Harnessing the Flow of Data:

Fintech opportunities for ecosystem management

IISD-ELA REPORT

Geoffrey Gunn
Madeline Stanley

August 2018

Published by the International Institute for Sustainable Development

International Institute for Sustainable Development

The International Institute for Sustainable Development (IISD) is an independent think tank championing sustainable solutions to 21st–century problems. Our mission is to promote human development and environmental sustainability. We do this through research, analysis and knowledge products that support sound policymaking. Our big-picture view allows us to address the root causes of some of the greatest challenges facing our planet today: ecological destruction, social exclusion, unfair laws and economic rules, a changing climate. IISD's staff of over 120 people, plus over 50 associates and 100 consultants, come from across the globe and from many disciplines. Our work affects lives in nearly 100 countries. Part scientist, part strategist—IISD delivers the knowledge to act.

IISD is registered as a charitable organization in Canada and has 501(c)(3) status in the United States. IISD receives core operating support from the Province of Manitoba and project funding from numerous governments inside and outside Canada, United Nations agencies, foundations, the private sector and individuals.

Head Office

111 Lombard Avenue, Suite 325
Winnipeg, Manitoba
Canada R3B 0T4

Tel: +1 (204) 958-7700
Website: www.iisd.org
Twitter: @IISD_news

About IISD-ELA

IISD Experimental Lakes Area (IISD-ELA) is the world's freshwater laboratory. A series of 58 lakes and their watersheds in northwestern Ontario, Canada, IISD-ELA is a unique scientific site where researchers can experiment directly on freshwater lakes to discover the impacts of human activity and pollutants. Since 1968, IISD-ELA has helped us reveal everything from the impact of phosphorus on algal blooms, to the effects of mercury on freshwater systems, to how acid rain affects lakes. The site works with local and global researchers and with local communities, First Nations, schools and universities. It is funded by the governments of Canada, Ontario and Manitoba, and by many other generous partners and donors.

IISD-ELA

111 Lombard Avenue, Suite 325
Winnipeg, Manitoba
Canada R3B 0T4

Tel: +1 (204) 958-7700
Website: www.iisd.org/ela
Twitter: @IISD_ELA

Harnessing the Flow of Data:
Fintech opportunities for ecosystem management

August 2018

Written by Geoffrey Gunn

Acknowledgements

Supported by the RBC Foundation.

The Water Challenge

"In many instances, science is lagging behind the commercial world in the ability to infer meaning from data and take action based on that meaning."

Gordon Bell, The Fourth Paradigm (2009)

In 1974, Canadian scientist John R. (Jack) Vallentyne, predicted a world in the year 2000 beset by human-caused water-quality problems, which he called the Algal Bowl. The "bowl" refers to a crisis similar in both in cause and substance to the 1930s Great Plains Dust Bowl. While the Dust Bowl was caused by poor soil management and a rapid expansion of crop tillage across western North America, the Algal Bowl would be caused by untreated sewage, livestock manure or crop fertilizer runoff, and dramatic losses of wetlands and ponds. Green scums on both inland lakes and marine estuaries would lead to collapses of economic fisheries, reductions of aesthetic value, and in the worst cases create toxic chemicals plumes caused by cyanobacteria that put human health and drinking water at risk.

Despite the considerable efforts of North American scientists and decision-makers, Vallentyne's prediction came true. Toxic algal blooms affect lakes and estuaries across North America, often with severe consequences to aquatic life and to people. In Lake Erie—one of the most affected of the Great Lakes—a recent report notes that algal blooms cost local homeowners USD 152 million in land value over six years, due to smelly green algal mats and poor water quality (Wolf & Klaiber, 2017). Some of the larger waterbodies in North America that have also been impacted by the blooms are Lake Winnipeg in Canada, Lake Okeechobee in Florida and Chesapeake Bay (Schindler, Hecky, & McCullough, 2012; Ballard, 2018; Li et al., 2015).

Lake Erie algal bloom, October 5, 2011. Photo credit: USGS.

In 1968, Jack Vallentyne and a team of scientists established the Experimental Lakes Area (ELA) in Ontario, Canada, to improve our understanding of water quality. This "big science" approach examined entire ecosystems to track the relationships between human disruption and environmental response. The precise cause of algal blooms in North American lakes—phosphates from fertilizers and detergents—was isolated in the late 1970s, a discovery that was

WICKED PROBLEMS

In 1973, Rittel and Webber introduced this term to describe planning issues with dramatic uncertainties, conflicting stakeholder desires and interdependencies that combined to prevent a simple or elegant solution.

followed by policy responses in the United States and Canada that banned phosphates from consumer detergents. But despite reasonable knowledge about the causes and effects of these impacts, algal blooms worsened and now cause serious damage to the economy, the environment and human health.

Why do some critical environmental challenges, like managing our fresh water, remain so onerous that it seems we are making little progress?

Many of the problems at the interface of the environment and the economy—climate change, food security, clean water—are best described as "wicked problems" (Rittel & Webber, 1973). Uncertainty and unpredictability of causes and the inherent difficulty of ascribing impacts make it easy for stakeholders to disagree about the importance of such problems, procrastinate on solutions and avoid legal responsibility. Many wicked problems also become more difficult to resolve the longer they remain unaddressed.

Even with modern methods for monitoring water quality, few jurisdictions across Canada are conducting adequate water-quality monitoring programs to understand the state and changes in trends in freshwater systems. In an ambitious project, WWF Canada assessed the health of and threats to Canada's major watersheds: a key finding was the poor state of data collection and organization amongst Canada's water agencies, particularly for water quality and ecosystem health indicators (WWF Canada, 2017).

To solve wicked problems, we need to rethink how science, engineering, finance and policy fit together. In a rapidly changing world, the traditional methods of the past may not work. This rethinking of science has been called "The Fourth Paradigm." In the Foreword to the 2009 book with that title, Microsoft researcher Gordon Bell noted that despite academic science inventing many of the technologies and concepts that drive innovation, scientists themselves are slow to adopt mature technologies. Since the time of writing, it has become more apparent that, "[i]n many instances, science is lagging behind the commercial world in the ability to infer meaning from data and take action based on that meaning" (Bell, 2009).

Now more than ever, ecosystem science and management systems need to adopt all the tools necessary to help society make informed decisions about an uncertain future.

KEY TECHNOLOGIES

Internet of things (IoT)—Internet connected devices and sensors, from smart phones to networked manufacturing equipment to buoys, able to transmit to and received data to the internet.

Big data—Datasets so large or complex that traditional analysis and even some statistics do not work. Data that is generated rapidly by sensors or in complex formats (social media posts, images, video) and that needs resources including high performance computing to effectively use.

Artificial intelligence (AI)—a family of technologies using advanced statistics and computing to build data-driven models. All AI methods (machine learning, graph theory and artificial neural networks) use relationships and contextual data to model the world.

Blockchain—A way of preventing data copying or modification without relying on a single authority. Blockchain refers to an immutable public ledger that records digitally stamped transactions of data.

The Fintech Revolution

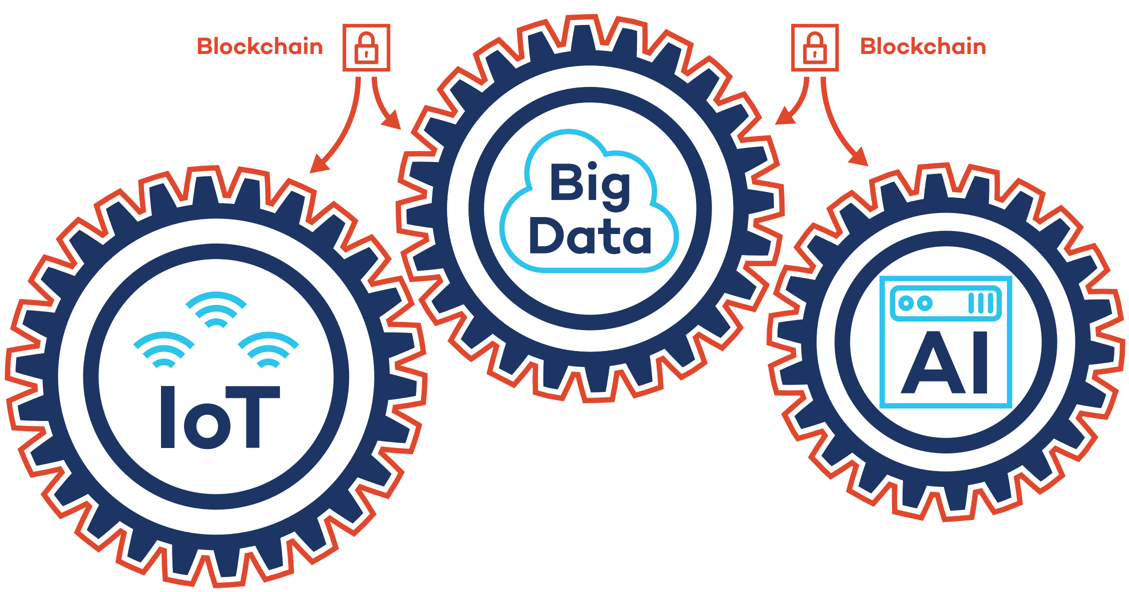
We have entered the next stage of the information age: the financial technology (or "fintech") revolution. Following the 2008/2009 global recession, a confluence of small high-tech start-ups and the maturation of new technologies produced major changes in how large quantities of the world's financial data are collected, managed and used. The advent of simple cloud computing, low-cost and high-performance parallel processing, and advanced cryptography is fundamentally altering the way business is done.

The accounting firm KPMG recently reported that global venture capital investment in fintech companies reached USD 8.7 billion in 2017, with a large proportion coming from corporate investment as multinationals seek to acquire technologies held by start-ups and small but maturing firms (KPMG, 2017). Many financial institutions are developing in-house expertise by founding data science hubs for internal or curiosity-driven research, like RBCs' Borealis AI (2018).

What Is Fintech?

Fintech is shorthand for a suite of technologies that have generated interest and investment in the financial world. These technologies share a digital foundation and change the way data are collected, stored, analyzed and communicated. The key technologies—the internet of things, blockchain, big data and artificial intelligence (see box)—are now regularly used alone, such as smartphones, cryptocurrencies or for business intelligence. But emerging research shows the next generation of revolution will be built upon interactions these new technologies have along the data pathway, meshing together like virtual gears. This relationship, noted in a 2016 UNEP report, was coined this fintech "gearbox" (Castilla-Rubio, Zadek, & Robins, 2016).

As a metaphor, a gearbox captures the selective meshing of teeth, much like how big data alone can drive a customer analytics system, but shifting streams of data into AI could accelerate the usefulness of the system. Alone each is powerful, but together they can increase the speed at which we collect, store and use data.



The rapidity of change and development within these technology families makes it challenging to keep up with the state of the art. In the next sections, we briefly discuss each technology in slight more detail.

Internet of Things

As wireless cellular and radio technology has advanced, becoming cheaper and more widespread, more devices are now connected to the Internet. Ranging from consumer smart phones to televisions or traffic cameras, smart factories and environmental sensors, the broad coverage of different network protocols has made it easy to collect and transmit data with less hard infrastructure. Network protocols like Bluetooth, Wi-Fi, 4G/LTE, and Iridium satellite communications have made it possible to link devices remotely in locations from busy New York street corners to the most remote parts of the globe.

The market research firm Gartner recently estimated that 8.3 billion devices are Internet-connected in 2018, and a 2017 Verizon report indicated the greatest growth in device type was in manufacturing, transportation and energy/utilities (Gartner, 2017). The consumer Internet of things (IoT) will likely continue to be dominated by smart phones, but recent growth in home assistants (e.g., Amazon Alexa and Google Home) indicates there are other untapped potential markets for web-connected devices.

Each IoT device is not only network connected, but often holds one or more sensors to detect sound, video/images, human input, acceleration, temperature, air pressure and dozens of other local parameters. Thanks to low-cost GPS chips, many devices record data that are explicitly spatial—located to a specific place at a specific time.

In some ways, the IoT is not entirely new within the digital age. Most of the world is served to some degree by a local weather station measuring temperature, wind speed, air pressure and humidity. While each station has some intrinsic individual value, the development of global monitoring standards in the 1950s revolutionized how we think about weather and dramatically increased the accuracy of daily forecasts (WMO, n.d.). By contextualizing spatially located environmental data, a global endeavour successfully improved weather prediction.

New devices that monitor other parameters in the atmosphere are now making a difference. In Beijing, a network of air quality sensors monitors particulates less than 2.5 μm (0.0025 mm) and has led to strategic decisions about closing old coal electricity-generating stations in favour of new natural gas plants (Stanway, 2018). Other shared resources, like water and biodiversity, are also candidates for public monitoring systems.

Low-cost sensors have broadened the scope of who can conduct environmental monitoring. Citizen science is the practice of engaging the public on scientific or research questions to gather robust information about human behaviour or natural systems. An ambitious new initiative developed by the Wilson Center for International Scholars seeks to collect one billion data points around the world on air and water quality, pollution and health (Wilson Center, 2018). Projects like this fill gaps in government-collected scientific data while also engaging the community. These projects often use existing IoT technologies—like cellphones, rain gauges or rulers—and could positively impact nations with strong monitoring systems (as validation datasets[1]) and fill the many global observation gaps in environmental monitoring or even map infrastructure.[2]

The Internet connectivity of IoT sensors dramatically increases the speed at which data is generated and can be analyzed. Near real-time collection of data could automate a considerable part of the analysis, shortening the gap between data collection and action. It can also mean more engagement with people who have traditionally been left out of monitoring and data collection.

These data will be more complex than traditional scientific monitoring data and could, in the future, generate very large, unwieldy datasets. Fortunately, the financial and broader commercial world has developed analytic systems to handle complex and large datasets which have become known as "big data."

Big Data

Scientists and environmental managers have long relied on monitoring and the resulting empirical data for analyzing results and making decisions. However, managing these datasets and ensuring that they are usable and useful has been challenging. As the cost of storage decreases and the speed of computing increases, the term "big data" has represented datasets just outside the reach of conventional management. In fact, one definition of the term is "data that exceeds the capacity of conventional database systems." A key aspect of big data is volume, the thresholds of which have changed over time. In the 1990s this could have described a dataset measured in gigabytes (1,000s of megabytes [Mbs]); in the 2000s a dataset measured in terabytes (1,000,000 Mb) and now a dataset would be measured well into the petabytes and exobytes (10^9 and 10^{12} Mb respectively).

A more descriptive and helpful definition of big data is the one used by IBM (n.d.) to include:

1. **Volume** (size and storage)
2. **Velocity** (frequency of data collection)
3. **Veracity** (uncertain confidence in data)
4. **Variety** (many types of data; non-tabular or unstructured)

This reflects the fact that volume is only one complicating dimension (and one eventually solved by computing power and storage capacities); the other three may consume more resources to turn into actionable and valuable information. Data from IoT sensors collected daily, hourly or sometimes at intervals of less than a second (like a live video stream) demonstrate high-**velocity** big data that requires high-speed Internet connections and advanced analytic processes to turn into actionable information. **Veracity** refers to data of uncertain quality, making robust decisions challenging, such as social media analytics that are subject to malicious attacks or challenges in separating bots from human inputs. Variety refers to growing interest in fusing diverse datasets to gather new insights and the challenges of validation and comparability—such as using social media-derived citizen science to supplement remote sensing data for environmental systems or gathering unstructured data from web pages (so-called "scraping").

A recent report from Bain Capital notes how businesses can see large returns from investments in big data analysis, but also notes the risks and costs of investment (Pearson & Wegener, 2013). The largest investment for many businesses is gathering archived or historical data—scanning or entering paper documents, organizing old databases and transitioning to cloud-based infrastructure. Before analytics, there must be organization and curation of datasets.

[1] E.g., Community Collaborative Rain, Hail and Snow Network (CoCoRaHS): see https://www.cocorahs.org/.

[2] E.g., Humanitarian Open Streetmap: see https://www.hotosm.org/.

The concept of big data is not new to the environmental sciences. In 1998, Vice President Al Gore called upon the scientific community to develop a "Digital Earth" (Gore, 1998). Envisioning a future of big data poised to manage human and natural systems—especially given the impacts of global economic and climate effects—it was a bold insight into the necessity and practicality of standardized environmental data and has since been partially adopted into a much larger network of Earth Observation satellites and improved geographic information systems.

Photo: ESA–Pierre Carril

Two decades later the scientific community has recognized the necessity of opening large datasets to the public. Important milestones included the elimination of fees for public satellite observation data by the United States in 2008, development of peer-review scientific data repositories and funder mandates of opening datasets, and new commercial platforms for public data such as Amazon Web Services[3] and Google Earth Engine.[4]

In addition to big data from the growing IoT, historical and archival data are becoming more available from public institutions, academic researchers and even private entities. This creates an environment of disparate and incomparable formats, especially from raw scientific data for which important contextual information—the so-called metadata—may be incomplete or entirely absent. Organization, curation and deployment of these data can be extremely challenging, often requiring considerable work to develop data models and incorporate standards and best practices to enable use and analysis by outside users.

For example, IISD-Experimental Lakes Area holds a 50-year dataset of whole-ecosystem manipulation and long-term ecological research parameters from the physical environment to lake chemistry and fish biology. Although relatively small in volume (approximately 20 GB), there is tremendous complexity in the data parameters collected and the amount of necessary metadata documenting each measurement's collection methods, location and quality assurance actions. This complexity highlights how important the other Vs—veracity and variety—are when considering environmental data. This dataset has supported production of at least 1,300 book chapters, theses and peer-reviewed articles alongside considerable changes in freshwater and aquatic policies.

The long-term monitoring at the Experimental Lakes Area and other research stations has helped inform a new generation of observatories designed explicitly to monitor ecosystem parameters and generate big data. In the United States, the National Ecological Observatory Network (NEON) is a network of 81 field sites monitoring ecosystem parameters like air quality, plant vigour and water quality.[5] A recent article noted that the streams of data produced required a transdisciplinary approach to generate useful and timely information products for researchers and decision-makers over the 30-year lifespan of the project (Lin, 2013).

As big datasets become the norm, scientists and managers will need to adapt and ensure there are plans for data acquisition, storage and analysis through and beyond a project lifecycle. Archiving of metadata and data on publicly

[3] See https://aws.amazon.com/earth/.

[4] See https://earthengine.google.com/.

[5] See https://www.neonscience.org/.

accessible platforms and models for publication of whole datasets—already adopted by some of the largest scientific journals—is becoming an expectation of some national-scale funding agencies (Nicol, Caruso, & Archambault, 2013). But beyond opening the data, delivering data in a way that can be analyzed and used will be necessary to unleash the potential of artificial intelligence (AI) and other large-scale analytical techniques.

Artificial Intelligence

Artificial intelligence (AI) is a broad family of technologies that arose from advanced multivariable statistics, many of which were developed throughout the 21st century for biological and social sciences. Some of these statistics were developed for clustering data—grouping measurements of individuals with those most alike—such as stands of trees or populations of animals. These statistical methods provided a better understanding of systems with larger datasets or multiple parameters (e.g., tree height, thickness and location), although severe limitations imposed by computing speed and memory limited wider applications.

As high-performance computing has become accessible to most researchers with off-the-shelf graphics processing units (GPUs, or video cards) and faster desktop computers, researchers are able to iterate—repeat—these statistical methods on enormous datasets with previous insights retained in algorithms: that is, learning. AI is simply statistical methods run on high-performance computers driven by large datasets over many iterations.

Simply, AI technologies use big data to statistically suggest relationships within the data without needing to know anything about the real-world processes beforehand. AI builds a model from data, and more data allow the AI to be trained and validated, exposing deeper insights and relationships. In the past three decades, environmental scientists have developed models based upon theoretical and mathematic understandings of how systems work or are thought to work in the real world—mechanistic models. Both approaches are used together: our theoretical understanding helps data collection (possibly using IoT systems), before then using an AI model for new, previously unseen insights from datasets.

While there are many types of AI techniques (e.g., Support Vector Machines, Random Forest, ISODATA), for simplicity we can describe two major groups: supervised methods and unsupervised methods. Supervised methods incorporate some previous knowledge to "train" the system. Nvidia recently demonstrated a technique where researchers used a large dataset of celebrity pictures separated into men and women and trained a system to generate two completely synthetic images of non-existent faces (Nvidia, 2018). The training data—measuring in the hundreds of images—allowed the system to understand a goal and progressively generate random images that moved toward that goal. Unsupervised techniques require only structured data with no goal in mind but can generate forecasts (if time is an element) or cluster large datasets (such as consumer types or habitat locations)—this technique is often used in exploratory phases of analysis.

While in some cases AI may replace or augment human insight, the greatest current benefits are digesting and analyzing datasets far too large for any person or even group of people to analyze. Many risks to fresh water do not have a single cause but many linked contributing factors, including toxic algal blooms occurring in many lakes around the world. With well-instrumented lakes or rivers, many researchers have examined how AI techniques can predict blooms before they occur or generate statistical likelihood of blooms impacting water treatment facilities or recreation areas (e.g., Chou, Ho, & Hoang, 2018). Research groups like IISD-ELA that have produced vast amounts of big data can now use AI to ask new questions in different ways. With technologies like AI, we can operate beyond our hypotheses, ask new and bigger questions, and reveal relationships we may have never considered.

While the confluence of more data and increased processing power is an enabling factor for AI, there are going to be many challenges to developing operational systems for prediction and deployment. The most pressing challenges are the cultural barriers present in governments and academia that prevent the open sharing and structured management of environmental data. We are undergoing an open data revolution—and cities, nations, and international organizations are making data "open by default"—but much of the data are poorly structured, unsearchable or have limitations to rapid use and analysis.

We expect that with time and effort the problem of data quality will improve; however, major risks include cultural barriers such as a lack of trust for data sharing. A 2015 study assessed open datasets from 100 publications on ecology and found 56 per cent were incomplete and 64 per cent were shared in a way that partially or completely prevented others from reusing the data (Roche et al., 2015). Hampton et al. (2013) discuss this cultural issue within ecology in depth. The authors call on ecologists to treat data as "an enduring part of research, not just a precursor to publication."

> "[Data are] an enduring part of research, not just a precursor to publication."
>
> Hampton et al., 2013

This cultural change will require a shift in how trust and rewards are assigned to public and academic researchers. To create an environment where AI can be used to answer broad questions about our environment, we will need to embrace technologies that give data generators the confidence to release their datasets and maintain ownership while still making them available for use.

Blockchain

Blockchain technology was developed to "bypass government currency controls and simplify online transactions" (Lucas, 2017). While still-anonymous developers created blockchain to develop a currency, the underlying technologies essentially prevent copying and alteration of data files using a mix of encryption and distributed computing—the so-called "immutable digital ledger" (Iansiti & Lakhani, 2017; Goldman Sachs., n.d.).

Modern accounting is based on a double ledger system: one ledger records transactions and is audited against original copies (e.g., receipts) or other authoritative records. This requires trust: it is why accounting firms take decades to build reputations as trustworthy and why auditing has become an essential part of financial management. Blockchain technology removes this by using advanced cryptography to ensure each transaction is validated against a distributed cloud. This is what bitcoin mining is doing: validating billions of data transactions in exchange for tokens.

Blockchain is an open system (public ledger) that records and verifies transactions within a database. Every change in the chain is accompanied with a digital signature that is time stamped, ensuring there is no duplication or modification of entries within the chain (Iansiti & Lakhani, 2017). Each transaction is designated as a "block" and they are linked together with a hash function—an encrypted code representing that transaction—that is unique to each block. Each previous hash function is added to the next, creating a chain

BLOCKCHAIN

is a series ("chain") of immutable records ("blocks") attached to a dataset that tell users where data have been, who has modified them and who collected them.

that cannot be broken or altered. Records are created, shared and validated in an open system rather than through a single host. The database is in a network of computers and with the chain function, nothing can be altered or deleted, creating security within big data (Martindale, 2018). This program can be used to digitally record every transaction, agreement, process, task, music, health care records, etc.

Another critical component of blockchain is that it decentralizes management of metadata into a network, which reduces the trust a user needs in an institution to not modify or alter the data. By not trusting any single institution to hold the data, trust can be improved using blockchain technology.

There are many descriptions for potential and active uses of blockchain technology for transactions of currency, use of initial coin offerings (ICOs) to fundraise, and even smart contracts to encourage sustainable actions (Dao, 2017). But an under-analyzed area of this emerging technology is the potential to secure public environmental data and ensure sustainable supply chains.

For scientific data, adding a trustworthy chain of custody could build a culture of openness. If a scientist or other data provider could allow public access to their dataset but still know it is being used by trusted actors or they can put firm limits on when and how it can be used (e.g., an embargo) that may encourage a culture of openness and access to more ecological datasets. Blockchain can ensure the metadata—the data that describes and qualifies the data—remains with the dataset and is not changed or altered by intermediaries. It can also help community data originators know how their effort is used and ensure appropriate credit is given to the authors. A vulnerable or high-security data platform could be built with blockchain from end to end, proving record integrity and monitoring data flows. When legal cases depend on scientific data, such as those respecting industrial development, blockchain could help communities demonstrate the time and date of collection and the impact of analyses performed.

Blockchain has already been used effectively for aquatic sustainability. Recently, a group of companies and charities including the WWF in Australia, New Zealand, and Fiji created a system to trace commercially caught fish from the ocean to the grocery store using blockchain and smartphone-traceable QR code tags placed on each fish.[6] It was developed to let consumers know the fish they were eating were sustainably caught and ethically processed—the blockchain records each step with metadata like time, location and which individuals handled the fish using a smartphone app.

[6] See https://www.wwf.org.nz/what_we_do/marine/blockchain_tuna_project/.

Financial Technologies for Sustainable Ecosystems

The risk with any new technology or suite of technologies—especially those experiencing surges of interest from investors and policy-makers—is dilution of the concrete values of the technology in favour of hype. The Gartner Group—a market research firm—developed a "hype cycle" charting the rapid rise of overinflated expectations followed by a trough of disillusionment before a longer period of maturity (Gartner Group, n.d). Understanding the true promise of new technologies means wading through the hype to reach a clear understanding of the core value each technology provides and how it can address real problems.

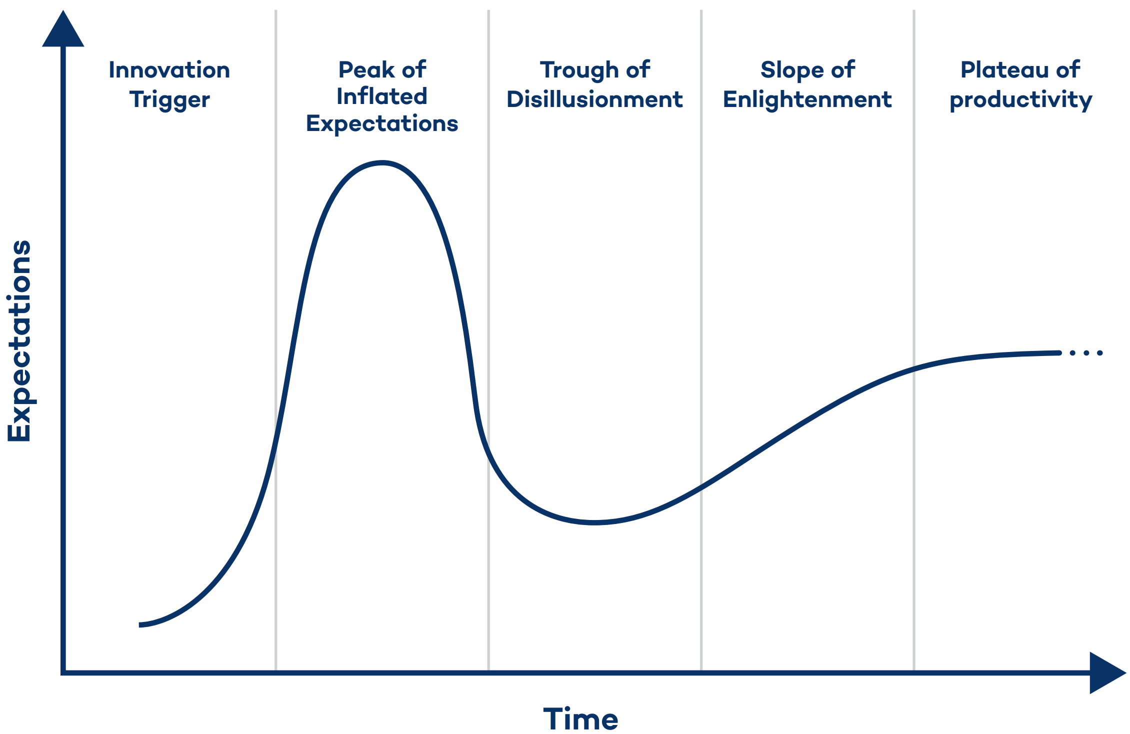


Figure 1. The Gartner Hype Cycle

These problems are highly complex. The 17 global sustainable development goals (SDGs), including Goal 6 on water and sanitation, are attempting to build worldwide momentum for positive change. The success of these outcomes is predicated on robust data systems that can inform us of the state of our world, the trends we are facing and the potential future challenges, so that we can deal with them effectively. Measuring the state of ecosystems, especially aquatic and marine ecosystems, is challenging but so is measuring the return on investment of actions that build resilience to these challenges.

Extreme climate events make these costs clear. According to the Insurance Bureau of Canada (IBC), insured losses are trending rapidly upwards. This is in part caused by major water-related disasters like the 2013 Alberta flood (which saw insured losses of CAD 1.6 billion, CAD 5 billion in estimated total costs and five deaths) and the 2016 Fort McMurray wildfire (with CAD 3.7 billion in insured losses, an estimated CAD 8.86 billion in total costs and two deaths) (IBC, 2018). Collapses of ecosystems and cascading economic costs—to tourism, to fisheries and to real estate—are even harder to measure, but the burden is no less real.

The key values of the discussed technologies align with the challenges faced by our environment and society, both now and in the coming decades. An internet of things, a mix of autonomous sensors and tools used by people in diverse environments, will broaden our detection of threats and trends. An individual with a smartphone can capture the calving of a glacier into the ocean, a new invasive species or an extreme weather event and communicate it to authorities and the world in seconds.

The growing archives of big data will allow us to understand the world in both space and time and deeper trends throughout complex networks. Long-term observation networks, for example, will help us untangle sudden changes from acute events from the chronic impacts of pollution and climate change. The scale and complexity of big data, if managed appropriately, can help us understand systems beyond the reach of an individual's cognition and could help us understand ecosystems, regions and global-scale events.

Artificial intelligence will help us rapidly handle these data by revealing patterns and trends that may be buried in the noise, or more likely in datasets that sit unanalyzed in archives. More efficient use of the limited analytical resources could alert us to problems and help us develop management systems. It is fortuitous that big data is an enabling factor, allowing development of stronger models to forecast the effects of our actions and of the changing climate.

Finally, blockchain technologies could build the trust needed to unlock datasets and encourage more individuals and groups to collect and share data. The next step from "open data" could be "authoritative open data" where the user is confident about the data's provenance and security.

There is, of course, a risk that this is all hype. If those of us generating environmental data do not recognize and prioritize a culture of data openness and transparency, we will not have the tools to take advantage of these technologies. However, five decades ago the Government of Canada took a risk on a "Big Science" endeavour, recognizing a clear need to understand how waterbodies respond to pollutants. In the new paradigm of data-driven science, we need an even larger effort to manage, organize and utilize data using all tools available—especially those improved on by commercial and industrial experts. An uncertain environment and changing climate is no excuse to not invest in a more sustainable future.

References

Bell, G. (2009). Foreword. In T. Hey, S. Tansley, & K. Tolle (Eds.), *The Fourth Paradigm* (xi–xv). Redmond, Washington, United States: Microsoft Research. Retrieved from http://www.astro.caltech.edu/~george/aybi199/4th_paradigm_book_complete_lr.pdf

Borealis AI. (n.d.). *Home page*. Retrieved from http://www.borealisai.com/

Castilla-Rubio, J. C., Zadek, S., & Robins, N. (2016). *Fintech and sustainable development: Assessing the implications*. Retrieved from http://unepinquiry.org/publication/fintech-and-sustainable-development-assessing-the-implications/

Chou, J.-S., Ho, C.-C. & Hoang, H.-S. (2018). Determining quality of water in reservoir using machine learning. *Ecological Informatics* 44 doi:10.1016/j.ecoinf.2018.01.005

Community Collaborative Rain, Hail and Snow Network (CoCoRaHS). (n.d.) *Condition reports*. Retrieved from https://www.cocorahs.org/

Dao, D. (2017). *AI smart contracts: The age of A.I. powered incentives*. Retrieved from https://medium.com/@daviddao/predictive-smart-contracts-dc15b9986d8c

Gartner.com. (2017). *Gartner says 8.4 billion connected "things" will be in use in 2017, up 31 percent from 2016* (Press release). Retrieved from https://www.gartner.com/newsroom/id/3598917

Gartner. (2018). *Gartner Hype Cycle*. Retrieved from https://www.gartner.com/technology/research/methodologies/hype-cycle.jsp

Goldman Sachs. (n.d.). *Blockchain – The new technology of trust*. Retrieved from www.goldmansachs.com/our-thinking/pages/blockchain

Gore, A. (2008). *The digital earth: Understanding our planet in the 21st century*. Speech given at the California Science Center, Los Angeles, CA January 31, 1998. Retrieved from https://www-tandfonline-com.uml.idm.oclc.org/doi/10.1080/00050348.1998.10558728

Hampton, S.E., Strasser, C.A., Tewksbury, J.J., Gram, W.K., Budden, A.E., Batcheller, A.L., . . . Porter, J.H. (2013). Big Data and the future of ecology. *Frontiers in Ecology and the Environment, 11*(3), 156-162. http://doi.org/10.1890/120103

Humanitarian Open Streetmap Team. (n.d.). *Home page*. Retrieved from https://www.hotosm.org/

Iansiti, M., & Lakhani, K.R. (2017). The truth about blockchain. *Harvard Business Review*. Retrieved from https://hbr.org/2017/01/the-truth-about-blockchain

Insurance Bureau of Canada. (2018). *2018 Facts of the property and casualty insurance industry in Canada*. http://assets.ibc.ca/Documents/Facts%20Book/Facts_Book/2018/IBC-Fact-Book-2018.pdf

IBM Big Data & Analytics Hub. (n.d.). *Extracting business value from the 4 V's of big data*. Retrieved from http://www.ibmbigdatahub.com/infographic/extracting-business-value-4-vs-big-data

KPMG. (2017). *The pulse of Fintech – Q4 2017*. Retrieved from https://home.kpmg.com/xx/en/home/insights/2018/02/pulse-of-fintech-q4-2017.html

Lin, T. (2013). Big data is too big for scientists to handle alone. *Wired*. Retrieved from https://www.wired.com/2013/10/big-data-science/

Lucas, M. (2017). *The difference between Bitcoin and blockchain for business*. IBM. Retrieved from https://www.ibm.com/blogs/blockchain/2017/05/the-difference-between-bitcoin-and-blockchain-for-business

Martindale, J. (2018). What is a blockchain? Here's everything you need to know. *Digital Trends*. Retrieved from https://www.digitaltrends.com/computing/what-is-a-blockchain

Nicol, A., Caruso, J., & Archambault, E. (2013). *Open data access policies and strategies in the European Research Area and beyond*. Science Metrix Retrieved from http://www.science-metrix.com/pdf/SM_EC_OA_Data.pdf

Nvidia. (2018). *Progressive growing of GANs for improved quality, stability, and variation*. Retrieved from http://research.nvidia.com/publication/2017-10_Progressive-Growing-of

Pearson, T. & Wegener, R. (2013). *Big data: The organizational challenge*. Bain Capital. Retrieved from http://www.bain.com/publications/articles/big_data_the_organizational_challenge.aspx

Rittel, H. W. J., & Webber, M. M. (1973). Dilemmas in a general theory of planning. *Policy Sciences, 4*(2), 155–169.

Roche, D. G., Kruuk, L. E. B., Lanfear, R., & Binning, S. A. (2015). Public data archiving in ecology and evolution: How well are we doing? *PLoS Biology, 13*(11), 1–13. https://doi.org/10.1371/journal.pbio.1002295

Schindler, D. W., Hecky, R. E., & McCullough, G. K. (2012). The rapid eutrophication of Lake Winnipeg: Greening under global change. *Journal of Great Lakes Research, 38*(SUPPL. 3), 6–13. https://doi.org/10.1016/j.jglr.2012.04.003

Stanway, D. (2018). Beijing shuts big coal-fired power plant to ease smog. *Scientific American*. Retrieved from https://www.scientificamerican.com/article/beijing-shuts-big-coal-fired-power-plant-to-ease-smog/

Wilson Center. (2018). *Earth Challenge 2020, a citizen science initiative*. Retrieved from https://www.wilsoncenter.org/article/earth-challenge-2020-citizen-science-initiative

Wolf, D., & Klaiber, H. A. (2017). Bloom and bust: Toxic algae's impact on nearby property values. *Ecological Economics, 135*, 209–221. https://doi.org/10.1016/j.ecolecon.2016.12.007

Wolf, D., Georgic, W., & Klaiber, H. A. (2017). Reeling in the damages: Harmful algal blooms' impact on Lake Erie's recreational fishing industry. *Journal of Environmental Management, 199*, 148–157. https://doi.org/10.1016/j.jenvman.2017.05.031

World Meteorological Organization (WMO). (n.d.). *History of WMO*. Retrieved from https://public.wmo.int/en/about-us/who-we-are/history-of-wmo

WWF Canada. (2017). *Watershed reports: A national assessment of Canada's freshwater*. Retrieved from http://assets.wwf.ca/downloads/Watershed_Reports_ExecSum.pdf

Published by the International Institute for Sustainable Development.

Head Office

111 Lombard Avenue, Suite 325
Winnipeg, Manitoba
Canada R3B 0T4

Tel: +1 (204) 958-7700
Website: www.iisd.org
Twitter: @IISD_news

IISD

iisd.org