Chapter 16
Machine Learning for ‘Strategic Conservation and Planning’: Patterns, Applications, Thoughts and Urgently Needed Global Progress for Sustainability

Falk Huettmann

> *“National Parks are just a rather poor transitional protection scheme by the currently dominating western world trying to put the more serious destruction on hold before better systems are found to truly achieve global sustainability”*
>
> *Source unknown, Writing Center, University of Alaska Fairbanks campus, 2014*

Arguably, the modern western life-style and culture has dramatically marginalized the state of the global environment and its natural resources (Daly and Farley 2011; see Czech et al. 2000 for impacts and Walther et al. 2016 for wider implications). It comes then to no surprise that - as a global pattern - the environment is by now in a state of global crisis (Mace et al. 2010 and Cockburn 2013 for a generic assessment). While humans have used the earth for millennia and made a certain footprint (see Groube et al. 1986 for an example of 40,000 years of documented human occupancy and Flannery 2002 for its benign impacts), the specific anthropogenic footprint and impact of the last four decades remain unprecedented in terms of extinction and global climate change (Rockström et al. 2009, Baltensperger and Huettmann 2015). It is noteworthy that the predominant governance paradigm during this period is globalization, based on Americanization (Czech 2000; Stiglitz 2003). The last few decades are arguably the worst managed in human history (Paehlke 2004; Alexander 2013). Actually, the history of the earth and universe as we know it has not produced such a destruction of life (by non-cosmic events) ever before (Cushman and Huettmann 2010); consider the outlook of what will easily be 10 billion people

F. Huettmann (✉)
EWHALE Lab, Biology and Wildlife Department, Institute of Arctic Biology, University of Alaska-Fairbanks, Fairbanks, AK, USA
e-mail: fhuettmann@alaska.edu

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in the next 100 years while global temperatures are also on the rise and most natural resources are already used up (Rockström et al. 2009)!

While I leave it here to others to assign that blame and to document impacts in great detail (Rich 1994; Czech et al. 2000; Huettmann 2011; Cockburn 2013), a way out of this crisis - moving forward in the best-possible fashion - is likely to be pro-active (e.g. to avoid problems before they occur) and to be pre-cautionary (e.g. to identify problems ahead of time and act carefully; Huettmann 2007a, b). The notion of "the need to know impacts ahead of time before they occur" are not new concepts in conservation though (Silva 2012), and they are by now mandatory by the U.N. and part of 'best professional practices' (http://unesdoc.unesco.org/images/0013/001395/139578e.pdf). This is a key ingredient for good governance and for a trusted leadership. Machine learning plays a central role in this approach, and for achieving the best-possible predictions, to be obtained by the best-available science (Huettmann 2007a, b) before impacts occur, e.g. for Alaska see Murphy et al. (2010), Baltensperger et al. (2015), Huettmann et al. (2017).

However, it is easy to show that, thus far, Strategic Conservation Planning does not use much machine learning (see Ardron et al. 2008 and Moilanen et al. 2009 for 'best professional practices' and textbook). Instead, the Strategic Conservation Planning tool has been almost entirely a stand-alone approach not connecting with machine learning. Mostly it relies just on optimization algorithms to find the best solution, such as for instance the 'simulated annealing' algorithm (as employed by MARXAN http://www.marxan.org/; Martin et al. 2008). Further, most MARXAN applications "do not look much into the future" , e.g. by using future scenarios obtained from machine learning and optimizing those ones (see Nielsen et al. 2008 and Murphy et al. 2010 for an application). Instead, latest developments actually deal with optimizing in 'zones' - subunits- (http://marxan.net/index.php/ marzone; Watts et al. 2009). I find this to be a problem on three accounts: (i) The latest science, machine learning, and related potential got ignored. (ii) Breaking down a spatial optimization problem into small separate, parsimonious, zones loses the overall optimization power, and (iii) relevant progress got somewhat stifled by forcing creative minds and their solutions back into existing administrative boundaries and units and thus just re-confirming existing problems and patterns. In this chapter, I outline how machine learning has been used and how it could play a larger role in Strategic Conservation Planning projects towards true progress beyond circular reasoning and traditional mind traps. I am adding relevant perspectives on carrying capacity, limits of the earth and global governance to achieve global sustainability.

16.1 How Machine Learning Predictions Feed into Strategic Conservation Planning: A Common Sense Workflow Still Widely Underused for its Conservation Potential

One of the largest Strategic Conservation Planning projects was designed to make recommendations for the marine protected area (MPA) networks. Similar to the terrestrial national parks of the world, it is meant to protect the world's oceans and assure that a fixed percentage (~10%) set aside (Aichi targets for 2020 by the U.N.: https://www.cbd.int/sp/targets/)! Strategic Conservation Planning has also been applied to terrestrial systems, although many of these earlier approaches were just *ad hoc* and not optimized much for relevant conservation gains (see Table 16.1). Global applications that involve wider and holistic concepts such as the atmosphere and its protection are still lacking (but see Huettmann 2012 how to include those aspects). Arguably though, one cannot achieve sustainable solutions on a small scale because all is highly connected and influenced globally.

In the marine world, the Great Barrier Reef, Australia, has one of the longest histories of Strategic Conservation Planning (UNESCO Great Barrier Reef Marine Park Authority 1981. Fernandes et al. 2005). The task was here to identify the most relevant reef locations for human enjoyment in perpetuity (see end of the chapter for its outcome, thus far) and much can be learned from that ‘experiment’ and exercise.

Widely used software for such Strategic Conservation Planning are MARXAN, but also ZONATION (Lehtomäki and Moilanen 2013), and C-Plan (http://www.edg.org.au/edg-free-resources/cplan.html) as well as many derivatives across operating systems and software implementations (e.g. https://www.aproposinfosystems.com/solutions/qmarxan-toolbox/). Such software helps users by finding ‘the optimal’ solution through an approximation for an assumed truth. The underlying theoretical differences between software packages is not described here but can be found in their respective manuals and URLs, as well as elsewhere in the conservation literature.

For being successful and without relevant errors, Strategic Conservation Planning projects usually require substantial input of information (data). Ideally, maps of species ranges and conservation features for the study area and its planning units are to be available. The study area consists of planning units (PUs, which are often ‘bins’ e.g. hexagons or pixels). This highly detailed information is widely missing for larger study areas, however, conservation decisions must still be made while destruction is ongoing (Alidina et al. 2008). That is specifically true for a global scale and on a macro-ecology perspective (see Forman 1995 for an effective balance using ‘a regional scale’). How can we overcome the problem of data gaps fast enough and with reliable information so that we can make informed conservation decisions in the best way possible for large areas of the globe?

In the past, so-called *ad hoc* decisions were made with political convenience and opportunism driving the agenda (see for instance Huettmann and Hazlett 2010 for Alaska). The protected area network for most of the circumpolar Arctic, in Russia (Spiridonov et al. 2012 for the Russian arctic) or all of North America reflects just that (‘*protection of rock and ice*’ Scott et al. 2001). Experts got used to identify and fill data gaps in Strategic Conservation Planning projects. In addition, scoping meetings are often held with commercial stakeholders. This is widely referred to as a delphi process (a non-scientific process that simply banks on agreements and compromises made during a session). The use of experts is known though to be biased and has been widely criticized for years and was assessed accordingly (e.g. Perera et al. 2012; see Gonzales et al. 2003 for a real-world example). Those planning efforts may not be representative; and often just the most effluent, vocal or

Table 16.1 Overview of a global selection of conservation priority areas and conservation networks

Project name and citation	Location	Relevance	Computational tools involved
Path of the panther ('Jaguar Trail'; http://www.ecoreserve.org/tag/path-of-the-panther/)	Central America	Probably the biggest initiative for connecting North and South America in ecological terms	None
YtoY (Yellowstone to Yukon; https://y2y.net/)	North America, Rocky Mountains	Tries to protect and connect areas in the Rocky Mountains, also relevant for major watersheds	None
10% protection of polar temperature and associated animals (Huettmann 2012)	Arctic, Antarctic and Hindu Kush Himalaya	The global climate chamber, endemic species as a world heritage	Marxan
Africa's traditional protected areas (e.g. http://www.critical improv.com/index.php/surg/article/view/1987/2670)	Africa	African wildlife and national parks as a world heritage	None
RAMSAR convention (http://www.ramsar.org/)	Global	Global wetland conservation policy	None
Important bird areas (IBAs; http://www.birdlife.org/worldwide/programmes/sites-habitats-ibas)	Global	Global waterbird conservation	None
Great barrier reef (e.g. Fernandes et al. 2005)	NW Australia	One of the finest coral reefs in the world	Marxan
California coastal protected zones (http://www.californiamsf.org/pages/about/strategicplan.html)	California	California as a land and coastal area of global relevance	Marxan, CALZONE etc.
Circumpolar Arctic	Polar	A global climate chamber, global endemism	None (Spiridonov et al. 2012; but see Huettmann 2012, Spiridonov et al. 2017 and Spiridonov et al. 2017 for Marxan)
Global MPA network (http://www.mpatlas.org/)	World-wide	The globe's ocean protection	Marxan

wealthy stakeholders drive the process. The delphi method can easily compromise the entire objectivity, fairness, quality and transparency of Strategic Conservation Planning and of its science, process and trustworthiness overall.

It is here where machine learning offers help. It can provide a solution to the problem of filling data gaps with the delphi method. As shown in Drew et al. (2011)

SDMs can be produced with transparent, repeatable methods using open access data (see GBIF.org for species data, and worldclim.org for environmental data) with open source models (e.g. Openmodeler http://openmodeller.sourceforge.net/om_desktop.html or commercial models (SPM https://www.salford-systems.com/). The SDMs with the highest accuracy tend to use machine learning; see Elith et al. 2006 and Fernandez-Delgado et al. 2014 for a review of the highly performing algorithms available.

However, despite the easy access, very few SDMs are actually run for, or used by, Strategic Conservation Planning projects (Moilanen et al. 2009; but see Beiring 2013 for an example how SDMs are employed for Strategic Conservation Planning). There are several reasons why that problem still exists, as outlined in Table 16.2.

In my experience, available SDM applications are never really sufficient and not truly complete for Strategic Conservation Planning exercises (see Table 16.3 for shared experiences). In addition, SDM accuracy is another topic to watch for. That's because SDM accuracies are usually inconsistent across species in a study area, and which does not allow then for consistent inference or application. Sometimes SDM performances can be too low to be useful or to be employed to larger areas (Aycrigg et al. 2015). Overall, I often find that limited and sparse raw data cannot provide consistent and year-round spatial estimates of important demographic and ecological parameters such as fecundity, winter survival and migration risk for instance. SDMs rarely are applied yet to provide demographically relevant spatial estimates such as mating places, productivity hotspots and mortality landscapes (often summarized as 'sources and sinks'; Pulliam 1988). On the one hand, the detail that would be ideal and needed is rarely possible to achieve with demographic tools

Table 16.2 Some reasons for SDMs not being used in strategic conservation planning projects

Reason	Implication	Fix	Comment
SDM does not make predictions widely available	SDM results are just 'shiny' and not used	Request all SDM model files to be fully open access with ISO metadata	This is a common problem in SDM projects, e.g. see Guisan and Zimmermann (2000); Guisan and Thuiller (2005); Franklin and Miller (2009) but see Drew et al. (2011)
Strategic conservation planning project runs out of time	Not all species considered and some information under-utilized	Realistic time window needed for planning	Many agencies do not have adequate resources for all planning projects
Strategic conservation planning project runs out of money	Not all species considered and some information under-utilized	Realistic budget planning; cost-effective methods needed	Many agencies do not have adequate resources or technical capacity for all planning projects
Strategic conservation planning project ignores ecological complexities involving 'all' species	A reductionist and simplistic approach gets applied	Admission of incompleteness; focus on multivariate approaches	A so-called pragmatic [a]approach is frequently applied

[a]Being pragmatic does not solve the initial problem and creates problems of its own

Table 16.3 Shared experiences for SDM approaches in strategic conservation planning type projects

Project	SDM application	Strength	Weakness
Conservation assessment for Asian passerine migrants (Beiring 2013)	Provide species range estimates as input into MARXAN	First models and migratory bird estimates produced	Lack of good data. Lack of stakeholder support. SDM accuracy rel. low
Alaska corridors (Murphy et al. 2010)	Provide species range estimates as input into MARXAN	First models and estimate for 4 species produced	Legal constraints not allowing to address land ownership issues and buy-outs or such discussions and planning. Virtually left unused by stakeholders.
Arctic protection (Huettmann and Hazlett 2010, Spiridonov et al. 2017, Solovyev et al. 2017)	Suggested to use SDMs to start strategic conservation planning	GIS data and model discussion starts the conservation gap and management work	Unless designed specifically with local knowledge and citizen science, it can be too much driven by GIS and disconnected from implementation networks
St. Lucia island, Caribbean (Evans et al. 2015)	No SDM directly applied, but employs concepts of risk	Allows for simulations and to test concepts and assumptions	No direct species occurrences and abundances used
Bears in US/CAN (Proctor et al. 2004, Singleton et al. 2004)	None (Habitat Suitability Analysis HSI, Resource Selection Functions (RSF))	None	No quantitative progress; potential left unused; ambiguous results
Alaska (Semmler 2010)	Species distributions for major predators and their food chains	Overcomes existing data gaps	Model assessments for each pixel. Not used by agencies and deciders

(Amstrup et al. 2006). On the other hand, conservation decisions are urgent and in times of a global conservation crisis (Rockström et al. 2009, Mace et al. 2010). And so even basic SDMs, such as species occurrence, help to provide information that is useful for the overall Strategic Conservation Planning process. By now, virtually all what is not parsimonious (e.g. using Generalized Linear Models (GLMs) and Akaike's Information Criteria (AIC); Arnold 2010) can be achieved as progress (Breiman 2001) considering the global environmental crisis mankind is facing.

Overall, the use of machine learning for SDM approaches has greatly improved Strategic Conservation Planning processes (Table 16.3). These projects are often the first of their kind allowing for these methods and approaches to be introduced to Strategic Conservation Planning in the region. While data must be available to run SDMs (but often are not openly shared in SDM publications, and hardly in webportals like Movebank https://www.movebank.org/) and model outputs could easily be improved, these projects then allow for a subsequent machine learning 'culture' of conservation to be set up, also based on stakeholders in a public forum. It's rather transparent that way; the contribution of GBIF in that context remain unchallenged (see for instance Beiring 2013). Beyond data and model accuracies, the actual introduction of such a new conservation culture may be the biggest contribution. The need for data models, transparency and stakeholder buy-in is essential for implementing management of natural resources (Clark 2002). Having that awareness and accept such a need of wider community buy-in might well present the main contribution in SDMs and Strategic Conservation Planning projects for a global sustainable society.

16.2 How Machine Learning Predictions can Also Be Used Directly for Strategic Conservation Planning: How it's 'ought to be' and towards 'Better' Solutions

Strategic Conservation Planning is usually employed with an optimization framework; rarely, it is used with forecast scenarios directly. The actual optimization is usually based on methods like 'solvers', namely the simulated annealing algorithm (Ardron et al. 2008), whereas machine learning just provides the input GIS layers for describing generic patterns in the landscape. The use of future scenarios is possible and has been increasingly applied though (see Murphy et al. 2010 for an example). SDMs built with explanatory variables that have future forecasts, such as downscale global climate models and for 2100 let's say, can be used to forecast future conditions for species. While Population Viability Analysis (PVA) lack much of the spatially explicit aspects (e.g. Proctor et al. 2004), a spatial population viability analysis (sPVA) offers interesting and relevant possibilities for forecasting future conditions for Strategic Conservation Planning (Nielsen et al. 2008 for an example). These techniques link demographic PVA approaches with GIS habitat data and future scenarios, all based on optimizations from Strategic Conservation Planning. It tends to represent the best science available!

Often, sPVAs themselves fall short on some of the principles of Strategic Conservation Planning, or leave them unaddressed (Table 16.4), such as lack of optimization and not comparing several scenarios in parallel but just favoring singularity and reductionism. However, the strengths of sPVAs linked with scenario planning (Peterson et al. 2003) are that they can be much better and directly applied and tested for specific management questions, including demographic sensitivities and outlooks. The use of well-thought out scenarios provide policy alternatives (e.g. Gonzales et al. 2003; Nielsen et al. 2008) as compared to the narrow, singular and

Table 16.4 Some principles of conservation planning and protected area design (as per Martin et al. 2008, Moilanen et al. 2009)

Principle	Meaning	Relevance
Efficiency	The process and protected area includes no 'waste' of effort	Conservation is time critical
Compactness and/or connectedness	The trade-off in the spatial arrangement is clear and correctly implemented	Species dispersal and gene flow
Flexibility	Alternative options exist to achieve the goal still	Reaching the goal regardless of obstacles
Complementarity	The process and solution matches the context	Taking into account ongoing and other efforts
Selection frequency vs irreplaceability	Unique sites are considered appropriately	Endemic hotspots vs. generalists
Representativeness	The protected area represents the wider landscape and all of its components	The solution is complete and meaningful, unbiased
Adequacy	The process and protected area is sufficient to achieve meaningful goals	Adequate effort and outcome
Optimizations based on decision-theory and mathematical programming	The best solution is found using best-available science	Best solution that humans can achieve, an ethical mandate
Best-available data used	The process and result is based on best-available information	An ethical mandate to find the best-available solution

traditionally used Strategic Conservation Planning solution (which often consist of just 'one' solution wiping all other thoughts off the agenda). Computationally, and for all work that includes machine learning, this can easily be achieved. However, the sPVA option and when applied with scenarios is not yet widely employed in wildlife management and it is not required by law (see Huettmann et al. 2005; Nielsen et al. 2008) but it can come rather close to the ideal of adaptive wildlife management (Walters 1986; Huettmann 2007a; b). In the meantime, scenario-planning starts to become more common (Peterson et al. 2003). e.g. for climate change outlooks (IPCC; http://www.ipcc.ch/). The use of scenarios is widely known in the social sciences but so far less common in the traditional North American Model of wildlife management (Organ et al. 2012; Silva 2012), or in most other natural resource management schemes in the world. Clearly, such work is computational intense, and the role of coding and linking tools and codes across operating platforms becomes a power tool to achieve such conservation solutions! It's all part of machine learning either way!

IMPUTATION: More Ways with Machine Learning to Fill Data Gaps and Smooth–Out Predictors with Information Gain for an Effective Science–Based Conservation Management

Most statistical analysis default on data gaps. It's a '*no go*' zone for modern science and it tends to result in statements of convenience such as '*no evidence exist.*' So what to do when your data set is gappy, missing records and gets labeled '*no go*' zone? This seemingly old question remains a 'hot button' item, and becomes now a key bottleneck to overcome for progress. This problem actually made it to the forefront of modern data analysis (e.g. Graham 2009). Many reasons can be envisioned why data gaps occur. But if that can be resolved, then new insights can be won, and a subject can be moved forward (see Kenward 2013 for health applications). Thus, finding methods to substitute and fill data gaps make for a classic but very relevant and modern problem that data miners and machine learners have to deal with. It's a typical case in conservation that data are gappy while decisions are to be made though.

Reason for data gap	Detail of the data gap	Comment
Predictor has a data gap	Data column is incomplete	This is a common problem.
Response has a data gap	Data column is incomplete	In times of open access data this probably the biggest problem.
Missing data *per se*	Entire absence of information	Probably the biggest issue for holding us back for making inference
Lacking data due to research design problems	Entire lack of a specific information	The 'best' research design is usually not known ahead of the study. At minimum, research design can always be improved in hindsight.
Wrong entries	Entry is not correct	Depending on the term 'wrong' and its definitions some datasets are said to feature 50% of such 'errors' and 'wrong' entries.
Entries got erased by accident	Hole in the data set	This has been observed quite a lot and when data are modified, re-formatted and sorted in spread sheets for instance, or when they get operated by inexperienced people.
Entries had to be removed due to uncertainties	Hole in the data set	This is a common problem, e.g. when metadata are missing and with older data. Doubts about geo-referencing, taxonomy and collection times are typical examples. Arguably, it's better to keep weak data than having none.

Reason for data gap	Detail of the data gap	Comment
Entries had to be removed due to copyrights	Hole in the data set	This is also a common problem when data are not shared.
Error simulations	Based on certain assumed backgrounds, some data might be acceptable whereas under other assumptions might make this data set viable	For advanced inference, data error simulation can provide new insights. While this can present questions for high-end data mining, it can be a relevant feature for high-end information gain and inference.

One can easily envision a situation where these 'real world' data gaps occur, and then, where they 'magically' could be overcome! So why not simply imputing them? [1] Conceptually, imputation means to replace data holes and to fill (substitute) them (Enders 2010). In reality that means they are to be modeled! It usually makes use of existing, neighboring, associated and surrounding attributes and data points. Based on those relationships in the data, data gaps can get filled. With the help of advanced computing and data science, it is less a question 'whether' that can be done (no problem really to do so). Instead, the issue is more 'how good' is the accuracy obtained for a certain purpose (many applications are happy to have a 75% modeled accuracy when compared to no data at all)? In a way, imputation is a specific method to model-predict data gaps. And this can be done, all with a certain estimation accuracy. A 100% prediction accuracy can probably not be achieved, but often it is not needed even. Instead, one can fill errors in a decent way, the models do not default, and which helps to move the overall process and progress forward for an analysis topic.

By now, imputation, as a statistical discipline, is evolving fast and many methods exist (see also for updates at the Wikipedia site https://en.wikipedia.org/wiki/Imputation_(statistics). Major techniques are for instance single imputations such as hot-deck, cold-deck, mean-substitution, regression. Multiple imputations are other powerful techniques. Often, these methods are

[1] It should be emphasized here that many other methods exist to overcome data gaps, including data cloning to stabilize models on poor data or to extend the data (Lele et al. 2007; Jiao et al. 2016 for machine learning application). The other, and equally exciting approach for overcoming data gaps is to explain why data gaps actually occur (forensics), often based on 'common sense'. It tends to work nicely because most data gaps have a reason for their existence! For instance, some field research data gaps are due to bad weather (rain), or inaccessibility of steep slope elevations. Those factors, data gaps, can then serve as explanations for the absence of certain events in the data. Tree-based models, and specifically the work from Friedman (2002), make use of such approaches with good success.

linked with sampling and re-sampling approaches. Of particular relevance are the geo-imputation methods as they allow interpolations in geographic information systems (GIS), linked with the discipline and tools from Spatial Statistics. Those are popular in forestry, canopy, remote sensing and image analysis too. Entire textbooks and journals are devoted to that topic, e.g. https://www.journals.elsevier.com/spatial-statistics.

There are several software approaches possible that allow to run imputations; see for instance Enders (2010). Similarly, Salford Systems Ltd. offers in TreeNet (stochastic gradient boosting) options to run analysis with 'gappy data' (Friedman 1999, Salford Systems Ltd. https://www.salford-systems.com/products/treenet)). In the R language, YAImpute is one of those packages that can 'impute' data based on using nearest neighbor observations (kNN; Crookston and Finley (2008; https://cran.r-project.org/web/ packages/ yaImpute/ index.html). See also applications of such R code by J. Evans (http://evansmurphy.wixsite.com/evansspatial).

While this is all pretty exciting, developing and moving forward fast, the sad news is that in wildlife conservation management, and for many natural resource applications, imputation convinces in the pure absence. The mainstream literature is extremely poor on making use of those methods and for advancing fields like conservation remote sensing, geo-locators, telemetry, wildlife surveys, disease outbreaks and citizen science. Two notable exceptions can be found though, namely climate as well as some forest work (Eskelson et al. 2009).

Literature

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16.3 A Wider Perspective against the Local Techno-Fix: Good Ethics and Ecological Governance Foundations to Achieve a Conservation Break–Through with Open Access Machine Learning and Strategic Conservation Planning Carrying a Global Perspective for Mankind

An honest assessment of the environment, and the strategy needed for its conservation will expose nothing but a crisis, which is footed on a failed management and leadership in an overall destructive global framework (Ostrom 2015). We are running out of space while most relevant species and habitats are not protected, or at least not protected well or optimal! (Table 16.5).

Table 16.5 Selected examples for lack of achievement with National Park concepts for conserving species effectively

Species	Status	Habitat area protection through National Parks
Snow leopard	Vulnerable (or endangered, as per recent debate)	Found widely outside of protected areas
Songbirds, virtually worldwide	Large declines	Found widely outside of protected areas, e.g. Beiring (2013), Jiao et al. (2016)
Shorebirds	Large declines, e.g. for arctic species	Found widely outside of protected areas
Tree Kangaroo	Large declines (several species; Australia and Papua New Guinea)	Found widely outside of protected areas (FH unpublished)
Langures	Large declines	Found widely outside of protected areas (FH unpublished
Red panda	Globally threatened	Found widely outside of protected areas, e.g. Kandel et al. (2015)
Great panda	Vulnerable (1,000 individuals in the wild)	Not well protected within the protected area (Xu et al. 2014)
Black-necked cranes	Vulnerable	Found widely outside of protected areas (Xuesong et al. 2017)
Grizzly Bear (Canada)	Species at risk, partly extinct	Not well protected within protected area (Gallus 2010)
Atlantic Puffin	Vulnerable	Almost no marine protected areas (MPA), e.g. Huettmann et al. (2016)
Sharks	Widely declining	Almost no marine protected areas (MPA)
Commercial food fish species worldwide	Widely declining	Almost no marine protected areas (MPA; no take-zones)
Gharial	Critically endangered	Not well protected within protected area and outside

The New World Order, and starting with Bretton Woods in 1944, The World Bank and its subsequent institutions such as IUCN and UNEP show us nothing but that (Rich 1994). All too often we then just get presented a techno fix used to present us with progress when there actually is none (Czech et al. 2000; Cockburn 2013); even basic principles of strategic conservation are consistently violated (Table 16.4). By now, the list of those technical 'innovations' and fixes are very long, almost comical if it were not that tragic. It is easy to see that machine learning, or optimization algorithms from strategic conservation planning could fall into that category. The challenge now remains to show that it is not and to apply them in a good ecological setting. On the one hand machine learning cannot really break out of the techno-trail. It's a technological high-end application. It also requires energy and resources as input, eventually. Some of the stakeholder workshops also leave a big financial and carbon footprint, for instance. However, on the good side, the outcome is more than its individual pieces. That is nowhere so true than in machine learning: just consider what the phrase '*many weak learners make for a strong learner*' (Schapire 1990) means in real life.

So, while we are easily trapped in our institutions and minds with certain techno-arguments and its neoliberal world, there can be a decent output for the better, and hopefully with a good life- balance to be found eventually. Tables 16.4 and 16.6 show some of the core components of Strategic Conservation Planning projects to be successful, but which are widely missing in real world applications still (Huettmann 2007a, b, 2008a, b for projects and related data and publications). Table 16.7 shows known failures and a mis-use of Strategic Conservation Planning.

Table 16.6 Components to further improve Strategic Conservation Planning with a 'good' machine learning component

Wider topic	Justification	Example and citation	Status in strategic conservation planning projects
Best predictions	Best predictions	SPM8 (https://www.salford-systems.com/)	Not fully employed, yet
Use of best data	Best information assures best inference	Open access, e.g. Freedom of information act (https://www.foia.gov/)	Not used to the full potential yet
Make final project data available	Repeatable and transparent conclusions	Kandel et al. (2015)	Almost never achieved
Ethics	Avoid mis-use and destructive science	Weaver (1996), Bandura (2007), Daly and Farley (2011) Steady state economy mother earth	Virtually ignored

(continued)

Table 16.6 (continued)

Wider topic	Justification	Example and citation	Status in strategic conservation planning projects
Dynamic re-runs	MPA conditions change and need to be constantly adjusted	Dynamic MPAs at sea that reflect ocean currents and climate change (Murphy et al. 2010)	Discussed for the marine environment but virtually left without implementation, e.g. for terrestrial applications
Enforcement and policy link	Laws are only as good as their enforcement culture and related budget	Legal theory	Virtually ignored (see for missing links in wildlife management, conservation biology and strategic conservation planning textbooks, e.g. Bolen and Robinson (2002), Silva (2012), Primack (2016), Ardron et al. (2008)
Ecological economics	The only known economy to achieve a 'steady state'	Czech (2000), Daly and Farley (2011)	Rarely considered, yet.

Table 16.7 Known failures of strategic conservation planning projects and their suggested fixes

Strategic conservation planning project	Known failure in the goal	Effective fix	Outlook
Great barrier reef	Overruled by political and global forces, e.g. Indian mining concessions in the wider watershed	Implement a better global governance	It is currently not realistic to assume a global governance that puts harmony and environmental balance at its core serving the wider public good
Terrestrial national parks	10% protection level too small for being effective or meaningful, Marxan not well used	30% protection levels, implement a better global governance	Unlikely to happen any time soon in ecological relevant terms
Global MPA ocean network	Most of the MPAs are usually not 'No Take' zones, lacking enforcement either way, greatly improve coverage	30% protection levels, implement a better and realistic global governance and enforcement	Unlikely to happen any time soon in ecological relevant terms
OSPAR (https://www.ospar.org/work-areas/bdc/marine-protected-areas)	Use of a MPA far offshore to mitigate climate change. Put MPAs where the diversity actually sits	Reduce industrial consumption as the underlying cause of climate change, improve ocean protection and management	Unlikely to happen any time soon in ecological relevant terms
Russian Arctic MPAs (Spiridonov et al. 2017, Solovyev et al. 2017)	Climate change futures not included	Re-run with climate change future outlook	Unlikely to happen any time soon in ecological relevant terms

In a way, I hope, machine learning, e.g. for Strategic Conservation Planning, can at least help to strike that balance better reaching a steady-state (Daly and Farley 2011). We can actually afford to spend some energy, as long it is sustainable and not excessive, on machine learning with Strategic Conservation Planning and for good decision-making reaching sustainability on a global level. As a matter of fact, if we have any energy, or effort for that matter handy, it should be invested into great decision-making, achieved with machine learning-aided Strategic Conservation Planning making good use of those techniques available to mankind. This can eventually lead to a global society respecting 'mother earth'. For global sustainability to become real, wider questions come to play, including universe ones, belief systems, spirituality, governance structures, distribution of wealth and the balance of life (Weaver 1996; Stiglitz 2003). But one way or another, machine learning is available and involved by now, and all one can ask for then is to make good and best-suitable use of this method; all done with good ethics and outcome for the wider public, global good. Anything that is not destructive science would be progress in that regard. Now, who would not agree?

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