Untapping the Potential of Technological Advancements in Strategic Environmental Assessment

Abstract

Strategic Environmental Assessment (SEA) requires the simultaneous assessment of multiple considerations to identify and mitigate any significant adverse effects on the environment resulting from plan/programme/policy implementation. In order to do this and support decision-making for sustainable development, it relies on sound and scientifically verifiable data from a variety of sources and on analytical tools to identify patterns and predict changes in the data. The advent of big data and technological advancements are highly relevant to SEA given their potential to enhance the evidence-base, better assess, anticipate and communicate environmental effects, and advance overall SEA practice. This review article explores the opportunities of an increased use of smart technologies and approaches in SEA, and proposes an operational framework for smartening SEA. It concludes by identifying a number of new research areas for exploring untapped opportunities in SEA.

Keywords: Strategic Environmental Assessment, Big data, Data analytics, Information and Communication Technology, Evidence-base.

1. Introduction

Strategic Environmental Assessment (SEA) requires that the effects of development plans, programmes and, in some countries, policies are assessed in order to identify and mitigate any significant adverse effects on population and human health, biodiversity, flora, fauna, water, air, climate, soils, geology, landscape, cultural heritage and material assets (Dalal-Clayton and Sadler, 2005; EC, 2001; Fischer, 2007). It simultaneously assesses multiple natural resources and features across spatio-temporal scales when taking into account their current state, likely evolution and potential adverse effects resulting from development and other anthropogenic interventions (Stinchcombe and Gibson, 2001). In order for SEA to achieve its aims and manage the complexities of human-environment interactions, relying on the contribution of knowledge and skills from various disciplines, and on sound, scientifically verifiable data is essential (Fischer 2007). Within this context, an interdisciplinary approach to SEA is crucial not only for unfolding these complexities, but also for addressing cumulative effects (e.g. Gunn and Noble, 2011; Willsteed et al., 2017). Yet, efforts to advance interdisciplinarity in practice are often hampered by knowledge gaps, data limitations and communication difficulties (CLG, 2009; EC, 2009; EPA, 2012). This is exacerbated in the science-practice exchange where scientists are complaining that their inputs are being ignored by decision-makers, whilst decision-makers are saying that scientific information is often not available, accessible and/or readily usable (Liu et al., 2008). It is therefore highly likely that these limitations are resulting in SEAs that are arguably less effective than their full potential, and in the widening of the science and policy/practice gap.

The advancements of Information and Communication Technologies (ICT), geospatial tools and of smart technologies in general are nevertheless transforming science and policy practice. They are producing large volumes of relevant data, commonly referred to as "big data"[1], and providing new means of communication – which can potentially reduce data and knowledge gaps in SEA, by reshaping information generation, management and dissemination. Spatially-specific quantitative and qualitative data collation, analysis and modelling efforts are, for example, already being acknowledged for their contribution to enhanced knowledge and understanding, and for supporting evidence-based assessments and decisions (Cartwright et al., 2016; González, 2012; Ghaemi et al., 2009). Further, open access big spatial datasets are increasingly being seen as central to improving the effectiveness and efficiency of planning and policy, and the transparency and accountability of decisions (Hardy and Maurushat, 2017). On this basis, it is therefore not surprising that the vast quantities, range and scales of data generated, and their accessibility, have led to some proposing data-driven science as a new and legitimate scientific paradigm, because of the way in which it is fundamentally transforming scientific processes and prompting new ways of thinking (Nelson 2009). Science has always relied on data, but it is the changes in the acquisition and storing of data that is making information "free" and accessible, thus creating new opportunities (ibid.). E-visualisation and e-sharing initiatives for open data are examples of how this is happening, contributing to making science and practice more accessible, transparent and accountable. Maximising and exploiting these untapped opportunities are likely to help bridge the science and practice gap; this in turn, can help addressing calls for more integrated, interdisciplinary and holistic approaches to SEA (Gazzola, 2011; Owens et al., 2004). By connecting the content from different disciplines to refine raw data and derive knowledge fit for decision-making, SEA could efficiently move up in the data-information-knowledge-wisdom hierarchy (Rowley, 2007), and provide a better understanding of the complexities and uncertainties inherent in its scope of application.

There is increasing empirical research on innovative methods for supporting SEA that capture some of the above approaches and benefits. However, there is also a dearth of literature on broader opportunities and challenges to the adoption of contemporary data and technology in SEA. This is illustrated by a Scopus search using the following search strings: ('Strategic environmental assessment' OR 'SEA') AND ('big data' OR 'technology' OR 'innovation') which renders no relevant results. The purpose of this paper is to address this gap in the literature, providing a basis for reflection and discussion on the contribution of technological and data innovation to managing/understanding the complexities integral to SEA. Can SEA be *smart* and make the most of the opportunities that research in big data analytics and intelligent ICT solutions can provide to advance practice? Informed by reviews of the literature and set within the context of a wider discussion about how science and data are informing SEA practice, this paper aims to explore the opportunities of an increased use of smart technologies and approaches in SEA, while acknowledging existing limitations. This is done by looking at the extent to which big data analytics and ICT solutions can contribute to SEA's procedural stages using the EU's SEA Directive as a reference – while it is acknowledged that other legislative frameworks exist, procedural stages are similar in other jurisdictions (refer to Dalal-Clayton and Sadler, 2005 and Fischer, 2007 for a review on established SEA systems). It also examines how new ways of thinking triggered by data-driven approaches could enhance and innovate practice. Upon reflection of the significant potential, a working framework for

[1] Big data entails volume (i.e. vast amounts), velocity (i.e. continually and rapidly generated and processed), and variety (many formats from multiple sources) (McAbee et al., 2017). It relates to datasets generated internally and externally (i.e. by the organisation or through the Internet), and actively or passively (e.g. stakeholder survey or location data on mobile phones) by public and private organisations.

facilitating a more proactive integration of contemporary data and technology into SEA practice is subsequently presented. Finally, conclusions are drawn and areas for further research are identified.

2. S*mart* Opportunities in SEA

SEA is applied globally to support decision-making with a view to promoting sustainable development. It is a legislative requirement within the European Union (EC, 2001), as well as in other countries such as Canada (Government of Canada, 2010) or China (Zhu and Ru, 2008). The European SEA Directive sets out the scope and procedure for an SEA, and establishes that the resulting environmental report "(…) shall include the information that may reasonably be required taking into account current knowledge and methods of assessment, (…)" (EC, 2001, article 5, point 2), thus acknowledging the importance of an evidence-base. The Directive also requires an examination of the inter-relationship among environmental factors and the likely accumulation of effects (i.e. cumulative impacts), recognising the complexity of the issues at stake and the need for interdisciplinary approaches.

In light of the above requirements, it can be argued that the contribution of data and technology is paramount to providing best available knowledge on environmental quality and on methods to examine and/or forecast and communicate effects. Interdisciplinary exploration of existing and emerging big data provides a growing potential to amplify the contribution that a smart approach to SEA could have in advancing our understanding of the complex, and offer new ways of thinking in support of decision-making. Subsequently, this section explores these opportunities in SEA and its procedural stages.

2.1. Screening and Scoping

Screening and scoping correspond to the preliminary stages of an SEA. Whilst the first aims to establish whether or not an SEA is required following the criteria set out in Annex II of the Directive, the latter determines the range of environmental issues to be covered by an SEA and their level of assessment detail, as required by Annex I. Carrying out these stages, amongst other tasks, entails establishing the baseline conditions against which any determination about the next stages of the process are made, for which data will need to be gathered. The data can be of various types, concern different environmental receptors, and be sourced from different applications and agencies.

Given the short time-frames allocated to the screening and scoping stages, supporting data are commonly gathered from readily available and publicly accessible sources (e.g. governmental data portals). They are used to provide a descriptive account of technical environmental characteristics, and identify critical vulnerabilities and issues. Data are complemented with interdisciplinary scoping workshops engaging stakeholders and scientists; their qualitative expert-judgments help define the scope of SEA. Simple Geographic Information Systems (GIS) are often used as support tools in scoping, by providing a quick account of the baseline environment, defining the geographical envelope and scale of the assessment, and facilitating science-practice communication (González et al., 2011; Bohman et al., 2015). Big data can augment the effectiveness of these stages and the potential of conventional analytical tools such as GIS. By enabling multi-scalar, multi-temporal and wide coverage data and information on past, present and future conditions of numerous socio-economic and environmental factors through SEA, big data can enhance our understanding of the multiple considerations and inter-related nature of environmental resources and human-environment interactions.

2.2. Impact Assessment, Alternatives and Mitigation

Once it is established that an SEA is needed and its scope has been defined, then the proposed plan, programme or policy (PPP) goes through an environmental assessment. This stage establishes the likely significant environmental effects, both positive and negative, of implementing a PPP. It includes the appraisal of reasonable alternatives, taking into account the extent to which viable mitigation measures might help to avoid, reduce or offset adverse effects.

Current SEA practice suggests that generic datasets and methods are commonly applied in these stages. The assessments often rely on either: a) matrix-based expert judgments to contrast PPP objectives against environmental protection objectives; or b) the use of GIS to spatially assess alternatives against previously prepared baseline maps (e.g. suitability analysis – Geneletti, 2008; González et al., 2011). Although efforts have been made to develop GIS-based decision-support-systems (DSS) for SEA (e.g. Chrysoulakis et al., 2013; González 2017), these have rarely been applied in practice; GIS applications in SEA remain basic (González, 2012, Riddlesden et al., 2012). Big data analytics can augment the evidence-base of such methods through data mining by means of descriptive models (to discern trends and patterns) and predictive models (to extrapolate from those trends and patterns and predict/anticipate changes) (Hardy and Maurushat, 2017). Certain SEA themes listed in Annex I of the Directive, such as air and climate, extensively avail of the many descriptive and predictive modelling applications linked to remote sensing data (e.g. Debbage and Sheperd, 2015; Gupta et al., 2006; Meesuk et al., 2017). Research on natural resource dynamics and valuation, related to the SEA-themes of biodiversity and water for example, have also been proven to significantly benefit from citizen science data and modelling (e.g. Gill and Mockler, 2016; Gontier et al., 2010; Li and Liu, 2017).

2.3. Monitoring

Monitoring is an important stage of SEA, as it seeks to ensure that once implemented, PPP are not generating unforeseen or more significant adverse environmental effects than those anticipated, and to ensure that the mitigation measures put in place are working. If not, where adverse effects are occurring, remedial action should be taken. Nevertheless, monitoring has been acknowledged to be problematic in practice (e.g. Gachechiladze-Bozhesku and Fischer, 2012; Partidario and Arts, 2005), and the associated data requirements costly and time-consuming advocating the use of existing data and monitoring arrangements (Cherp et al., 2010; Partidario and Arts, 2005).

Recent technological advancements on remote sensing data access and manipulation provide opportunities to perform spatially continuous and frequent observations of multiple natural resources and parameters enabling identification of change which could be easily integrated into SEA monitoring. This could be complemented with the benefits of localised monitoring through citizen science. Stepenuck and Green (2015) provide a systematic review of volunteer environmental monitoring, and a number of ongoing international projects promote citizen engagement in monitoring urban environmental pressures (Carton and Ache, 2017).

2.4. Public and Stakeholder Participation, Consultation and Engagement

SEA processes require stakeholder consultation under the Aarhus convention and the provisions of the related Directive 2003/35/EEC on public participation. SEA effectiveness reviews have pointed to current practice being affected by diverging levels of effort in facilitating public participation (CLG, 2009; EC, 2009; EPA, 2012). ICT innovation provides new opportunities for public engagement: from the timely, meaningful and accessible dissemination of scientific information through online interfaces, to the use of social media and participatory GIS for collating values and perceptions of stakeholders, practitioners and the general public on environmental resources and services (e.g. Kingston et al., 2000; Majumdar, 2017; Oteros-Rozas et al., 2017; Wagner Figueroa-Alfaro and Tang, 2017; Weiner and Harris, 2003). Although current practice suggests that ICT is commonly used for information delivery rather than exchange (i.e. two-way communication), technology-aided online communication and participation tools not only enable greater access to scientific data and environmental assessment processes, but also benefit assessments by improving data quality through local knowledge (González et al., 2008). Geospatial tools such as participative mapping and DSS, for example, also enable the incorporation of subjective values on relative importance and significance of natural resources (e.g. González et al., 2011; Marull et al., 2007). These tools complement citizen science initiatives for data collation.

Based on the review presented, there is therefore scope for big data analytics and ICT to contribute to improving the effectiveness of SEA, by transforming the way in which science informs practice and supports decision-making, replacing former model-driven approaches to data-driven methods, and promoting more open and participative processes. The next section explores in more detail how a transition to a smarter approach to SEA could be achieved, by looking at how these untapped opportunities could inform technological strategies for advancing SEA practice.

3. Technological Strategies for Advancing SEA Practice

There is no denying that we live in an information-based society, and that there is scope for the vast amount of data and information generated to be used to reduce the science and practice gap, and to be better exploited for the benefit of the wider society and of the natural environment. In this context, adopting a *smart* approach to SEA could be instrumental and offer a framework within which big data, data analytics and communication technologies can be used to understand and better manage the complexities surrounding human-environment interactions in a more transparent, open and accountable manner, strengthening the evidence basis for decision-making. In this context, three technological strategies for achieving *smarter* SEA are explored in more detail, and their opportunities and pitfalls are summarised in Tables 1, 2 and 3.

3.1. Big Data – Increasing the Evidence-base

As discussed above, technological advancements, increased deployment of satellites and sensors, and the rapid uptake of citizen science apps have resulted in a big data explosion. However, many environmental areas are still suffering from a shortage, and often an absolute lack of relevant data (Wehn and Evers, 2015), despite good practice calling for evidence-based informed decisions. To address this gap, remotely sensed data (e.g. Earth observation and sensor networks, commonly referred to as big Earth data) and citizen science (e.g. crowdsourcing initiatives) are increasingly being integrated in environmental studies (e.g. de Araujo Barbosa et al., 2015; Liu and Liu, 2017;

McKinley et al., 2017), and evidence of their contribution to environmental policy is starting to emerge (e.g. Sizo et al., 2016; Vann-Sander et al., 2016).

The substantial increase in the number of Earth observation satellites and sensors enables uninterrupted observation of Earth phenomena (e.g. socio-economic pressures and environmental receptors), their location, spatial distribution, processes and status. They enable systematic, replicable and cost-efficient monitoring of large areas, providing valuable information impossible to be acquired by field assessment alone (Nagendra, 2001). Increased geospatial computation capabilities are facilitating associated data processing, unveiling new insights in the service of informed development (Guo et al., 2016). Big data from space includes multiple temporal and spatial scales within the Earth system, enabling an historical examination of multiple variables at various levels of detail, whilst facilitating detection of environmental change. This ability to address and capture spatio-temporal scales is highly relevant to SEA given the varying geographical and temporal extents of plans/programmes.

Guo et al., (2016) observe that knowledge mining from remote sensing data implies data-intensive storage, advanced automation of data processing and intelligent computing which, in the context of SEA, require collaborative approaches. Geospatial tools have the capacity to tackle some of these requirements (González 2012; Palomino et al., 2017), though more research is needed. The parameters of big Earth data (e.g. captured variables and their resolution) can directly influence assessments and should be carefully considered in terms of SEA scale and desired strategic planning outcomes (Sizo et al., 2016). Moreover, big Earth data are commonly collated through time-bound research funding calls which do not always enable long-term series, and corporate initiatives (e.g. NASA, Google) may limit accessibility to certain data (Guo et al., 2016; Petrou et al., 2015). Although certain sources are increasingly made available (e.g. Landsat and Sentinel), the ability to discover data is variable, given the complex set of portals, geo-libraries, and data centres that users access (Guo et al., 2016). Even when accessible, they have not yet been fully exploited in operational tasks (Pettorelli et al., 2014), mainly because of the technical challenges in handling and examining the data by non-experts which can also affect cross-sectoral communication – e.g. between environmental scientists and remote-sensing scientists (Petrou et al., 2015).

The interdisciplinary nature inherent to SEA, its baseline and monitoring data requirements, and its public engagement and consultation obligations can significantly benefit from the local evidence and perceptions captured by citizen science initiatives (McDonough MacKenzie et al., 2017; McKinley et al., 2017). Citizen observatories, for example, are being developed by scientists and independently by concerned community groups to provide a platform for information gathering and exchange on specific research areas (e.g. flood risk – Wehn and Evers, 2015; microplastics – Galgani and Loiselle, 2017; climate change and plant phenology – McDonough MacKenzie et al., 2017), in a manner that is more efficient than conventional science as they operate at larger geographic extents and over longer periods at greater resolutions (McKinley et al., 2017; Nelms et al., 2017). The wider social media has also been applied to gather perception-driven qualitative information and data (e.g. Oteros-Rozas et al., 2017; Vogel et al., 2007; Wagner Figueroa-Alfaro and Tang, 2017). By enabling cooperation between citizens and decision-makers, these initiatives can often promote joint-up thinking and co-creation of innovative shared solutions (e.g. Carton and Ache, 2017; Vogel et al., 2007).

Despite the various applications and perceived benefits, McKinley et al., (2017) observe a number of limitations affecting the contribution of citizen science to science including: the knowledge, skills and ability of volunteers to meaningfully contribute; the popularity, public interest or concern of the research area; and the geographic location of required measurements/data. They also point to the localised nature of certain projects, limiting the extent of use of collated datasets in wider geographical areas and assessments. Unlike remote sensing, the contemporary nature of citizen science limits its contribution to the analysis of historical trends (as present-day data are only available). As a result, the credibility, legitimacy and utility of such information in decision-making has been widely questioned, and a number of authors call for careful data review and quality checks (e.g. Majundar, 2017; McKinley et al., 2017; Starbird et al., 2012).

[INSERT TABLE 1 HERE]

Table 1. Key opportunities and pitfalls of applying big data to support Strategic Environmental Assessment (SEA).

3.2. Data Analytics – Advancing Understanding of Human-Environment Interactions

Data analysis and associated modelling have been recognised to provide an impartial lens on the world; they can provide empirically valid explanations of natural, technological, and socio-economic processes, and anticipate the consequences of such processes on society and the environment (Hutchings and Stenseth, 2016). Contemporary research shows an increasing trend in the importance of geospatial tools and modelling to examine human-environment interactions, anticipate future environmental change and solve environmental problems (Hritonenko and Yatsenko, 2013; Sun et al., 2016). This is gaining momentum with the prospects of such analytical tools tapping into big data to derive new insights and knowledge. Big data analytics make data-driven knowledge discovery possible. However, big data analytics are considered complex due to computational platforms, computing power, machine learning and data processing knowledge requirements (Akoka et al., 2017; Horita et al., 2017). Yet Guo et al., (2016) argue that data-driven approaches seem to be an inevitable trend in science for studying the objective world and discovering patterns. Such quantitative and objective approaches can be complemented with more qualitative and subjective data, so that values, common knowledge and uncertainties related to the political nature of decision-making are also fed into the process (Gazzola, 2011). Incorporation of biophysical variables with subjective public values (e.g. examination of remote sensing data through public participation GIS) enables contextualising assessments by capturing differentiations in sectoral and local perceptions (Adger, 2006). Interdisciplinary expert knowledge and perceptions can also further the evidence-base (Dietz and Stern, 2008; Gupta, 2008). In this context, participative GIS and DSS can provide tools for multi-criteria analytics that account for objective and subjective considerations (e.g. Chrysoulakis et al., 2013; Geneletti et al., 2007; González et al., 2011; Marull et al., 2007), both relevant to SEA.

The application of modelling in SEA is constrained by the inability of models to be systematically applied to the wide range of issues considered (Fedra, 2004; Mcintosh et al., 2005). Similarly, multi-criteria GIS and DSS approaches are generally research-oriented and have seldom translated into SEA practice – possibly because they are data intensive and require specialised skills and input (González, 2017; Mcintosh et al., 2005; Riddlesden et al., 2012). The growing uptake and publication of complex data mining and modelling approaches has been reported to muddle knowledge – practitioners and researchers often struggle to comprehend forecasting methods and results (Green and Amstrong, 2015). Similarly, the existence of uncertainties is likely to affect the trustworthiness of the data and the assessment results (Petrou et al., 2015). Although data analytics are used to identify trends and patterns, and model future changes (of which little we know and data do not exist), the absence of reliable and accurate foundational data (representing a baseline or historical trends) or incorrect analytical/modelling assumptions could hinder the capacity of the assessment framework to generate any meaningful and/or reliable results (Ciffroy et al., 2016). These uncertainties are further exacerbated when multiple scientific disciplines are jointly considered and a large number of data are necessary within the model or the analytical framework (ibid), as is the case in SEA.

The above has significant implications for SEA, as the main objective of the assessment is to integrate environmental considerations into planning and decision-making (EC, 2001; Fischer, 2007). This objective can hardly be achieved without an understanding of the environmental implications of the proposed PPP actions. Making policy and planning decisions on the basis of poorly understood assessments could be characterised as faith-based decision-making (Green and Amstrong, 2015).

[INSERT TABLE 2 HERE]

Table 2. Key opportunities and pitfalls of applying data analytics to support Strategic Environmental Assessment (SEA).

3.3. Communication Technology – Bridging Science, Practice and Governance

Empirical data and expert knowledge can be critical in resolving complex environmental problems; not communicating them responsibly and not using them wisely and efficiently can lead to misguided understanding, lack of stakeholder confidence and poor decision-making (Green and Armstrong, 2015) and, ultimately, result in significant environmental costs (Hutchings and Stenseth, 2016). Numerous studies illustrate the use of scientific data and knowledge to guide regulatory and policy development and decision-making, as well as to evaluate the hypothetical outcomes of substitute decision routes (e.g. Hutchings and Stenseth, 2016; Milkoreit et al., 2015; Sizo et al., 2016). The weight of evidence derived from scientific research is constantly subject to peer review, promoting clarity and accountability in backing or opposing a given environmental policy or measure. This provides a clear opportunity for addressing the mandatory requirement for best available contemporary knowledge to support SEA and effectively inform decision-making. To achieve this, there is a need for better science communication (Bohman et al., 2015; Cartwright et al., 2016; Milkoreit et al., 2015), between scientists and stakeholders, and between modellers and practitioners.

A number of studies have examined the effectiveness of communication mechanisms to convey complex science to stakeholders and the general public (e.g. Cartwright et al., 2016; Michielsen et al., 2016). When applying big data analytics in SEA, there are two key aspects that need to be efficiently communicated to stakeholders: a) the nature and characteristics of the data incorporated into the model/analysis; and b) the accuracy/credibility of the model/analysis (i.e. mathematical algorithm, assumptions and uncertainties). It needs to be done in a comprehendible format to match the interpretative abilities of stakeholders and decision-makers. This can be achieved using boundary objects that intersect the science, practice and policy domains, such as interactive indexes, maps or infographics which can ease scientific information into practice and policy debates (Leith et al., 2014). The visualisation capabilities of GIS in particular have the potential to facilitate communication and understanding (Bohman et al., 2015; González et al., 2008).

Although not always easy to conceptualise and understand by a non-scientific audience, communicating any associated uncertainties is also imperative as uncertainties can influence decisions, and their miscommunication can increase distrust in science (Wardekker et al., 2008). Argent et al., (2016) also observe that modelling results and certain boundary objects are, occasionally, not fully trusted as they can be wrongly perceived as being subject to manipulation by experts and policy-makers. This is potentially due to the highly politicized, complex and recurrent relationship between forecasting and decision-making (Ludwig, 2001; Sarewitz, 2004), or to the relative suitability of the boundary objects used (Leith et al., 2014). As a result, there is a growing community of scholars who are operating at the boundary between science and practice/policy (Milkoreit et al., 2015), to cultivate effective communication. Social media can be used to alert the public about ongoing initiatives and issues, and communication metrics can give an indication on environmental awareness or concerns (e.g. Finch et al., 2016; Hynes and Wilson, 2016). Similarly, e-Government is emerging as a tool for improving communication and consultation channels and information management in a cost-effective, accountable and transparent manner (e.g. through e-sharing and e-visualisation of data and information). Although a range of online tools are emerging to inform policy and practice, these are yet to be systematically integrated into SEA for a meaningful contribution to the process. Moreover, e-literacy limitations and lack of access to Internet can hamper the effectiveness of online communication and the achievements of the improvements expected (González et al., 2008), and result in segmentation of the population based on income and education and loss of person-to-person contact affecting participative decision-making.

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Table 3. Key opportunities and pitfalls of applying Information and Communication Technology (ICT) to support Strategic Environmental Assessment (SEA).

4. An Operational Framework for Integrating Big Data, Analytics and Communication Technology Advancements in SEA

Based on the opportunities and pitfalls presented, an operational framework for integrating big data analytics and intelligent ICT solutions in SEA practice is subsequently proposed and represented in Figure 1. The framework is intended to provide a basis for their proactive consideration. While acknowledging that some of these data and technological advancements may already be applied in discrete SEAs, it is argued that a more systematic integration has the potential to advance SEA practice. This is based on the view that recent (and ongoing) technological advancements can be instrumental in managing and understanding the complexities of human-environment interactions integral to SEA's scope and nature, as a process that sits at the interface between science and policy. Nevertheless, in order for this to occur, it is essential that scientists, SEA practitioners and technology experts are able to communicate across technical backgrounds, languages and sectors, so that (big) data generated can be relevant to the purpose of SEA, readily usable as evidence and accessible to policy-makers and the wider public. Fluidity and openness in communications should also be extended to the way in which big data is used in SEA's procedural stages, so that the iterativeness between stages, knowledge and flow of data are maximised.

As shown in Figure 1, big data can provide significant opportunities to enhance the initial and latter stages of SEA in particular, that is, the baseline and monitoring stages. The provision of high-quality and detailed data over wide geographical areas can address some of the existing data limitations in SEA such as resolution issues and data gaps relating to geospatial extents and attribute completeness (González, 2012), and provide a more accurate account of existing environmental conditions. In addition, the ability of Earth observation sensors and citizen science to record data long-term and, in some cases, make it available real-time can enable rapid identification of unforeseen impacts and examination of change over time, provided that efforts are made to support data continuity, long-time series and accessibility (Kuenzer et al., 2014; Turner et al., 2013).

[INSERT FIGURE 1 HERE]

Figure 1. Proposed operational framework for integration of big data and technological advancements in Strategic Environmental Assessment (SEA).

Data analytics are most applicable to the central stages of SEA, entailing the identification and definition of alternatives, their assessment and the mitigation of any identified impacts. Their capacity to extract spatio-temporal trends and patterns from big data, and to forecast scenarios can contribute to systematic, objective and robust assessments and promote data-driven decision-making (Cartwright et al., 2016), whilst augmenting traditional assessment methods (González, 2012). Through computational tools, multiple datasets (of various sources and formats, and gathered in different places at different times) can be brought together in SEA. Though this has always been possible on a small scale, emerging geospatial data management and analytical capabilities can support the practice of assessments of unprecedented complexity and scope (McAbee et al., 2017). For example, tailored DSSs based on advanced GIS applications and predictive modelling can facilitate a rapid and efficient manipulation of big data, and more geographic, participative and comprehensive assessments to increase knowledge, raise awareness and better inform decision-making (e.g. Barford and Salling, 2015; Chrysoulakis et al., 2013; González 2017; Kontokosta and Johnson, 2017). A systematic and transparent approach to SEA is also imperative for effective communication and enhanced public understanding. As previously discussed, ICT can play a significant role in promoting wider public participation in environmental decision-making and better environmental governance, for example through e-Government initiatives supported by appropriate boundary objects tailored to the relevant audience.

5. Conclusions and Future Research

In the current “smart” era, there is no doubt that technology, data and analytics are all playing integral roles in our information-based society and knowledge-driven economy which ultimately operates within and informs policy. But it is the rapid technological progress for big data generation, exploitation and dissemination that are presenting significant yet untapped opportunities to improve our understanding of human-environment interactions through SEA practice. They have the potential to transform the sciences of the complex, by identifying, explaining or measuring connections and correlations between data about real and concrete things prompting new ways of thinking.

The question of how smart do SEAs need to be to understand and manage the complexities of human-environment interactions and provide useful information and relevant recommendations to decision-makers can be endlessly argued. This paper is to contribute to this wider debate around the science and art of SEA. Whilst it is true that there are untapped opportunities that could strengthen the scientific basis of SEA and render it smarter, it is also important to take note of the pitfalls identified affecting outcomes, and avoid falling in the trap of scientific obscurity. From an SEA perspective, it is particularly crucial that whilst becoming *smarter*, the process is participative and inclusive, so that the interests of all stakeholders and the views of all participants are taken into account, and access to valuable intrinsic expert, technical and local knowledge is not lost altogether, or lost in translation. It is also important that the interdisciplinary, and often political, character of SEA does not become overwhelmed by scientific data and complex analytical methods. This implies understanding what is the 'right' information for decision-making (i.e. what is meaningful evidence in a given context), and communicating scientific data appropriately across the various governance tiers and to all relevant players. At the heart of SEA is the need to facilitate understanding and foresight on potential significant adverse effects and, in this context, "simple is good" (Zellner, 2001). Thus, SEA should be "smart" enough to continue to rely on knowledge and skills from various disciplines informed by different types of data to convey the complex in simple terms. Ultimately, this can contribute to making more informed and robust decisions.

In light of the above and of the proposed operational framework, four new research areas of untapped opportunities for advancing SEA practice are put forward. First, big data mining to enhance the evidence-base of SEA as there is a dearth of research in the use and integration of remotely sensed data and citizen science in SEA. Second, applications of advanced data analytics in real-life case studies to identify environmental change and foresee impacts should be conducted; as noted by Guo et al., (2016), more integration of research is needed for fusing multi-source spatial and non-spatial data of physical, chemical and biological characteristics to obtain a comprehensive evidence-base. Third, more research into how SEA can tap into smart technologies as a mechanism for strengthening and widening participatory decision-making and achieving better governance is needed. These three research areas warrant a reflection upon the capacity of science to substantiate the political nature of the process. It is imperative to examine existing differences between what data constitutes evidence and what is considered evidence by whom and in which context. And in light of this, tailor the collection of relevant and purposeful data for providing meaningful information. As discussed throughout this paper, the potential of big data and technological advancements to enhance and smarten SEA practice is also curtailed by a number of limitations. The applicability of the proposed operational framework warrants therefore further examination, presenting an additional overarching research area so that the identified opportunities and pitfalls can be validated and explored, and new ones uncovered.

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