

The New (Ab)Normal: Outliers, Everyday Exceptionality, and the Politics of Data Management in the Anthropocene

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The Anthropocene affects how we manage the environment in many ways, perhaps most importantly by undermining how past conditions act as baselines for future expectations. In a period when historical analogues become less meaningful, we need to forge new practices and methods of environmental monitoring and management, including how to categorize, manage, and analyze the deluge of environmental data. In particular, we need practices to detect emerging hazards, changing baselines, and amplified risk. Some current data practices, however, especially the designation and dismissal of outliers, might mislead efforts to better adapt to new environmental conditions. In this article we ask these questions: What are the politics of determining what counts as “abnormal” and is worthy of exclusion in an era of the ever-changing “normal”? What do data exclusions, often in the form of outliers, do to our ability to understand and regulate in the Anthropocene? We identify a recursive process of distortion at play where constructing categories of abnormal–normal allows for the exclusion of “outliers” from data sets, which ultimately produces a false rarity and hides environmental changes. To illustrate this, we draw on a handful of examples in regulatory science and management, including the Exceptional Event Rule of the Clean Air Act, beach erosion models for nourishment projects, and the undetected ozone hole. We conclude with a call for attention to the construction of “normal” and “abnormal” events, systems, data, and natures in the Anthropocene. *Key Words:* climate adaptation, data exclusions, environmental change, extreme events, rarity.

One expected consequence of continuing global change is that the behavior of environmental systems will transform, particularly in ways that increase extreme events (Walsh et al. 2014; Hayhoe et al. 2018). Extremes—those rare, high-magnitude events that stretch out into the tail of a distribution—destroy property and infrastructure, strain government functioning and budgets, and in many cases lead to injury or death. To make decisions about how to protect populations—how high to build a levee, designate evacuation routes, or restrict zoning for new development—regulators rely on historical data to calculate probabilities and risk and to compare costs and benefits. Although using historic ranges or baselines is a well-established practice (Ruhl and Salzman 2011), it is losing efficacy as historic variability becomes a less reliable guide to future variability (Hirsch 2020).

The Anthropocene is a recognition that we have entered a phase in which human–environment interactions pervade most major earth systems (Crutzen and Steffen 2003; Zalasiewicz et al. 2010; S. L. Lewis

and Maslin 2015). In many ways, this is a step by physical geographers closer to the work and critiques of human geographers to recognize the powerful role that social processes play in shaping the physical environment. The process of designating, and even naming, the Anthropocene has drawn thoughtful critique (Buck 2015; Haraway 2015, 2016; Moore 2016); here, rather than delve into its driving forces and debates over definition and onset, we focus on how society might engage with the impacts of the Anthropocene on environmental management.

Even in a past when distributions of environmental variables were seen as stable, determining what data counted as “abnormal” or “outlier” was difficult and consequential work, and the challenge only increases in an era of environmental change. As the Anthropocene brings novel conditions, it is worth asking how scientific practices, like the exclusion of outliers meant to clean up and normalize data by removing “bad” or “atypical” observations, might fundamentally alter our understanding and management of changing earth systems. In an era where

normal is a moving target and baselines will shift, determining what is abnormal, atypical, and bad data will be difficult. It is an overstatement to claim as some have that “outliers are now the norm” (Coleman 2019), but how do we evolve our thinking about both outliers and normals, as well as our corresponding data management practices, to effectively apprehend the Anthropocene?

In the Anthropocene we need practices that acknowledge changing baselines to detect emerging hazards and better adapt to new environmental conditions. What are the stakes of determining what counts as “abnormal” and is worthy of inclusion or exclusion in environmental analyses during an era of change, of ever-shifting “normal”? How do data outliers affect our ability to understand and manage the environment in the Anthropocene?

We argue for attention to the construction of normal and abnormal events, data, and natures in the Anthropocene, an era in which environmental change makes seemingly simple divisions between normal and abnormal more complex. More specifically, scholars need to look at how constructions of abnormality influence data exclusions and understandings of rarity in a way that focuses on the relational and mutually dependent processes of (mis)understanding a changing environment. This type of inquiry requires combining approaches often not in conversation: quantitative risk assessment and critical theory. In this article we, as geographers steeped in two different subfields, attempt to build a bridge between hazards and risk analysis and science and technology studies (STS) and other critical geographies of the environment. Our aim is that this article speaks to both sets of scholars and makes ideas from one subfield accessible to the other.

New Normals, Shifting Baselines, and Outliers

Most systems for managing the environment, from stormwater infrastructure to forestry to agriculture, are predicated on the notion of an expected or “normal” range of conditions, usually arrayed in a statistical distribution of values huddled around the mean (in normal distributions) or the median (in skewed distributions; Figure 1). Distributions might be empirically derived (a histogram of observed values) or theoretical (a distribution with a shape that fits theoretical understanding of a system’s behavior

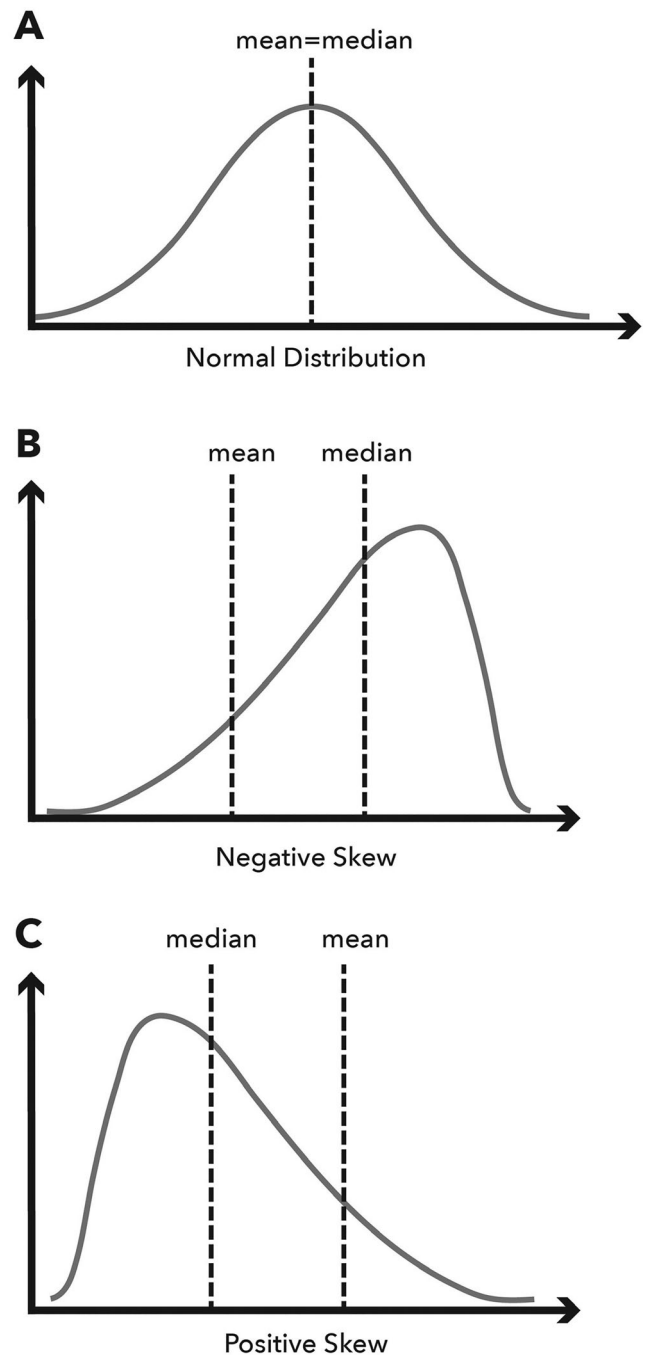


Figure 1. A range of statistical distributions: (A) normal, (B) negative skew, and (C) positive skew.

and can be used to estimate values not yet observed). In both cases the past is prologue, and although environmental scientists recognize that systems evolve over time, many analytical and management approaches still rely on the future behaving like the past. The death knell of stationarity (Milly et al. 2008) was perhaps sounded too early. This is especially true, we argue, in approaches that crave

the longest historical records to flesh out the statistical distributions on which risk assessments for extremes and intervention plans are based.

Alternatively, a key intellectual pursuit of the Anthropocene should be to understand how environmental systems are changing, to better envision how different they will look in the future. An army of climate and earth systems modelers has been engaged in precisely this complicated and important work, building new worlds within their models to offer glimpses of what is to come (Edwards 2001). One of their challenges is not to allow parameters based on past data to overly constrain the future conditions their models can predict, keeping in mind that a transformed future suffers from the “no analogue” problem (J. W. Williams and Jackson 2007): Models trained on the past struggle with novel futures.

The sense that the future will differ markedly from the past is signaled by emerging conditions, like greenhouse gas concentrations in the atmosphere, not observed for millennia, but also by the quotidian experience of extreme weather and climate. Such palpable changes are especially difficult to foretell; the distributions of climate variables will shift in uncertain ways and could usher in many different “normals.” Even for temperature change, about which earth scientists are most confident (Collins et al. 2013; Kirtman et al. 2013), warming could manifest in many possible future distributions, with longer or shorter tails (Figure 2), perhaps a shift to higher temperatures while maintaining the same relationships between extreme and average events (Figure 2A), or to a different normal in which the average persists but the range expands, offering greater variability and more extremes (Figure 2B). Perhaps both average (shifting the mean) and variance (altering the shape of the distribution and relationship between average and extreme events) could change (Figure 2C).

Such simple illustrations of statistical distributions for current and future climate reveal a lot but also hide much. First, the distributions are typically graphed as normal curves, neglecting the fact that many climate variables exhibit skewed distributions. Climate projections point both to more extreme high temperatures (Collins et al. 2013) and a skew toward more intense precipitation events (Kirtman et al. 2013). Projections also point to increasing contrasts between wet and dry spells (Kirtman et al. 2013), yielding the awkward notion that global

warming brings both more floods and droughts. Expectations of bigger changes in extremes than in means have long been part of the climate literature (Wigley 2009) but are difficult to translate into environmental management protocols.

These technical twists are echoed in the popular alliterative phrase “new normal,” which S. C. Lewis, King, and Perkins-Kirkpatrick (2017) noted is “widely used in mainstream media reports to succinctly categorize observed extreme weather and climate events as both unusual and influenced, in some regard, by anthropogenic climate change” (1139). Alliteration is not always veracity, however, and the contradictory notion of abnormal conditions coming to be considered normal works in some ways and not in others. S. C. Lewis, King, and Perkins-Kirkpatrick (2017), who sought to define “new normal” in a scientific manner, admitted that it is “used ambiguously without precise definition in both scientific literature and public commentary on climate change” (1140). Moreover, they noted that a “system under the influence of anthropogenic warming is nonstationary and exhibits a non-constant mean,” and thus “in a true statistical sense ‘new’ and ‘normal’ are essentially oxymoronic” (S. C. Lewis, King, and Perkins-Kirkpatrick 2017, 1141).

To make some sense of the new normal in the Anthropocene—indeed, to make sense of the Anthropocene—we must attend to the matter of the baseline on which any expectation is founded. Because the new normal is so often (and in contradiction to its *prima facie* meaning) tied to extremes, we must also evaluate how exceptional events, outliers, and atypicality are defined. We must also recognize that, in environmental management regimes, baselines and outliers are both epistemic and legal (Hirsch 2020) and steeped in the coproduction of science and regulatory law (Jasanoff 2004). Establishing a baseline is not a straightforward nor necessarily objective act (Ureta, Lekan, and von Hardenberg 2020), and the same is true for establishing the range of normal, which is needed to evaluate the abnormal. Just as the production of baselines is often framed as objective yet is value-laden and frequently the site of legal battles (Hirsch 2020), so, too, is distinguishing normal from abnormal.

One of the valuable contributions from STS is the recognition that data management is always political (Hacking 1990; Porter 1996; Desrosières 2002; Bowker 2008; Gitelman 2013; Pine and Liboiron 2015; Dillon et al. 2019), and politics are

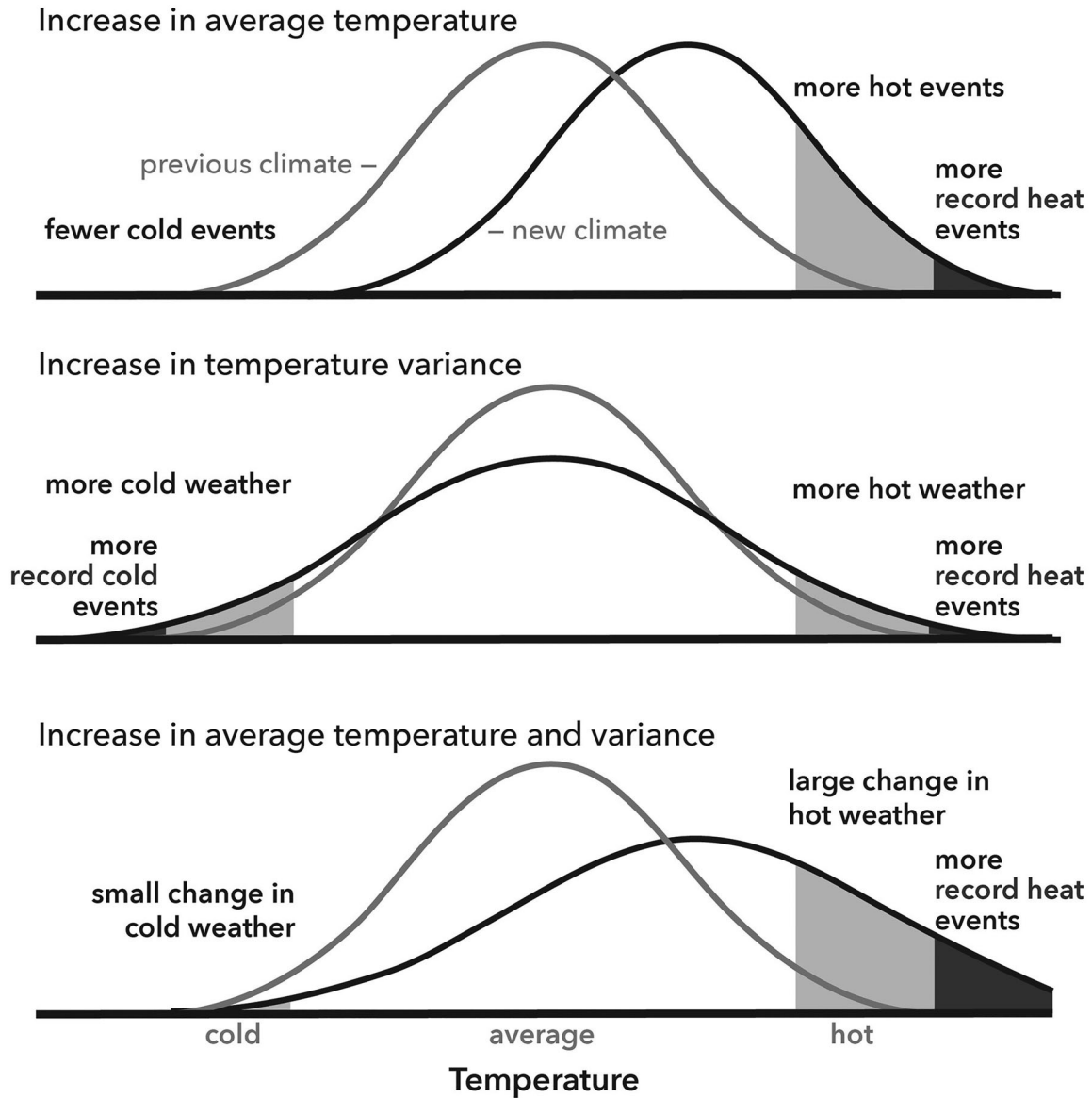


Figure 2. Different temperature distribution shifts. The three graphs show how changes in average, variance, or both alter the amount of extremes.

heightened in the Anthropocene. In this article, then, “politics” is not just referring to partisan politics, power grabs, or intentional actions. We use politics in a much broader, more encompassing way to include both those overt actions as well as more covert and even unintentional politics. Drawing on the work of STS scholars who explore the politics of science, we understand politics to mean a process that is not neutral or inevitable and instead one that is situated, subjective, and full of small but important choices that can be seen as technical but are often shaped by value-laden assumptions and judgments of scientists.¹

Of course, definitions of politics vary across and among different intellectual communities; even within geography, subfields interpret politics to mean many things. We find it useful to distinguish between the uses of politics, specifically between Big-P Politics and small-p politics (King and Tadaki 2018). Big-P Politics refers to politicized science, with most of the politics touching science after its produced to determine how it is used or whether people believe it. This type of Big-P Politics is intentional and explicit and usually harnessed to support the end goals of certain actors. Small-p politics, however, refers to choices scientists make while

conducting science, including choices of theories, data collection methods, and statistical analyses. King and Tadaki (2018) defined small-p politics of science “as the ways in which scientists make (intentional or unintentional) value-laden choices within the scientific realm that produce distinct consequences (social meanings, inequalities, power relations) for real people and environments” (72). Assumptions and judgments by scientists about how systems work shape how they set out to study and track them. Each choice has trade-offs and cannot be looked at as neutral regardless of intention; these small-p political choices embedded in science make some things known and others not. Pine and Liboiron (2015) insisted that “data—and attendant processes of measurement, database production, stabilization, curation, maintenance and use—reproduce power dynamics, knowledge systems, and culturally-based assumptions” (1). In this way, “the scientific method is *inherently* political” (King and Tadaki 2018, 68) and data are never “raw” (Ribes and Jackson 2013).

Establishing what is normal also establishes what is an outlier. When these two categories are unsettled by shifting and morphing system-level changes, they often are redefined, and redefining one category (e.g., normal or abnormal) redefines the other. Both definitions are dependent, relational, and mutually constructive.

Outliers can take many forms, are called different names, and are justified by different logics. Data are considered “outliers” when they are markedly different from the rest of the sample, sometimes based on statistical metrics like standard deviation cutoffs. They might then be thrown out. The assumption here is that outlying data are so different from typical data that they might be influenced by other variables or reflect different underlying causes or patterns. For example, if a dam breaches and results in flooding, it might be excluded from the hydrologic data set for calculating flood frequency because it reflected an “unnatural” driver or influence. Outliers could also be categorized as “errors,” assuming they were a product of faulty measurement. For example, an instrument can produce errors due to location, monitor drift over time, or malfunction. In some cases, data are excluded based on less technical criteria, sometimes simply because the data do not seem to fit or do not appear normal; sometimes data are excluded because they are deemed rare or exceptional.

Examining the production of outliers also requires a stand on what counts as normal. All of these categories rely on normal for their own defining criteria. Although categories of “natural” have long been critiqued and shown to rely on a false divide (R. Williams 1977; Cronon 1996; Mansfield et al. 2015; Cantor 2016; Davis 2016), normal is equally a subjective category based on similar false dualisms. Normal requires constructing a boundary between the normal and abnormal as though there are clear lines rather than arbitrary elements of normativity. Canguilhem (2008) argued that normal is a category that “has no absolute meaning” (132–33), outside of narrow statistical definition. Yet when applied to data analysis, the category of normal often is framed as a technical assessment, especially when statistical demarcations (e.g., standard deviation) are applied. How to divide up data into normal and outlier or error, however, is a judgment that often has political outcomes in terms of, for example, what in the environment gets monitored, what conditions are considered acceptable or not, and when some management intervention is triggered.

Outlying: Making and Remaking Fictional Rarity through Data Management

The politics of data management (i.e., the stakes of data decisions) are heightened in the Anthropocene. If we do not examine our understanding of abnormal as environmental systems transform, we might exclude data telling us about change, resulting in distorted understandings of the evolving environment. Here we argue that it is important to attend to a chain of distortion that could affect our ability to track change, with consequences that reverberate through science and management spheres, and that will become more consequential in the Anthropocene.

In the process of distortion, three key elements work together in a recursive way (Figure 3). First comes the boundary work of categorizing normal and, importantly, the abnormal. Second, outliers may be excluded, based on their abnormal categorization. Third, this exclusion distorts depictions of the environment and renders a “false rarity” as the extremes disappear from the data. That false rarity can then actually work to help bolster new events to be excluded from the data set as abnormal as their

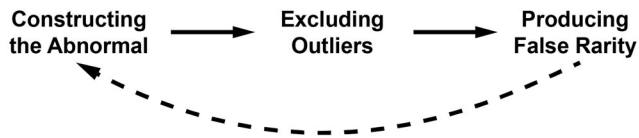


Figure 3. The process of distortion. Categorizing certain data as abnormal then allows those data to be excluded as outliers, which in turn produces a false rarity. This process can be recursive as the false rarity feeds back into how we categorize data.

previous peers have been excluded and rendered invisible. Thus, this process is always at work, making and remaking normal and abnormal environments. We suspect that the speed, scope, and level of distortion will expand in the Anthropocene. False rarity has staying power as it is stabilized and maintained, even as it increasingly differs from the true state of the system. Many scholars have documented how false understandings and representations take on a life of their own—for example, Simon (2010) in the case of 100th meridian and Sayre (2017) for rangeland management—and false representations of rarity could harden through this process, go unquestioned, and find their way into important legal and management decisions.

Inaccurate understandings of variability are not necessarily a product of environmental change; even without environmental change, distorted representations create messy, problematic, and risky outcomes. For example, Stakhiv (2011) argued that a standard statistical distribution used in the design of water management projects in the United States downplays hydrologic extremes, both floods and drought. He concluded that, although safety buffers have prevented failures, “underdesign” will become more of a problem in a changing climate. Similarly, false rarity hides the realities of variability and the potential for increasing extremes, allowing managers to approve activities and land uses that can lead to dangerous outcomes. Even in an environment that is not changing and where normals are not new, excluding data as outliers makes it easier and easier to exclude future data because, in comparison to a revised data set, new extremes appear even more abnormal.

Here we highlight each of the three elements of the process just described and examine how they could work together to distort and hide certain system behavior.

1. Constructing the Abnormal

When written into laws and regulations, categories for abnormal data become even more powerful

and consequential because they ultimately shape actions and interventions in environmental systems (Cantor 2016). Categories of abnormal data shape how regulatory frameworks understand and manage environmental systems. Extreme events—the observations likely to be considered outliers due to their infrequency—are the most valuable data for risk assessment and preparedness. As we move toward expecting greater levels of change, outliers—particularly those enshrined in laws and regulation—will only amplify the complications of the already difficult tasks of environmental monitoring and management.

We can see the work done by categorizing certain environmental events—and their data—as abnormal in current air quality regulations. The Exceptional Event Rule (EER), which is part of the Clean Air Act, allows for “exceptional” air quality events to be excluded from state regulatory data sets nationwide. High pollution days can be nullified by removing those events, and this similarly erases regulatory violations (i.e., the fines, increased governance, and costs of not meeting standards). An “exceptional” event is defined as either conditions that are unlikely to reoccur again (aligning well with common understandings of exceptional) or an event that is natural (regardless of its frequency), like a dust storm. Of course, natural is a highly debated category (R. Williams 1977; Cronon 1996; Mansfield et al. 2015; Cantor 2016; Davis 2016) because, especially in setting regulations, its definition often involves drawing arbitrary boundaries between nature and society rather than recognizing how most elements are hybrid. This challenge increases in the Anthropocene as it becomes even harder to disentangle the two (Harden 2012; Castree 2014; Purdy 2015; Mansfield and Doyle 2017). Further, both types of events—the truly extreme and the common, everyday, but bothersome “natural” air quality events—are important data for apprehending how a system behaves.

Once events are categorized as exceptional, they can be removed from regulatory data sets; this has the potential to hide important environmental risk as well as the true conditions of poor air quality. For example, Maricopa County, Arizona (where Phoenix is located), categorized more than twenty days with dust as “exceptional” in 2011 alone and explicitly stated that they would use the rule to avoid nonattainment status (Maricopa Association of Governments n.d.). Dust storms are caused by

environmental factors like increasing aridity but also a slew of land use practices surrounding the desert city. Through the use of this rule, the county is attempting to be in attainment (i.e., meet air quality standards) for the first time in more than twenty years.

Exclusions based on the EER also can hide changes in air quality, which are particularly important to track because the Anthropocene is likely to exhibit increased dust (Romm 2011) and smoke (McKenzie et al. 2014) from elevating temperatures and aridity. Yet data for those increases will be hidden, contradicting the obvious clues in plain sight. It is through the creation of exceptional events, constructing this category of abnormal or outlier, that the EER underwrites this exclusion and changes the story coming from the data. Ultimately the EER and its exclusions of exceptional events are working against the goals of the Clean Air Act, to protect human health and public welfare, because they allow high levels of pollution to go unregulated and hidden from analysis (Clifford 2020).

2. Excluding Outliers

Excluding extreme events due to their infrequency, or outliers due to their abnormality, can erase the variability of a system, artificially constructing a distribution with little variance and small standard deviations that renders events or changes invisible. In a sense, detectable (and maybe dangerous) extreme events disappear, at least in the data. Many and repeated alterations to the data transform how we understand a system in more than just discursive ways because distributions are heavily relied on for studies of risk, regulations of environmental hazards, and other critical management decisions.

Blinders constructed by data exclusions have already affected our tracking of the Anthropocene. For years, scientists missed the growing “ozone hole” over Antarctica despite technological advancements in monitoring atmospheric processes and increasing efforts by the National Aeronautics and Space Administration to measure and understand earth systems (von Hobe 2007). Ironically, it was not technological advancements that made the ozone hole detectable but instead reverting back to old, “obsolete” methods (Farman, Gardiner, and Shanklin 1985). Nor was it the complexity of the hole that left it invisible but instead data management practices, specifically exclusions.

The data exclusions that hid the ozone hole were not the act of an individual who reviewed the data and threw them out but instead were built into the data management algorithms that acted as an intermediary between the instruments collecting data and the models and scientific assessments using the data. The algorithms were set to exclude data that fell outside of what was expected in the system (what was envisioned as possible). In this case, outliers took the role of “errors.” Errors are different than other types of outliers: Instead of theoretically referring to an accurate depiction of a rare event that is deemed beyond or outlying typical system functioning, they signal a malfunction of the instrument or incorrect information. Yet the algorithms’ categorization of errors highlights the very subjective and dangerous politics of thinking about normal. We often think of normal as historic (i.e., what happened in the past) or present (i.e., how systems behave now), but this forecloses the possibility of how the system might shift and evolve.

Ironically, the ozone hole was eventually detected by basic instruments that did not have the automated exclusions. At first, the scientists observing the hole (Farman, Gardiner, and Shanklin 1985) faced some skepticism because their data were collected by less advanced instruments and it was only once the National Aeronautics and Space Administration scientists reran their models with the “error” data that the ozone hole became legible (Stolarski et al. 1986). It should have been clearly detectable for some time but was hidden through data exclusions that allowed an inaccurate representation of the atmosphere to persist.

3. Producing False Rarity and Erasing Variability

Bias against including plausible extreme events in the planning of projects that could fail given those events could also make the Anthropocene more dangerous than we expect. The statistics of natural system behavior essentially ensure that a place that experiences a significant range of intensity of natural events will also experience events several times larger than, say, those at one or two standard deviations from the mean. The costly implications of including extremes in project planning might encourage their neglect or exclusion and also yield a false sense of their rarity. When included in plans, extremes usually support larger and more costly hazard protection (e.g., higher sea walls, more robust

seismic building protections, etc.). Studies of the 2011 Fukushima nuclear power plant disaster found that the target wave height used for tsunami protection at the plant was inadequate; even when a historic tsunami comparable to the 2011 event was recognized by seismologists, it was neglected in the risk assessment when plant infrastructure was upgraded in 2002 (Earthquake Engineering Research Institute 2011; The Fukushima Nuclear Accident Independent Investigation Commission 2012; National Research Council 2014; Wheatley, Sovacool, and Sornette 2017).

A tendency to discount the likelihood of large events in a project lifetime is another form of data truncation, one that creates false rarity. Critics of coastal engineering on U.S. shores argue that large storm events are more common than models and plans allow for. Pilkey and Pilkey-Jarvis (2007; see also Pilkey, Young, and Cooper 2013) contended that the concept of beach erosion taking place through slow processes was constructed by treating coastal storm events as unusual or abnormal, when in fact they are common. This is especially important in beach nourishment projects, the multibillion-dollar efforts to rebuild beaches, especially on the U.S. East Coast, after storms and long-term erosion have worn them (and the residents and tourists that use them) away. Static numbers reified into models for calculating key variables, like sand transport rates, can have the effect of making variability disappear in projections of beach erosion (Young et al. 1995). Pilkey and Pilkey-Jarvis (2007) argued that

when artificial beaches are lost more rapidly than predicted by the models, the most common excuse is that the storm that caused the beach loss was unusual and unexpected. Certainly the unusual storm can occur, but the label “unusual” is used so frequently with lost artificial beaches as to imply that the last few decades have been truly extraordinary in their storminess. (135)

No beach lasts forever in an era of rising sea level, and coastal storms able to significantly whittle away beach width are not rare. Beach nourishment can slow this loss but not always as well as advertised. To improve beach project plans, the U.S. Army Corps of Engineers and others invested significant modeling efforts to include storms in erosion models (National Research Council 1995; Thieler et al. 2000). Estimating how likely those storms are over some project duration remains a big challenge

(Toimil et al. 2020), however, and critics claim that beach prediction models produce numbers that might overstate beach stability, tip benefit–cost analyses in favor of nourishment, and hide trends in beach erosion caused by storms and rising sea level.

Outlying in the Anthropocene

The stakes of false rarity increase in the Anthropocene. Removing “outliers” or other abnormal data critically shapes our understanding of the system not only because we miss events but because historical distributions, and changing distributions over time, are what we use to understand whether a system is changing. In other words, removing data about current extreme events cripples our ability to detect change and understand future environments. Moreover, as Pine and Liboiron (2015) reminded us, “the interplay of inclusion and exclusion *makes things*” (3). The normal makes the outlier and vice versa. Distorted pictures of environmental systems rely on data exclusions; those alternative data would rebuke notions of rarity. The consequences of false understandings about dynamic environmental systems is that they often lead to management strategies that do not work or work against the stated goals (Sayre 2017). Data exclusion is an Achilles’ heel in the Anthropocene.

All three of the examples presented exemplify the consequences of how constructing outliers can produce a skewed understanding of environmental behavior, particularly inaccurate claims of low variability. The stakes increase in the Anthropocene because they are not just associated with missing current system behavior but also with delaying recognition of larger changes and hindering adaptation responses.

Treating dust storms in the U.S. Southwest as “exceptional” or outliers, despite their frequency and historical analogues, makes it harder to see signals of emerging threats. Little imagination is required to think about how increasing air pollution events like dust storms or wildfire smoke could be disastrous; many have called the Dust Bowl the nation’s greatest “natural” disaster. Yet, we know that the Dust Bowl was driven at least in part by land use and allowed to amplify by officials (and farmers) ignoring signs of increased soil erosion (Worster 2004). Discarding “exceptional” events from regulatory analysis could halt proactive action that might be able to slow changes or facilitate adaptation.

The undetected ozone hole might be one of the most powerful analogues we have for thinking about outliers in the Anthropocene. We missed a significant change—one that we had data about—and that slowed our response. We run the same risk of missing important and likely high-consequence environmental changes in the Anthropocene if we exclude data that depart from a historical normal. In a time where we are increasingly automating and outsourcing decisions to algorithms and artificial intelligence, the ozone hole offers a cautionary note on how automating exclusions might make emerging risks less visible.

In the case of beach nourishment, treating severe storms as outliers in models can handicap analysis and undermine interventions, particularly if models overstate the effectiveness of beach nourishment. Sea level rise and warming oceans that could lead to worsened storms (Bindoff et al. 2013) mean that the gap between environmental realities and model outputs will only widen and likely lead to greater “surprises” as beach nourishments endure a dwindling fraction of projected life spans. The Anthropocene nullifies beaches but not beach simulation models.

Conclusion: Warning Signs

The chances of successful climate adaptation will improve if we can avoid false depictions of rarity and monitor the changing environment more accurately. Thus, we need to return to previously asked questions of normality: How does thinking about the “new normal” influence our understanding of outliers and other abnormal data? Conversely, how does excluding outliers affect our ability to apprehend the evolving Anthropocene?

An era of accelerating environmental change raises the stakes of outliers and false rarity. How distributions will evolve in the Anthropocene remains uncertain, so our monitoring must be open to surprise, to the abnormal. Early clues of how a system is changing provide critical information for management strategies to respond and protect communities. Combined, false representations of rarity and increasing variability have the potential for greater distortion of system behavior and more likely surprises and unanticipated events, ultimately undermining climate adaptation and environmental laws.

We invite others to examine these questions in other environmental systems. As scholars engaged in studying this new epoch and tracking transformation, we need to wrestle with how our own (and others’) notions of normal and abnormal affect inquiries into environmental change. Such inquiries are integral to knowing (or not knowing) environmental change, because change itself is again a departure from some defined normal state or baseline. Future work should further examine how outliers are produced and excluded, as well as the consequences of false rarity in risk management, legal paradigms, and climate adaptation efforts. How are data boundaries between normal and abnormal being negotiated? Has false rarity been produced through debatable exclusions and problematic characterizations? How is this process—and categories of normal–abnormal, data exclusions, and false rarity—reproduced and reified in legal and policy spheres? These questions can provide important insight into understanding and mitigating risk in the Anthropocene.

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Note

1. By referring to the situatedness of science, we are not critiquing science or its findings but illuminating the decisions, assumptions, and trade-offs in the process. Scientists and regulators who crunch numbers and analyze systems make a slew of decisions in the collection and analysis of data; it is impossible to make science without such decisions, but it is also important to note that these decisions do imbue scientific data and analysis, our understanding of a system, and decisions about how to intervene in that system. STS scholars and

geographers building on this thinking have long documented how the decisions scientists make during the production of science are influenced by neoliberal forces (Lave 2012), available instruments and technologies (Clarke and Fujimura 1992; Frickel and Vincent 2007), disciplinary forces (Clarke and Fujimura 1992; Murphy 2006; Kleinman and Suryanarayanan 2013), problem orientation (Frickel et al. 2010), time frame of analysis (Sedell 2019), and use of categories (Bowker and Star 2000; Duvall, Butt, and Neely 2018).

References

- Bindoff, N. L., P. A. Stott, K. M. AchutaRao, M. R. Allen, N. Gillett, D. Gutzler, K. Hansingo, et al. 2013. Detection and attribution of climate change: From global to regional. In *Climate Change 2013: The physical science basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, and P. M. Midgley. Cambridge, UK: Cambridge University Press.
- Bowker, G. C. 2008. *Memory practices in the sciences*. Cambridge, MA: The MIT Press.
- Bowker, G. C., and S. L. Star. 2000. *Sorting things out: Classification and its consequences*. Cambridge, MA: MIT Press.
- Buck, H. J. 2015. On the possibilities of a charming Anthropocene. *Annals of the Association of American Geographers* 105 (2):369–77. doi:10.1080/00045608.2014.973005.
- Canguilhem, G. 2008. *Knowledge of life*, trans. S. Geroulanos and D. Ginsburg. New York: Fordham University Press.
- Cantor, A. 2016. The public trust doctrine and critical legal geographies of water in California. *Geoforum* 72:49–57. doi:10.1016/j.geoforum.2016.01.007.
- Castree, N. 2014. The Anthropocene and geography I: The back story. *Geography Compass* 8 (7):436–49. doi:10.1111/gec3.12141.
- Clarke, A. E., and J. H. Fujimura, eds. 1992. *The right tools for the job: At work in twentieth-century life sciences*. Princeton, NJ: Princeton University Press.
- Clifford, K. R. 2020. Problematic Exclusions: Analysis of the Clean Air Act's Exceptional Event Rule Revisions. *Society & Natural Resources*. doi: 10.1080/08941920.2020.1780358.
- Coleman, H. 2019. Climate is getting more extreme in every possible way. *Massive Science* (blog), January 8. Accessed April 13, 2020. <https://massivesci.com/articles/climate-change-wildfires-hurricanes/>.
- Collins, M., R. Knutti, J. Arblaster, J.-L. Dufresne, T. Fichet, P. Friedlingstein, X. Gao, et al. 2013. Long-term climate change: Projections, commitments and irreversibility. In *Climate Change 2013: The physical science basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, and P. M. Midgley. Cambridge, UK: Cambridge University Press.
- Cronon, W. 1996. The trouble with wilderness: Or, getting back to the wrong nature. *Environmental History* 1 (1):7–28. doi:10.2307/3985059.
- Crutzen, P. J., and W. Steffen. 2003. How long have we been in the Anthropocene era? *Climatic Change* 61 (3):251–57. doi:10.1023/B:CLIM.0000004708.74871.62.
- Davis, D. K. 2016. *The arid lands: History, power, knowledge*. Cambridge, MA: MIT Press.
- Desrosières, A. 2002. *The politics of large numbers: A history of statistical reasoning*. Cambridge, MA: Harvard University Press.
- Dillon, L., R. Lave, B. Mansfield, S. Wylie, N. Shapiro, A. S. Chan, and M. Murphy. 2019. Situating data in a Trumpian era: The environmental data and governance initiative. *Annals of the American Association of Geographers* 109 (2):545–55. doi:10.1080/24694452.2018.1511410.
- Duvall, C. S., B. Butt, and A. Neely. 2018. The trouble with savanna and other environmental categories, especially in Africa. In *The Palgrave handbook of critical physical geography*, eds. Lave, R., Biermann, C., & Lane, S. N. 107–27. Cham, Switzerland: Palgrave Macmillan.
- Earthquake Engineering Research Institute. 2011. The Japan Tohoku Tsunami of March 11, 2011. EERI Special Earthquake Report, Oakland, CA: Earthquake Engineering Research Institute.
- Edwards, P. N. 2001. Representing the global atmosphere: Computer models, data, and knowledge about climate change. In *Changing the atmosphere: Expert knowledge and environmental governance*, ed. C. A. Miller and P. N. Edwards, 31–33. Cambridge, MA: MIT Press.
- Farman, J. C., B. G. Gardiner, and J. D. Shanklin. 1985. Large losses of total ozone in Antarctica reveal seasonal ClOx/NOx interaction. *Nature* 315 (6016):207–10. doi:10.1038/315207a0.
- Frickel, S., S. Gibbon, J. Howard, J. Kempner, G. Ottinger, and D. J. Hess. 2010. Undone science: Charting social movement and civil society challenges to research agenda setting. *Science, Technology, & Human Values* 35 (4):444–73. doi:10.1177/0162243909345836.
- Frickel, S., and M. B. Vincent. 2007. Hurricane Katrina, contamination, and the unintended organization of ignorance. *Technology in Society* 29 (2):181–88. doi:10.1016/j.techsoc.2007.01.007.
- The Fukushima Nuclear Accident Independent Investigation Commission. 2012. The national diet of Japan. https://www.nirs.org/wp-content/uploads/fukushima/naic_report.pdf.
- Gitelman, L. 2013. *Raw data is an oxymoron*. Cambridge, MA: MIT Press.
- Hacking, I. 1990. *The taming of chance*. Cambridge, UK: Cambridge University Press.
- Haraway, D. 2015. Anthropocene, capitalocene, plantationocene, chthulucene: Making kin. *Environmental Humanities* 6 (1):159–65. doi:10.1215/22011919-3615934.
- Haraway, D. 2016. *Staying with the trouble: Making kin in the Chthulucene*. Durham, NC: Duke University Press.

- Harden, C. P. 2012. Framing and reframing questions of human–environment interactions. *Annals of the Association of American Geographers* 102 (4):737–47. doi:10.1080/00045608.2012.678035.
- Hayhoe, K., D. J. Wuebbles, D. R. Easterling, D. W. Fahey, S. Doherty, J. Kossin, W. Sweet, R. Vose, and M. Wehner. 2018. Our changing climate. In *Impacts, risks, and adaptation in the United States: Fourth National Climate Assessment*, ed. D. R. Reidmiller, C. W. Avery, D. R. Easterling, K. E. Kunkel, K. L. M. Lewis, T. K. Maycock, and B. C. Stewart, vol. II, 72–144. Washington, DC: U.S. Global Change Research Program. doi:10.7930/NCA4.2018.CH2.
- Hirsch, S. L. 2020. Anticipatory practices: Shifting baselines and environmental imaginaries of ecological restoration in the Columbia River Basin. *Environment and Planning E: Nature and Space* 3 (1):40–57. doi:10.1177/2514848619857523.
- Jasanoff, S., ed. 2004. *States of knowledge: The co-production of science and the social order*. London and New York: Routledge.
- King, L., and M. Tadaki. 2018. A framework for understanding the politics of science (Core Tenet #2). In *The Palgrave handbook of critical physical geography*, 67–88, ed. Lave, R., Biermann, C., & Lane, S. N. Cham, Switzerland: Palgrave Macmillan.
- Kirtman, B., S. B. Power, J. A. Adedoyin, G. J. Boer, R. Bojariu, I. Camilloni, F. J. Doblas-Reyes, et al. 2013. Near-term climate change: Projections and predictability. In *Climate Change 2013: The physical science basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, 953–1028, ed. T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, and P. M. Midgley. Cambridge, UK: Cambridge University Press.
- Kleinman, D. L., and S. Suryanarayanan. 2013. Dying bees and the social production of ignorance. *Science, Technology, & Human Values* 38 (4):492–517. doi:10.1177/0162243912442575.
- Lave, R. 2012. Neoliberalism and the production of environmental knowledge. *Environment and Society* 3 (1):19–38. doi:10.3167/ares.2012.030103.
- Lewis, S. C., A. D. King, and S. E. Perkins-Kirkpatrick. 2017. Defining a new normal for extremes in a warming world. *Bulletin of the American Meteorological Society* 98 (6):1139–52. doi:10.1175/BAMS-D-16-0183.1.
- Lewis, S. L., and M. A. Maslin. 2015. Defining the anthropocene. *Nature* 519 (7542):171–80. doi:10.1038/nature14258.
- Mansfield, B., C. Biermann, K. McSweeney, J. Law, C. Gallemore, L. Horner, and D. K. Munroe. 2015. Environmental politics after nature: Conflicting socio-ecological futures. *Annals of the Association of American Geographers* 105 (2):284–93. doi:10.1080/00045608.2014.973802.
- Mansfield, B., and M. Doyle. 2017. Nature: A conversation in three parts. *Annals of the American Association of Geographers* 107 (1):22–27. doi:10.1080/24694452.2016.1230418.
- Maricopa Association of Governments. n.d. PM-10 monitoring data. <http://azmag.gov/Programs/Maps-and-Data/Air-Quality>.
- McKenzie, D., U. Shankar, R. E. Keane, E. N. Stavros, W. E. Heilman, D. G. Fox, and A. C. Riebau. 2014. Smoke consequences of new wildfire regimes driven by climate change. *Earth's Future* 2 (2):35–59. doi:10.1002/2013EF000180.
- Milly, P. C. D., J. Betancourt, M. Falkenmark, R. M. Hirsch, Z. W. Kundzewicz, D. P. Lettenmaier, and R. J. Stouffer. 2008. Stationarity is dead: Whither water management? *Science* 319 (5863):573–74. doi:10.1126/science.1151915.
- Moore, J. W., ed. 2016. *Anthropocene or Capitalocene? Nature, history, and the crisis of capitalism*. Oakland, CA: PM Press.
- Murphy, M. 2006. *Sick building syndrome and the problem of uncertainty: Environmental politics, technoscience, and women workers*. Durham, NC: Duke University Press.
- National Research Council. 1995. *Beach Nourishment and Protection*. Washington, DC: The National Academies Press. doi: 10.17226/4984.
- National Research Council. 2014. *Lessons learned from the Fukushima nuclear accident for improving safety and security of U.S. nuclear plants*. Washington, DC: National Academies Press.
- Pilkey, O. H., and L. Pilkey-Jarvis. 2007. *Useless arithmetic: Why environmental scientists can't predict the future*. New York: Columbia University Press.
- Pilkey, O. H., R. Young, and A. Cooper. 2013. Quantitative modeling of coastal processes: A boom or a bust for society? *Special Papers of the Geological Society of America* 502 (7):135–44. doi:10.1130/2013.2502(07).
- Pine, K. H., and M. Liboiron. 2015. The politics of measurement and action. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 1–10. ACM. doi:10.1145/2702123.2702298.
- Porter, T. M. 1996. *Trust in numbers: The pursuit of objectivity in science and public life*. Princeton, NJ: Princeton University Press.
- Purdy, J. 2015. *After nature: A politics for the Anthropocene*. Cambridge, MA: Harvard University Press.
- Ribes, D., and S. J. Jackson. 2013. Data bite man: The work of sustaining a long-term study. In “Raw data” is an oxymoron, 147–66, ed. R. Kitchin. Cambridge, MA: MIT Press.
- Romm, J. 2011. Desertification: The next dust bowl. *Nature* 478 (7370):450–51. doi:10.1038/478450a.
- Ruhl, J. B., and J. E. Salzman. 2011. Gaming the past: The theory and practice of historic baselines in the administrative state. *Vanderbilt Law Review* 64 (1):1–57. doi:10.2139/ssrn.1553484.
- Sayre, N. F. 2017. *The politics of scale: A history of rangeland science*. Chicago, IL: University of Chicago Press.
- Sedell, J. K. 2019. No fly zone? Spatializing regimes of perceptibility, uncertainty, and the ontological fight over quarantine pests in California. *Geoforum*. doi:10.1016/j.geoforum.2019.04.008.
- Simon, G. L. 2010. The 100th meridian, ecological boundaries, and the problem of reification. *Society & Natural Resources* 24 (1):95–101. doi:10.1080/08941920903284374.

- Stakhiv, E. Z. 2011. Pragmatic approaches for water management under climate change uncertainty. *JAWRA: Journal of the American Water Resources Association* 47 (6):1183–96. doi:10.1111/j.1752-1688.2011.00589.x.
- Stolarski, R. S., A. J. Krueger, M. R. Schoeberl, R. D. McPeters, P. A. Newman, and J. C. Alpert. 1986. Nimbus 7 satellite measurements of the springtime Antarctic ozone decrease. *Nature* 322 (6082):808–11. doi:10.1038/322808a0.
- Thieler, E. R., O. H. Pilkey, R. S. Young, D. M. Bush, and F. Chai. 2000. The use of mathematical models to predict beach behavior for U.S. coastal engineering: A critical review. *Journal of Coastal Research* 16 (1):48–70.
- Toimil, A., I. J. Losada, R. J. Nicholls, R. A. Dalrymple, and M. J. F. Stive. 2020. Addressing the challenges of climate change risks and adaptation in coastal areas: A review. *Coastal Engineering* 156:103611. doi:10.1016/j.coastaleng.2019.103611.
- Ureta, S., T. Lekan, and W. G. von Hardenberg. 2020. Baseline nature: An introduction. *Environment and Planning E: Nature and Space* 3 (1):3–19. doi:10.1177/2514848619898092.
- von Hobe, M. 2007. Atmospheric science. Revisiting ozone depletion. *Science* 318 (5858):1878–79. doi:10.1126/science.1151597.
- Walsh, J., D. Wuebbles, K. Hayhoe, J. Kossin, K. Kunkel, G. Stephens, P. Thorne, et al. 2014. Our changing climate. In *Climate change impacts in the United States: The Third National Climate Assessment*, ed. J. M. Melillo, T. C. Richmond, and G. W. Yohe, 19–67. Washington, DC: U.S. Global Change Research Program. doi:10.7930/J0KW5CXT.
- Wheatley, S., B. Sovacool, and D. Sornette. 2017. Of disasters and dragon kings: A statistical analysis of nuclear power incidents and accidents. *Risk Analysis: An Official Publication of the Society for Risk Analysis* 37 (1):99–115. doi:10.1111/risa.12587.
- Wigley, T. M. L. 2009. The effect of changing climate on the frequency of absolute extreme events. *Climatic Change* 97 (1–2):67–76. doi:10.1007/s10584-009-9654-7.
- Williams, J. W., and S. T. Jackson. 2007. Novel climates, no-analog communities, and ecological surprises. *Frontiers in Ecology and the Environment* 5 (9):475–82. doi:10.1890/070037.
- Williams, R. 1977. *Keywords: A vocabulary of culture and society*. London and New York: Routledge.
- Worster, D. 2004. *Dust bowl: The southern plains in the 1930s*. New York: Oxford University Press. doi:10.1086/ahr/85.3.732.
- Young, R. S., O. H. Pilkey, D. M. Bush, and E. R. Thieler. 1995. A discussion of the generalized model for simulating shoreline change (GENESIS). *Journal of Coastal Research* 11 (3):875–86.
- Zalasiewicz, J., M. Williams, W. Steffen, and P. Crutzen. 2010. The new world of the Anthropocene. *Environmental Science & Technology* 44 (7):2228–31. doi:10.1021/es903118j.

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