reported cases of Zika (see Figure 3): “What is the time since the last reported confirmed case?” If there is a confirmed Zika case reported within the last 12-month period, the algorithm asks about the length of the period where Zika cases have been reported. If the period is less than two years long, the country is classified as “Category 1: Area with new introduction and re-introduction with ongoing transmission.” If the period is more than two years long, the country is classified as “Category 2: Area with endemic transmission.” If there are no confirmed cases within 12 months the country/area is assigned to “Category 3: Area with interrupted transmission with potential for future transmission.”

By asking these questions Bertrand erects several temporal boundaries that define different

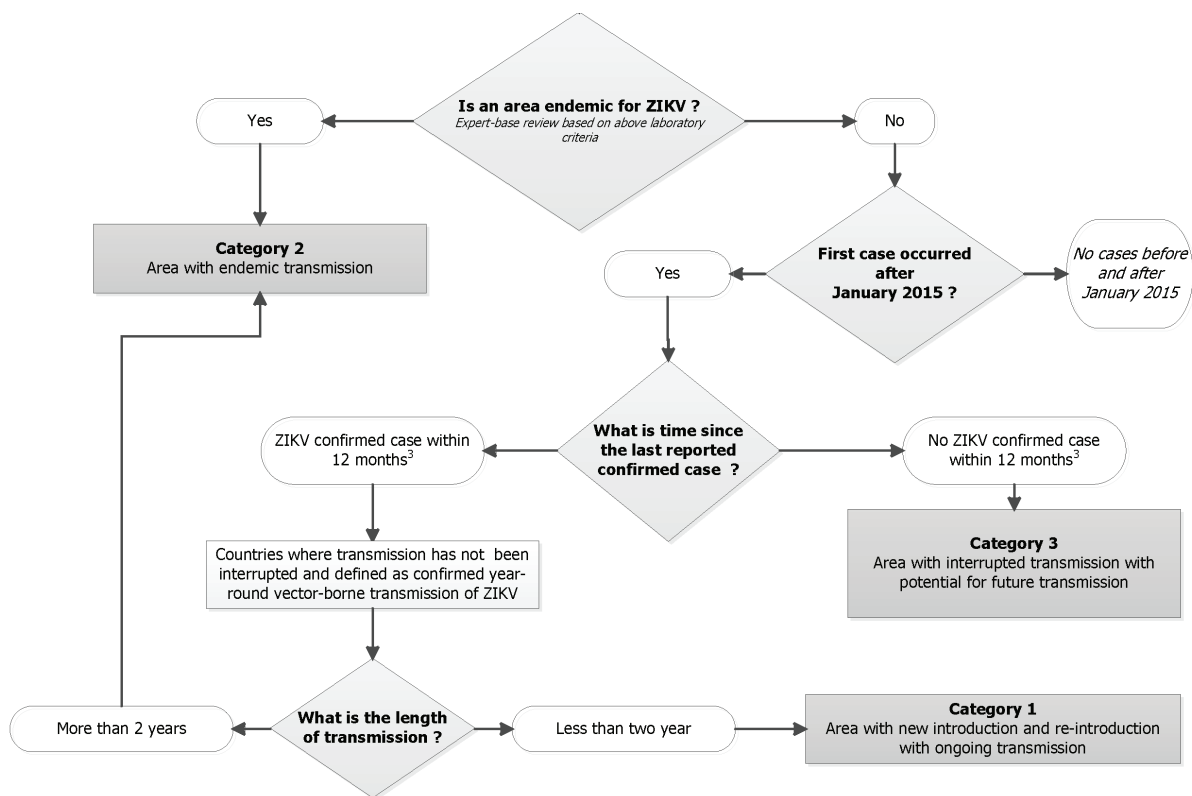


Figure 3. A bifurcation in the Zika algorithm. A zoomed in version of the Zika Algorithm above.

classes of Zika transmission: zero Zika-cases in the last 12 months means interrupted transmission. More than two years of transmission means that the area has endemic transmission. The Zika cases are ordered temporally, counted, and used to construct different classes of Zika risk.

However, in a footnote to the flowchart version of the algorithm, Bertrand’s and Thomas’ concern for the quality of disease control—“The Brazilian CDC is very good”—and the yellow tinted column of data that Bertrand showed on the wall-screen is brought to the fore. The footnote specifies that the 12-month temporal boundary between different categories should be reduced to 3 months if the quality of the disease surveillance infrastructure of a country is deemed to be good. The Zika Algorithm thus links the counting of cases to the quality of surveillance. The footnote consequently outlines a bifurcation in how reported confirmed Zika cases are counted:

[The] Period might be reduced to 3 months in settings with high capacity for diagnostic testing, timely reporting of diagnostic results, a comprehensive arboviral surveillance system [...] (see Figure 2)

To define the quality of the countries disease surveillance the algorithm asks more questions: Does the country have diagnostic capacity? Timely reporting? A good surveillance system? Which Thomas, at the meeting, shortens to “The Brazilian CDC is very good!” The reported confirmed cases of Zika are counted differently, which has the effect that each Zika case does not carry the same weight on the scale of Zika risk.

A consequence of this bifurcation of the yardsticks for Zika risk is that the boundary between different classes of Zika risk is not equal for all countries. Some groups of countries are judged by certain temporal yardsticks (12 months), while other countries are judged with another yardstick (3 months). But there is no visible trace of this bifurcation of boundaries in the Current Zika State. Clearly apparent categories of disease intensity are made visible on the map—red, orange, grey, white. No intermediate colors or categories. No fuzziness between classes. And no bifurcations of yardsticks. The categories and classifications of the Zika map appear as neatly delineated and unambiguous. The Current Zika State projects an image

of an unambiguous world where Zika presence is clearly visible and bounded.

The Zika Algorithm intertwines quantification, judgment, agency, and opacity in several ways. That is, there are many ways that the algorithm composes power. *This is a matter of the ontological politics of algorithms, of where choices can be made, and where power to effect things clots.*

First, the configuration of choice: The Zika Algorithm was designed to “simply count cases in space and time.” But the boundaries between different classes of disease intensity were also intimately intertwined with the judgment of the quality of disease surveillance. The algorithmic logic of the Zika map was not only about quantities, counting cases in space and time, but about qualities as well. Algorithmic quantification and judgment were entwined—but not equally distributed.¹⁶

Second, the making of situated algorithmic opacities: these struggles point to the importance of attending to the assembling of opacities in practice. For the general public viewing the Current Zika State map online, the map, the algorithm, and the choices made around it, are completely opaque. It seems to be a stable map of the Current Zika State. A classic algorithmic black box if there ever was one. However, the bifurcation of yardsticks was clearly visible, present, and understood by Thomas and Bertrand in the Emergency Operations Centre. *Different degrees of opacity depend on the actors’ locations. This is an important methodological and analytical point: opacity is not binary or universal, opacity is situated.*

Third, this points to how the making of algorithmic agency, opacity and power is an achievement in practice. In this particular moment,

agency and power to classify countries into different Zika zones was located with a particular set of experts in the Emergency Operations Centre at the ECDC. However, other actors, not present in the Emergency Operations Centre, were excluded from this moment of choice, and this particular moment of power. *The making of opacity and power happens in practice. And different algorithmic assemblages configure opacity, agency, and power in different ways* (cf. Mackenzie, 2014).

Oxford: layered translucencies | dispersed agencies

But there is also a different and parallel mode of sensing Zika at work in producing the Current Zika State, which creates another configuration of agency and power: that of environmental and ecological modeling. In this mode of sensing the Zika Algorithm is assembled to make Zika risk predictions based on computational models instead of on counting cases. For the algorithm, and the disease surveillance team at the ECDC, the attention is switched from counting disease cases in space and time to computing the potential presence of a Zika disease vector. Here, the algorithm moves from classifying a country based on counting reported confirmed cases of Zika to classifying the Zika state of a country based on computer modeling and risk prediction. In this mode of sensing Zika, the algorithm asks several additional questions:

- ◇ Is the *Aedes aegypti* mosquito “expected to be present” in the area?
- ◇ Does the area “share a physical ground border” with an endemic area?

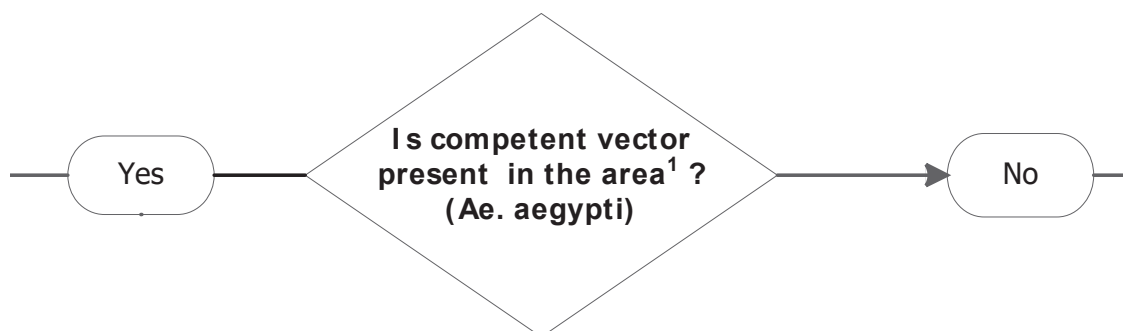


Figure 4. The Zika Algorithm branches out in time and space.



Figure 5. The *Aedes aegypti*.¹⁹

- ◇ Are the areas part of the “same ecological zone?”
- ◇ Is there “evidence of year-round dengue virus transmission?”

Each of these questions entangle the Current Zika State with other objects: mosquito ecologies and ecological zones (Is *Aedes aegypti* expected to be present?), physical geographies (Does the area share a physical ground border?), as well as with other diseases (dengue fever is also spread by the *Aedes aegypti*). Due to these questions, several different computer models become entwined with the Current Zika State. The Zika Algorithm is not only assembled to ask “Where is Zika?” but also “Where is the *Aedes aegypti* mosquito?,” “Where is there dengue-fever?,” and “Where is a fitting ecological zone?” To follow one part of this rhizome of algorithmic classification, we shift our attention to how the *Aedes aegypti* mosquito is included in the Zika Algorithm (see Figure 5).¹⁷

Importantly, for our story, is that the *Aedes aegypti* mosquito is understood to be the most important disease vector for the Zika virus.¹⁸ The actors’ argument is that knowledge of where the mosquito roams, will also allow an assessment of

the risk of Zika virus transmission. Thus, to know where the *Aedes aegypti* might exist expands the modes of sensing Zika.

To trace how the *Aedes aegypti* becomes included in the assemblage we move our story to a group of ecological modelers at Oxford University, where the computational model that the ECDC uses to predict *Aedes aegypti* presence was produced (see Figure 6). Over several decades, this group has developed a modelling approach that attempted to find covariances between species’ habitat and environmental factors:

[...] we concentrate on the use of maps to increase our understanding of the biological and other processes that determine the distribution and abundance of species in space and time. Which are the important variables; how do they act; and how do they differ [...]?

(Rogers, 2007: 3)

The group’s computational methodology to trace different species was based on linking known geographical habitats with environmental factors extracted from satellite data or climate databases, such as temperature, rain, elevation, or density of

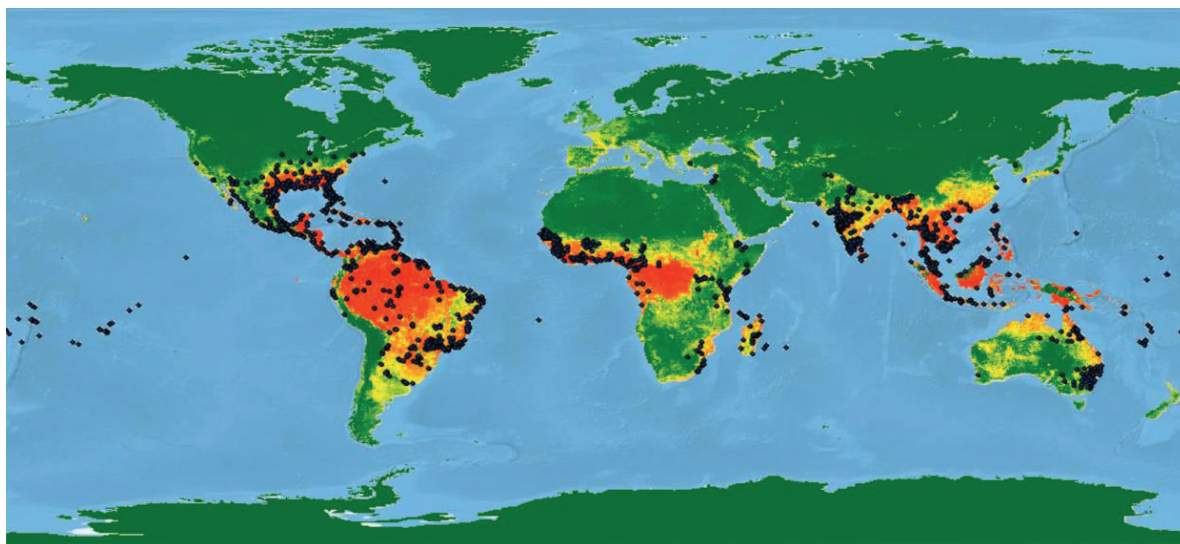


Figure 6. Map of *Aedes aegypti* risk. Green marks low risk. Yellow and orange denotes increasing risk for presence of *Aedes aegypti*.²⁰

human habitation. The model used at the ECDC matched known locations of the *Aedes aegypti* with environmental characteristics to predict the mosquito risk on a global scale.

The Oxford group used two sets of data to model *Aedes aegypti* risk: First, a bespoke database

of where the *Aedes aegypti* is found. This database was produced by combining known *Aedes aegypti* occurrences harvested from the scientific literature, with an *Aedes aegypti* map produced by the United States CDC (see Figure 7).²¹ Second, the group utilized environmental data stemming

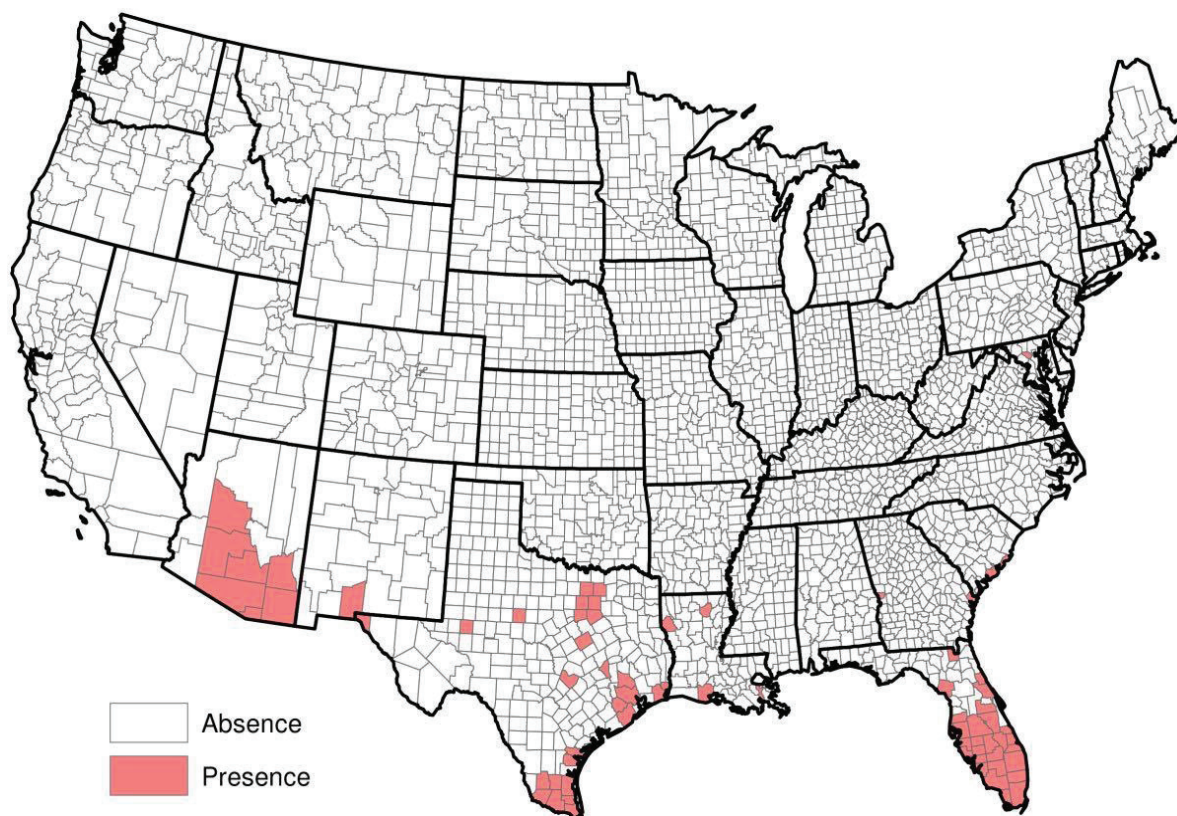


Figure 7. *Aedes aegypti* map of the USA from 2008.²³

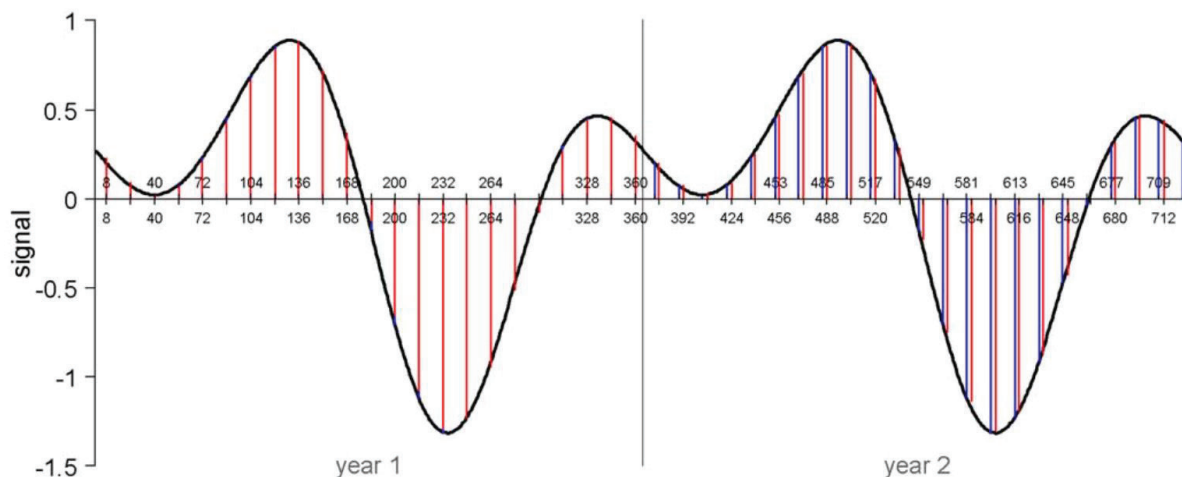


Figure 8. An illustration of the result of a Temporal Fourier analysis of environmental data (Scharlemann et al., 2008: 8).

from satellites and climate databases from a host of different sources. For example, they used “satellite rainfall estimates” stemming from the US National Weather Service (which incorporated data from nine different satellites) as well as data from several different climate models.²²

This was the basis for their modeling of the *Aedes aegypti*: finding covariances between a bespoke database of mosquito occurrences and several layers of environmental data taken from many different sources.

In order to simplify the global environmental data, the team used a mathematical technique

called temporal Fourier analysis, which is used to simplify the representation of different types of signals (see Figure 8). By using this technique the Oxford team transformed the environmental data into a series of mathematical formulas that aimed to describe “information about the seasonal cycles of these indices in terms of their annual, bi-annual, tri-annual etc. cycles (or ‘harmonics’), each one described by its phase and amplitude” (Rogers, 2000: 138). These “harmonics” were then used to create several climate zones, that the team sometimes represented by transforming the environmental harmonics into colors on a map (see Figure 9).

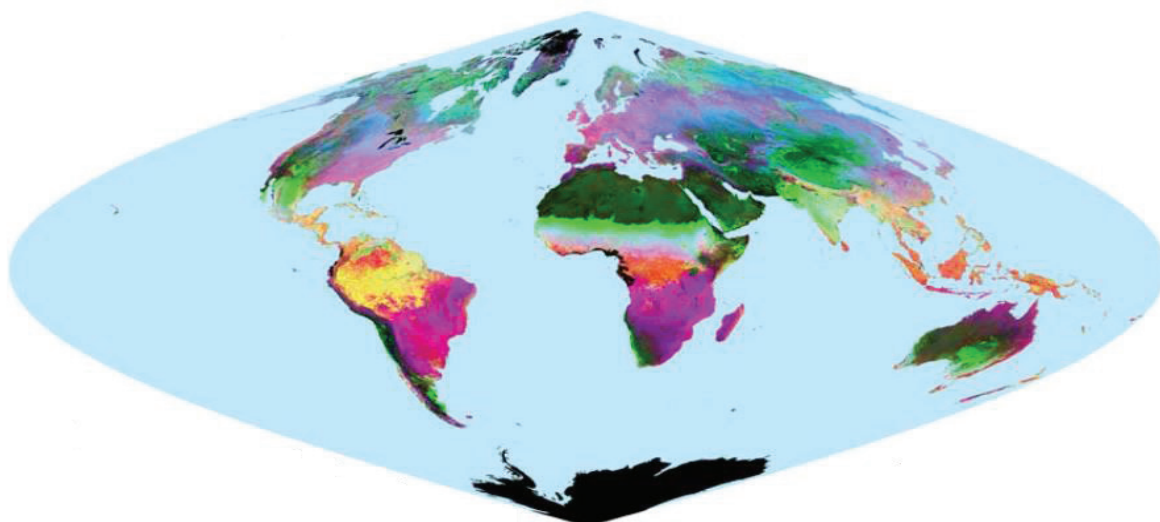


Figure 9. Temporal Fourier analysis of global Enhanced Vegetation Index (EVI) translated into ecological zones on a map (Scharlemann et al., 2008: 7).

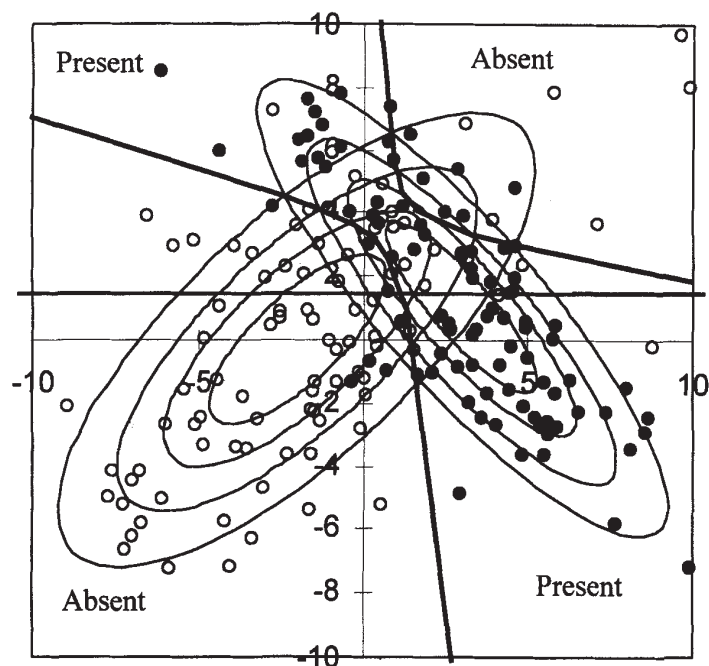


Figure 10. Illustration of Non-linear discriminant analysis (Robinson et al., 1997: 237).

To then find covariances between the environmental data, derived from the temporal Fourier analysis, and the mosquito data, the Oxford group employed a computational technique called non-linear discriminant analysis (see Figure 10). This technique was used to predict the risk of *Aedes aegypti* occurrences on the basis of the many different environmental harmonics outlined above (rainfall, vegetation, etc.).

The mode of sensing described above illustrates how the Current Zika State is built by incorporating many different times, places, people, computations, and efforts. And, as I hinted at the outset of this section, the Current Zika State is not only tied to the *Aedes aegypti* model. The Zika Algorithm also incorporated a dengue fever model produced by the same Oxford team, as well as a climate classification of the world based on the commonly used Köppen-Geiger climate classification of the globe—which was first published in 1884 (see Figure 11 for a recently updated version). The algorithm thus expanded backwards and outwards in both time and space. Through a veritable flood of computational resources, a map of Zika risk was born.

Let us now return to our questions of assembling of agency and opacity. That is, to how the assembling of the Zika Algorithm enacts particular patterns of power. Where is agency to classify located when Zika is sensed by modelling risk of mosquito presence? What types of situated transparencies are made through the Zika algorithm? And where is power located?

In the case of the *Aedes aegypti* risk map, agency is certainly focused in Oxford, with the team of ecological modelers. But agency is also dispersed over a vast array of places and times: it is located at the US CDC in producing the *Aedes aegypti* map of the USA; in entomological expeditions globally trying to determine where the *Aedes aegypti* thrives; in satellite sensors that detect radiation, rainfall or vegetation; and at the ECDC who have commissioned the modelling from the Oxford team and integrated it into their work (cf. Segata 2020, Edwards, 2010).

Agency and power are thus dispersed over time and space, in various parts of the algorithmic assemblage at different locations, with relations to other infrastructures, other scientific teams, and other practices. There is a myriad of classifications made in a myriad of places. There is no center of

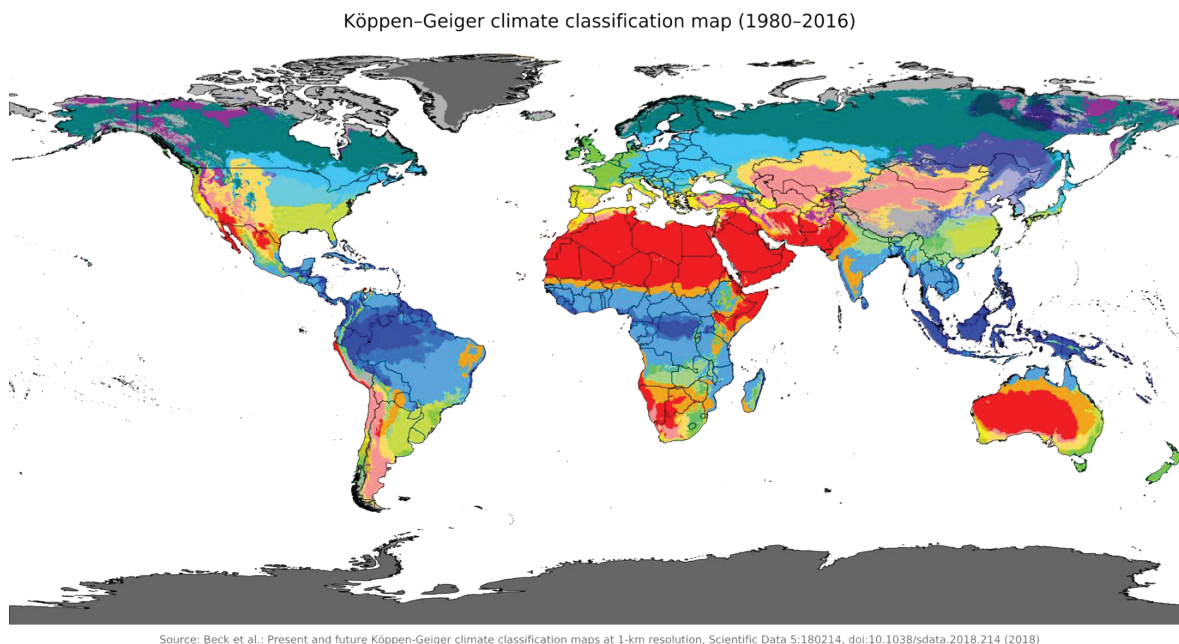


Figure 11. A Köppen-Geiger climate classification map.²⁴

calculation, nor a central algorithm, but a heterogeneous assemblage of dispersed calculative efforts (cf. Latour, 1987).

Consequently, in terms of enacting opacity and calculative power, the classification of Zika risk is multilayered, multi-situated and extremely dispersed. For a handful of people at the ECDC some layers of computation (the *Aedes aegypti* risk map, the Dengue map, or the Köppen-Geiger map) are visible as computational possibilities. But some parts of the computational assemblage, recede into the fog of the unknown.

Various facets of algorithmic classification and valuation thus drop in and out of visibility depending on the actors’ location in the assemblage. The algorithm is never completely opaque, but neither is it completely transparent. My argument is that opacity is multi-situated and dispersed. There is a series of translucencies of varying degrees that spread over different practices (cf. Jordan and Lynch, 1992). In contrast to the counting cases in space and time, this mode of sensing, seems to produce a dispersed calculative power which is not located in a single place.

Sri Lanka and Pakistan: translucency and situatedness

Coming back to Thomas’ and Bertrand’s meeting, another senior team member, Sergio, has joined the meeting in the Emergency Operations Centre. Talk has moved to the question if a country or area shares “a physical ground border,” another question inscribed in the algorithm, and if this can be handled automatically. Sergio brings up Sri Lanka:

“Is Sri Lanka ecologically connected to India?” he asks.

On the scale of a world map, Sri Lanka and Tamil Nadu look quite separate. I don’t understand the question. But Sergio points to the series of shoals and small islands called Rama’s Bridge (see Figure 12). Does Rama’s Bridge connect the two land masses? And more importantly, is it a passage for the *Aedes aegypti* mosquito? On the map of the Current Zika State, Tamil Nadu in southern India is classified as having Zika transmission, and tinted orange. Should Sri Lanka then be classified as being at risk or not?

Bertrand and Sergio are arguing that there needs to be a “sort of expert-based judgment” on whether a country shares a physical ground border or not.



Figure 12. Rama's bridge between Tamil Nadu and Sri Lanka.²⁵

"There will always be exceptions. We can't automate bordering countries," Bertrand says. (Fieldnotes)

Apparently, the algorithm cannot handle all physical ground borders.

The challenges that Rama's bridge, and cases like it, pose to the mapping of Zika across the globe are monumental. Disentangling and classifying the world's geographical borders in terms of mosquito—geography is an enormous task, needing intimate knowledge about the geographies and ecologies of regions as well as reliable and comprehensive data on the range of the *Aedes aegypti* mosquito (cf. Segata 2020). Thus, the alluring promise of algorithmic classification threatens to fall apart in the face of ecologies and the range of the infamous *Aedes aegypti*. Thomas, Bertrand and Sergio are caught in an algorithmic dilemma. What parts of the Zika Algorithm are possible to automate fully? And what parts need human judgment? Where should agency reside? Ontological politics to the highest degree.

A few weeks after the meeting I visit Thomas and Bertrand to discuss the Current Zika State again. Thomas tells me that the ECDC and the WHO have had a disagreement about the Zika classification of

India. The point of contention was that two cases of Zika had been reported in Pakistan. According to the Zika Algorithm, that event should have reclassified the whole sub-continent of India as having risk for Zika transmission. However, the ECDC argued that the reclassification of the whole Indian sub-continent on the basis of two travel-related cases was absurd. A billion people would have been affected. The WHO on the other hand argued that the algorithm should be followed. The challenge was one of judging the output of the algorithm. What was a good tipping point for reclassifying the whole Indian sub-continent? Were two travel-related cases enough? (Fieldnotes)

The data points of disease surveillance are shifting, ambiguous, and spotty (cf. Gitelman, 2013). They change over time, they come with different definitions. Is this case laboratory confirmed? Does it fit with the current definition of a case? What did the contact-tracing of the case show? Was the case travel-related? The counting of cases takes judgment and choice. How should two travel related cases in Pakistan be counted? And in the case of Rama's Bridge: How should the intertwining of mosquito ecologies and political geographies be handled?

My point is that data—even counting disease cases—is also translucent to different degrees, depending on your location in the assemblage. In the case of Rama's Bridge, Sergio struggled with the qualities of geographical boundaries. The simple algorithmic definition of “sharing a ground border” is judged to be too complex to automate when dealing with mosquito ecology. That is, Sergio grappled with reconciling the qualities of ecological zones, the challenge of judging the possibility of zika transmission over ecological habitats, and how to make this disease risk visible in terms of political geography.

An algorithm for classifying the world necessarily needs to simplify, but in the simplification, we might attend to what is made visible and invisible. What is hidden from view, and for whom? And what are the consequences of doing this? At the ECDC, the space for choosing path—agency and power—was often large. The Zika algorithm and the underlying data was constantly challenged, tweaked, and reconfigured before it was published as the Current Zika State. However, the spaces for choosing path were not equally distributed. Different modes of sensing produced different configurations of power.

Some lessons about the politics of algorithms: punctualization, situated translucency, and power

Above, I have followed how the Current Zika State was assembled, in doing this I attended to how different modes of algorithmic sensing produced different spaces for agency, translucency, and power. But rather than taking as point of departure preconceived notions about the power or effects of the algorithm I have traced how agency and translucency varies depending on the configuration of the assemblage.

What is at stake with this intervention are issues of politics and power. I argue that by analyzing algorithmic assemblages as they branch out in multiple and situated practices, we gain a better understanding of how algorithmic power is structured and works to shape the world. Hopefully, this will allow us to leave the determinist and reductionist logic of “black boxed algorithms that control our future” behind us. The point of this exercise is to prevent that the performed object—

algorithm—defines, delimits, and steers our inquiries into the politics of algorithms.

There are several lessons to be learned from tracing the Zika Algorithm, and I therefore suggest three methodological rules to protect us against falling in the epistemic trap of the stabilized algorithm.

Rule 1: Don't punctualize agency | Attend to how agency and choice are assembled

Our first lesson. Do not treat algorithms as stable objects out there for us to apprehend and analyze. Attend to algorithmic assemblages as always already distributed and performed. Algorithmic assemblages are truly fluid, heterogeneous, and dispersed. Not only in the sense that they include agencies of different shapes and forms, but also in how the qualities and characteristics of algorithmic assemblages shift and meander. These are well worn perspectives in STS, but the tendency to ascribe and punctualize agency to the powerful algorithm is tempting—and continues to tempt us.

The consequence of the assembled perspective on algorithms is that agency must be analyzed as being entangled with the objects that we perform as algorithms—not as an inherent property of them. In practice there are almost always struggles about how these assemblages should be structured. Thus, the composition of algorithmic assemblages often becomes the site of political struggles and practical tinkering to assemble these elements in different ways.²⁶

For instance, as I have shown above, the space for challenging the Zika classification of a country is large in certain spaces at the ECDC—but the space for challenging the global range of the *Aedes aegypti* is smaller. The expertise and knowledge about the mathematics of mosquito prediction being located with a group of modelers of mosquitos, while expertise about disease classification was located at the ECDC. What we can observe is that the space for agency, action, or judgment is not equally distributed. The spaces for choice and action are redistributed by the different modes of sensing that the algorithm engenders.

Consequently, the power of algorithms is not a stable proposition, where some actors (e.g.

Google's or Facebook's algorithms) have all the power, and others (the technical dope that uncritically clicks on search results or consume their daily Facebook feed) have none (Garfinkel, 1967; Lynch, 2012). That is, algorithms move choice around, and the space for choice is not the same for everyone.

The point is that we can attend to how spaces for agency and choice open up and close in various places of the assemblage—how they are assembled—without succumbing to the epistemic trap of punctualization. This perspective instead raises several questions about the ontological politics of algorithms (Mol, 1999). These are age-old questions about choice and power. Where can choice be located? Who can make choices? Who or what can act? What types of actions or choices are enabled or disabled? Where? When?

Rule 2: Abandon the opaque/transparent binary | Attend to situated translucencies

Our second lesson. Do not treat algorithms as being binarily opaque or transparent. Algorithmic assemblages are always situated and translucent to various degrees (cf. Jordan and Lynch, 1992).²⁷ For the sociologist of algorithms it has become common to lament the power, inscrutability, and opacity of the algorithm. But the proliferation of articles classifying different types of opacity hints at a marked analytical unease about the binary notion of transparency/opacity in critical studies of algorithms.²⁸

As with agency, algorithmic translucencies are assembled in multiple locations, in multiple versions, in relation to multiple people (cf. Mol, 2002). People have situated knowledge about the algorithm (Haraway, 1988). Which means that algorithmic assemblages can be differently understood in different situations and are therefore neither completely opaque, nor completely transparent. Opacity is not only varying in degree or type, but also varies depending on the actor's situatedness.²⁹

In the assembling of the Zika Algorithm, choices and judgments were clearly transparent, discussed, and available for scrutiny in certain rooms and moments, like when my informants judged countries' quality of disease surveillance and inscribed their judgments into the algorithm. In other places, choices, computa-

tions, and judgments faded away and became an invisible part of an opaque algorithm, as when my informants harnessed the modelling of mosquito presence to make risk assessments about Zika. Translucencies are thus constantly opened and closed, made and remade in practice.

Our lesson is that, in practice, algorithmic opacity is neither binary nor homogeneous. It is situated, gradual, and affects different actors in different ways. We need to *analyze these various translucencies as they are enacted in various and situated practices.* What is made visible? How is it made visible? To whom or to what? Where?

Rule 3: Abandon the algorithm as the prime mover | Attend to how power clusters

As a consequence of these insights, I argue that algorithmic politics should be analyzed by paying attention to how algorithmic assemblages configure agency, translucency, and power in practice—not by auditing a sole algorithm for biases. As we have seen, different modes of sensing the Zika pandemic, makes for very different configurations of agency, translucency, and power. Counting cases and entering them into a geopolitical time and space makes for a particular configuration of agency and translucency, while environmental modelling to predict disease risk makes for a very different configuration (cf. Mackenzie, 2014). *We should therefore attend to the performance, locations, and unevenness of power in algorithmic assemblages.*

This is our third lesson, which is about investigating the assembling of power (cf. Callon and Law, 2005; Callon and Muniesa, 2005). The algorithmic production of the Current Zika State is a dispersed assemblage in practice. It is spread over time and space. The algorithm does not produce a center of calculation (Latour, 1987), but a vast *network of calculation* extending outward in time and space (Edwards, 2010). Thus, just as the Arizona stock exchange, shopping lists, prices on shelves, and shopping carts open and close certain spaces for visibility, calculation, and agency, so does the Zika Algorithm open and close spaces for choice and intervention. It opens and closes spaces for algorithmic power.³⁰

Thus, algorithmic power accumulates in different places—as a cluster in a multitude, or a

knot in a rhizome—which can include both the mundane and the exotic, the human and the non-human. Where an algorithmic assemblage will concentrate power is not a given but negotiated in multiple situations. We need to understand how this happens to truly understand algorithmic power.

For sociologists trying to understand how algorithms shape society it is not enough to audit the stabilized algorithm for fairness or transparency. As Strathern has pointed out, “audit cannot afford to tolerate loose ends, unpredictability, or disconnections. [...] This means that what may be brilliant accounting is bound to be very poor sociology” (Strathern, 2002: 309).

Hence, it is crucial to move beyond the trope of auditing the powerful algorithm, and to analyze how algorithmic systems *are designed, tinkered with, and interpreted in practice* (Neyland, 2018; Ziewitz, 2017). Algorithms involve countless situations where quantification and judgment are entwined in different ways.³¹ Rather than auditing *the algorithm* (stable singular) for fairness this analytical move opens for description of how spaces for agency and avenues of seeing are made in algorithmic assemblages. Rather than focusing on the binary opacity/transparency of the algorithm, these methodological rules open for an analysis of different actors facing different degrees of agency and transparency.

Rather than punctualizing the inherent oppression or bias to the algorithm, it would open for a situated understanding of multiple power effects. Not as disembodied black boxes—truly *deus ex machina*—that reshape the economy, oppress the poor, or are race/sex/*-ist. But as assemblages of varying degrees of power (that certainly can lead to oppressive outcomes!). *By doing this we could better understand how algorithmic politics works in practice. Which (for sure!) can have effects that are oppressive, racist, and sexist.*

Conclusion: some elements in a sociology of algorithms

As multiple waves of pandemics and epidemics sweep the world—not least in the midst of the current COVID-19 pandemic—the nature and characteristics of each successive pandemic becomes increasingly tied to algorithms, models,

and computation. This article has traced how a particular pandemic, of Zika, was assembled with an algorithm. I have shown how algorithms play a crucial role in assembling the intensities, risks, and projections for the future.

A pandemic is made in a web of infrastructures and practices around the world. The state of the Zika pandemic depended on practices of counting (cases and mosquitos—in hospitals, jungles, and elsewhere), computational modelling, decisions in organizations and by algorithms, and so on. In this case, the counting of cases was also folded with climate data and risk modelling the presence of mosquitos. What this shows, is that a pandemic can be composed in many different manners that are often folded together as a seamless whole (cf. Mackenzie, 2014).

But, as we have seen, not least in the current COVID-19 pandemic, constant debates about how to count erupt. What do these numbers mean? How much are we testing? Are these tests reliable? Can we trace disease through sewage? Should we count nationally or regionally? Over time, the manners in which the pandemic is enacted unfolds in different manners. That is, different manners of assembling and visualizing the pandemic are intensely political, and choices are made by different actors, in different times and places. However, it is not a politics of a sole algorithm. It is a myriad of relations that assemble a pandemic.

The article has followed some of the practices of assembling the Zika epidemic with an algorithm. Apart from making this global epidemic in particular ways, the effect of harnessing the algorithm is that it opens and closes particular calculative spaces that move agency and choice, produce particular visibilities, and shape asymmetries of power. Drawing on this analysis I have proposed three methodological rules for the social analyst of algorithms.

Rule 1: Don't punctualize agency, attend to how agency and choice are assembled

Rule 2: Abandon the opaque/transparent binary, attend to multiple and situated translucencies

Rule 3: Abandon the algorithm as the prime mover, attend to how power clusters and disperses

This analytical strategy has allowed me to outline an alternate route to analyzing politics, opacity, and the assembling of power with algorithms. This route emphasizes that algorithms are intertwined with multiple practices, and not set apart from them.

Importantly this approach bypasses the epistemic trap that results in treating algorithms as powerful black boxes that shape our lives and oppress the poor, and opens up a route for an analysis of algorithmic power as it unfolds in practice (cf. Muniesa, 2019). Thus, rather than attending to algorithms as singular and deterministic moments of fairness/bias, or as being binarily opaque/transparent, the article has followed the many ways in which algorithms come to shape agency, visibilities, and power, as well as the making of a threatening pandemic.

These analytical strategies can help focus questions around algorithmic functions beyond the common adages of “algorithms are a modern myth,” “algorithms are opaque,” and “algorithms shape our world.” Asking about how algorithms open and close different spaces for agency and choice, produce particular visibilities, and shape asymmetries of power enables us to tell stories that are sensitive to the fluidity of algorithms, and enables an analysis of their power—as it is assembled in practice.

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Disclaimer

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Notes

- 1 See Kelly et al. (2020) and Löwy (2017) for a background on the Zika crisis in Brazil.
- 2 In this, I use the concept of assemblage drawing on Actor-Network sensibilities. That is, I see an assemblage as a network of objects of heterogeneous character whose ongoing relations shape the direction of the whole network (Callon, 2007). Other synonyms for assemblage analysis are: actant-rhizome ontology (Latour, 1999), hybrid collectifs (Callon and Law, 1995), or agencement (Deleuze and Guattari, 1987). The point of such an analysis is to not presume where agency resides, but rather to trace the relations by which it is assembled in particular locations.
- 3 The computer science definition of an algorithm seems to be the dominant definition in STS. In computer science thick catalogs of optimal algorithms for different tasks are published and updated regularly (Knuth, 1997). In the *The New Oxford American Dictionary* algorithms are defined as “a process or set of rules to be followed in calculations or other problem-solving operations, especially by a computer: a basic algorithm for division.” The word itself is said to hark back to the name of the Persian mathematician al-Khwārizmī, who developed a systematic method for solving equations—laying the foundation for modern algebra. In other settings, an algorithm can be a simple (or complex) flowchart for medical treatment. I.e. take a sample for culture from a patient, let sample sit in a petri-dish, if there are bacteria there, give the patient antibiotics, if no bacteria are present tell her that it is probably a virus and that s/he needs to rest.
- 4 Thanks David Moats for this useful comment on the politics of algorithms.
- 5 This analytical stance draws on practice-oriented post-ANT sensibilities (Lee et al., 2019; Neyland, 2018; Ziewitz, 2017).
- 6 As many have pointed out algorithms are often part of a distributed assemblage (Ananny, 2016; Gillespie, 2014; Kitchin, 2016; Seaver, 2018). For instance, Seaver points out that “Presuming that algorithms must have a stable and coherent existence makes it harder, not easier, to grapple with their production and ongoing maintenance.” (Seaver, 2017)
- 7 Sometimes these understandings of algorithms go hand in hand, for instance when complexity and the fearful opacity of algorithms seem to meet (Burrell, 2016).
- 8 <https://facctconference.org/>
- 9 This epistemic trap has led to the unfortunate state of affairs where the black box metaphor in actor-network theory—which was a cry for opening black boxes—has become conflated with lamentations of methodological problems of field access, secrecy, and understanding complexity. The black box metaphor in actor-network theory was never meant to be used to describe a stable state of affairs, but to highlight the human and social tendency to punctualize networks of relations in black boxes. Opening the black box was always a metaphor for uncovering heterogeneous networks of performances, relations, stabilizations of the world. The conflation is understandable, but unfortunate, if we want to actually do social analyses of the unfolding algorithmic society.
- 10 In the words of Muniesa: “Often qualified as critical, this alternative [analysis of algorithms], is expressed today by an abundant literature that [...] is recognized in the rhetoric of the “black box:” that of the computer code, it is that is to say that of the political, economic, cultural encoding that this code serves, an encoding that it is therefore a question of “decrypting” in order to expose the “power of algorithms”. This alternative, generally endowed with a more or less emancipatory vision, however, often seeks more to renew the premises cultivated by the computer environment than to free itself from them.” (Muniesa, 2019: 205)
- 11 In the terminology of Lakoff (2010), disease surveillance sits squarely in the “global health security regime” which focuses on preventing disease threats toward the population, in this case the population of the EU. See also Lakoff (Keck and Lakoff, 2013; Lakoff, 2017b).

- 12 Different parts of the network of disease surveillance are important for different diseases. For instance for the surveillance of the seasonal (or otherwise) flu, disease surveillance in Hong Kong and Indonesia are important centers (Keck, 2014; Lakoff, 2010).
- 13 For the politics of disease surveillance, see for instance the wide-ranging scholarship centered around studying the politics and expertise of biosecurity (Bingham and Hinchliffe, 2019; Fearnley, 2008; Hinchliffe et al., 2012; Lakoff, 2008, 2014, 2017a; Lakoff and Collier, 2008). On Salmonella politics see Lee (2020).
- 14 The Zika Algorithm is not a sentinel device in the sense that it serves as an early warning system, but it nevertheless serves to produce a particular charismatic image of the Zika epidemic. It produces the pandemic as an object in society and nature. On sentinel devices, see Keck and Lakoff (2013) on the power of charismatic evidence see Kelly (2018).
- 15 The ranking of different countries' disease surveillance resonates with MacPhail's (2014: 6) discussion about the assessment of "good" information in US disease surveillance.
- 16 Compare to the counting of genes and protestors in (Martin and Lynch, 2009).
- 17 We could drill down in all these risk classifications, but it will suffice to focus on one to make my points.
- 18 Mosquitos regularly become targets for intervention in disease control and surveillance. Different breeds are adept at spreading different diseases. The *Aedes aegypti* spreads Chikungunya, Dengue, and Zika. While other breeds spread for instance Yellow fever, West Nile fever, or Malaria. Mosquitos have therefore played a significant role in public health work in tropical climates (Kelly and Lezaun, 2013; cf. Löwy, 2017; Mitchell, 2002; Shapin, 2020). Birds also regularly become the targets of disease surveillance, especially in the wake of the multiple forms of bird flu. See for instance (Keck, 2014, 2020; Porter, 2012, 2013, 2019)
- 19 Downloaded from: https://en.wikipedia.org/wiki/Aedes_aegypti#/media/File:Aedes_aegypti.jpg.
- 20 Downloaded from <https://e3geoportal.ecdc.europa.eu/SitePages/E3%20Map%20Viewer.aspx#>
- 21 The bespoke database produced by the Oxford team was assembled by searching the scientific literature, in PubMed and Web of Science, for locations where *Aedes aegypti* had been found. The US CDC database of *Aedes aegypti* occurrences was a map of counties in the USA where *Aedes aegypti* existed. This map was originally published in 1965 and augmented in 2008.
- 22 They used NASA's Terra satellite to obtain spectroradiometer data and elevation. From the Worldclim database they incorporated temperatures and rainfall. They also drew on the HADCM3 climate model, which was produced for the IPCC. Lastly, estimated human population density/km² was obtained from the Global Rural-Urban Mapping project.
- 23 US CDC map unavailable at the original location, however it is republished in Wang et al. (2014).
- 24 See https://en.wikipedia.org/wiki/K%C3%B6ppen_climate_classification#/media/File:K%C3%B6ppen-Geiger_Climate_Classification_Map.png
- 25 Downloaded from <https://earth.esa.int/documents/257246/3374126/Adams-Bridge-Sentinel-2-17112017-full>
- 26 See for instance Cochoy's (2008) analysis of how agency to calculate is configured in shopping practices.
- 27 Opacity and transparency can be seen as two sides of the same coin. See for instance (Tsoukas, 1997).

- 28 The literature on algorithms has dealt with the shifting nature of opacity by for instance identifying more typologies for transparency/opacity (Ananny and Crawford, 2018); and by acknowledging that transparency/opacity is not a binary affair, but a gradual continuum between total transparency and total opacity (Diakopoulos, 2020). For instance, Burrell (2016) identifies three types of opacity, while Ananny & Crawford (2018) discuss the challenges of the transparency/opacity ideal. There is also a growing analytical awareness that “The convoluted interrelationships among different technical and human components often complicate and tend to obfuscate accountability for lapses of ethical behavior.” (Diakopoulos, 2020). See also de Fine Licht and de Fine Licht (2020)
- 29 Which Seaver (2017: 5) has observed in terms of the anthropological interest in secrecy. See also (Albu and Flyverbom, 2019) for an organizational argument for analyzing transparency/accountability in practice.
- 30 For shopping carts, see Cochoy (2008), and for an analysis of the Arizona stock exchange, see Muniesa (2014).
- 31 Qualculation one might even say (Callon and Law, 2005; Cochoy, 2008).