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Review

The role of satellite remote sensing in structured ecosystem risk assessments

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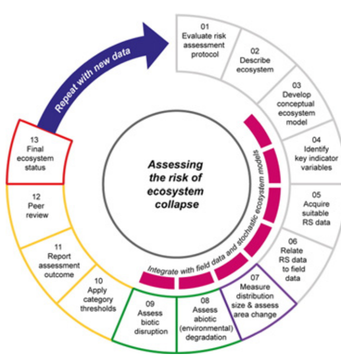
HIGHLIGHTS

- Ecosystem risk assessment protocols enable the use of a wide range of data to assess the changing status of ecosystems.
- Unstructured use of remote sensing data for assessing ecosystem dynamics can introduce substantial error and uncertainty.
- We identify case studies that have used satellite remote sensing to assess degradation of marine, aquatic and terrestrial ecosystem types.
- We provide guidance and a framework for integrating remote sensing data into ecosystem risk assessment.

GRAPHICAL ABSTRACT



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ABSTRACT

The current set of global conservation targets requires methods for monitoring the changing status of ecosystems. Protocols for ecosystem risk assessment are uniquely suited to this task, providing objective syntheses of a wide range of data to estimate the likelihood of ecosystem collapse. Satellite remote sensing can deliver ecologically relevant, long-term datasets suitable for analysing changes in ecosystem area, structure and function at temporal and spatial scales relevant to risk assessment protocols. However, there is considerable uncertainty about how to select and effectively utilise remotely sensed variables for risk assessment. Here, we review the use of satellite remote sensing for assessing spatial and functional changes of ecosystems, with the aim of providing guidance on the use of these data in ecosystem risk assessment. We suggest that decisions on the use of satellite remote sensing should be made *a priori* and deductively with the assistance of conceptual ecosystem models that identify the primary indicators representing the dynamics of a focal ecosystem.

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Contents

1. Introduction

Habitat loss, degradation and fragmentation continue to threaten ecosystems worldwide (Tittensor et al., 2014). The adoption of the Aichi 2020 Targets, agreed by 194 nations under the Convention on Biological Diversity (Convention on Biological Diversity, 2014), and the 2030 Sustainable Development Goals (UNDP, 2015) are crucial global policy responses to counteract these fundamental drivers of biodiversity loss. These agreements explicitly include goals on the conservation and restoration of ecosystems and their characteristic biota. For example, five of the twenty Aichi Targets relate directly to the status of ecosystems (Convention on Biological Diversity, 2014). Yet identifying tools that can be used to assess progress towards these ecosystem-based conservation targets remains a fundamental challenge (Collen and Nicholson, 2014; Tittensor et al., 2014). The emergence of ecosystem risk assessment protocols such as the IUCN Red List of Ecosystems (www.iucnrle.org), which provide decision rules for classifying ecosystems according to their risk of collapse, can help address this challenge.

Ecosystem risk assessment protocols aim to estimate the probability of ecosystem collapse over a specified time frame (Keith, 2015). Currently, >30 countries assess ecosystems, ecological communities, or habitats to estimate the risks they face, with the conservation status of at least 725 ecosystem types formally reviewed (Murray, unpub. data). For the purposes of risk assessment, ecosystems are normally defined as complexes of organisms and their physical environment within a particular area (see Nicholson et al., 2015 for a review of terms used in ecosystem risk assessment). They are recognized as having four essential elements: a biotic complex, an abiotic environment, the interactions within and between them, and a physical space in which these operate (Tansley, 1935). Risk assessments typically require information on the geographic distribution of an ecosystem, changes in spatial extent, and changes in ecosystem function over time (Nicholson et al., 2009; Nicholson et al., 2015). For example, the International Union for Conservation of Nature's (IUCN) Red List of Ecosystems, the only global protocol for ecosystem risk assessment, comprises a risk assessment model with five quantitative criteria that integrate multiple symptoms of ecosystem collapse (Fig. 1; Keith et al., 2013; Rodríguez et al., 2015). The Red List of Ecosystems criteria consider both the spatial aspects of ecosystem decline, including reductions in area (Criterion A) and susceptibility to spatially explicit threats (Criterion B), and the functional aspects of decline that focus on both abiotic and biotic symptoms of ecosystem degradation (Criteria C and D; Fig. 1). A fifth criterion allows the use of stochastic ecosystem models that may incorporate both the spatial and functional aspects of decline to estimate risks of collapse (Criterion E; Keith et al., 2013). Declines in geographic distribution and both biotic and abiotic functions are typically measured over a 50-year timeframe to capture long-term directional changes in ecosystem dynamics, although future projections to a 50-year time frame may also be used (Bland et al., 2017a).

Many data sources are relevant for ecosystem risk assessment, including those from short and long term monitoring programs, field surveys, and underwater, aerial and satellite sensors. Of these, satellite remote sensing offers the greatest opportunity to evaluate ecosystem change beyond the site level (Turner et al., 2003) and to scale the risk assessment process to provincial, national and continental jurisdictions. However, the need for interdisciplinary expert skills in the identification and use of satellite remote sensing data is a central factor that has limited the uptake of this source of environmental information by ecologists and slowed the development of national, continental and global lists of threatened ecosystems. Furthermore, the increasing availability of data from an ever-growing range of sensors has led to a bewildering choice of remotely sensed data that seem suitable for assessing ecosystem change over a range of time periods (Kennedy et al., 2014; Porter et al., 2012).

In this review we aim to investigate the proven capabilities and future potential of satellite remote sensing for assessing the status of ecosystems across a range of major ecosystem types, and identify important mechanisms and processes of ecosystem change and the sensors that best represent them. We identify recent case studies that demonstrate the advantages, challenges and key considerations of using remotely sensed data in studies of ecosystem dynamics. In doing so, we aim to provide a primer for environmental managers, risk assessors, and ecosystem scientists to judiciously utilise remote sensing for ecosystem risk assessments at a range of spatial scales. Lastly, we develop a simple framework for incorporating indicators that can be monitored with satellite remote sensing across a wide range of ecosystem types, with the aim of establishing a clear assessment workflow to progress a global list of threatened ecosystems.

2. Spatial distribution of ecosystems

Accurate maps of the geographic distributions of ecosystems and how they change over time are fundamental components of most ecosystem risk assessment protocols (Fig. 1; Nicholson et al., 2015). Ecosystems with small geographic range size are at greater risk of collapse from environmental catastrophes than those that are distributed over large areas (Keith et al., 2017; Murray et al., 2017a). Similarly, the rate of areal change is a widely used indicator of an ecosystem's trajectory towards collapse, because a decline in area reduces the ability of an ecosystem to maintain its characteristic biota and fundamental processes (Keith et al., 2013). The areal trajectories of many of Earth's major ecosystem types have been quantified with time-series remote sensing data. Examples of estimated annual rates of change in extent include −3.7% for tropical peatlands (Wilcove et al., 2013), −2% for coastal wetlands in East Asia (Murray et al., 2014; Murray et al., 2015) and >1% for forests globally (Hansen et al., 2013). However, producing time series of ecosystem maps at spatial and temporal scales that underpin such estimates of change is a specialist task. The need for detailed knowledge of available data, advanced analytical methods, and an understanding of constraints and uncertainties of remote sensing has limited the availability of highly accurate and consistent maps that can be used operationally for ecosystem risk assessments.

Traditional remote sensing methods, such as visual interpretation and classification of satellite, aerial and underwater imagery have

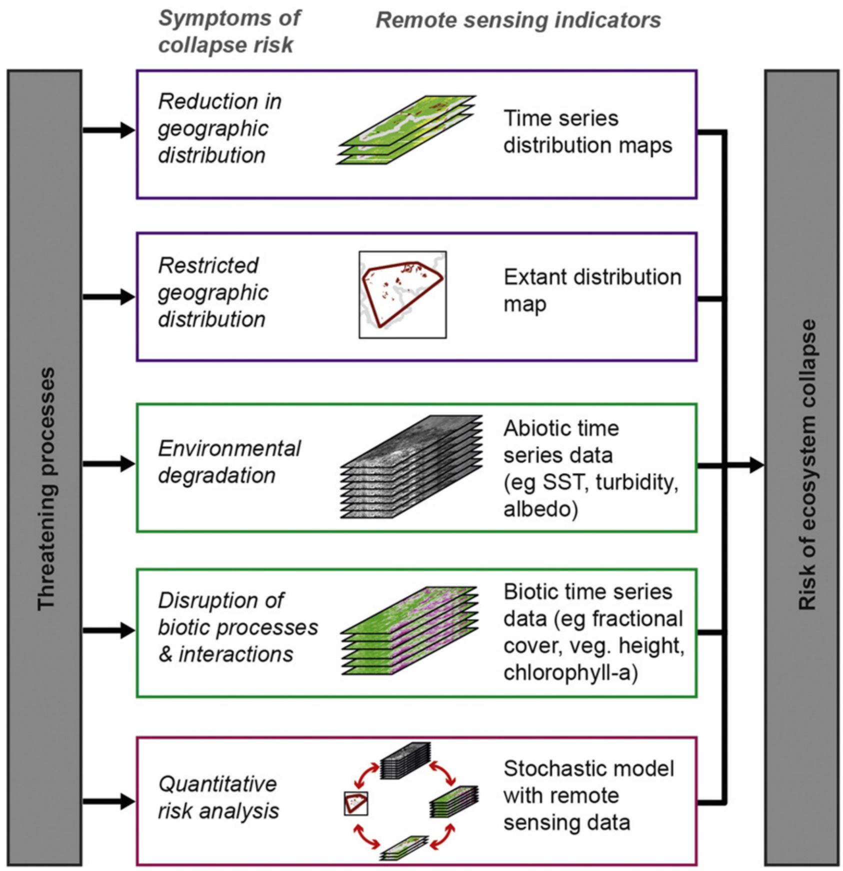

Fig. 1. Overview of the IUCN Red List of Ecosystems risk assessment protocol, showing potential remote sensing indicators useful for assessing the risk of ecosystem collapse. Purple boxes indicate spatial distribution symptoms of collapse risk, green boxes indicate functional symptoms, and the magenta box indicates where all symptoms of collapse can be integrated into a single risk analysis.

been widely used to generate fine (<10-m) to coarse (>1-km) grain maps of ecosystems over the last few decades. However, the investment required to produce map time series can be prohibitive for managers seeking to implement ecosystem risk assessment protocols, particularly in developing countries (Mumby et al., 1999). To achieve accurate, high resolution time-series maps of ecosystem distributions, it is often necessary to host large amounts of spatial data, access sufficient computing infrastructure and manage highly technical workflows. New geospatial analysis platforms have solved many limitations of ecosystem-scale remote sensing by storing vast spatial data archives and allowing users to develop complex analyses at no-cost. These platforms operate at global (e.g., Google Earth Engine) and continental scales (e.g., The Australian Geoscience Data Cube) and are beginning to make near real-time analyses of ecosystem change at these scales commonplace (Gorelick et al., 2017; Hansen et al., 2016). As an example, the collapse of the Aral Sea ecosystem (Keith et al., 2013) has now been documented over a 32-year period at high spatial (30-meter) and temporal (monthly) resolution as part of a global analysis of more than three million Landsat satellite images (Pekel et al., 2016).

The development of 'virtual constellations' to integrate data from different satellite sensors and the rapidly increasing use of composite images (Fig. 3) can enable the development of high-quality maps in areas previously limited by chronic cloud cover or poor data coverage (Wulder et al., 2015). Time series of ecosystem extent may be extended into the past with historical data, such as topographic maps (e.g., Murray et al., 2014) and aerial photographs (e.g., Palandro et al., 2003), or by models that allow projections over time (Soares-Filho et al., 2006). This allows the long-term spatial dynamics of ecosystem distributions to be mapped to match the decadal time-frames required by ecosystem risk assessment protocols (Fig. 3). Similarly, the growing use of machine learning methods to analyse large sets of biological, biophysical, spectral and climatological data against a limited amount of training data has enabled accurate differentiation of a wide range of ecosystem types from the surrounding landscape over rapidly increasing spatial domains (e.g., Hansen et al., 2013). For example, the global forest change dataset was developed by classifying pixels using >15 high-resolution global composite images as predictors, each of which were developed from >500,000 Landsat images (Hansen et al., 2013). Other approaches, including automated remote sensing systems such as the Earth Observation Data for Habitat Monitoring system (EODHaM; Lucas et al., 2015) utilise several remote sensing methods (e.g., image segmentation and supervised classification) within their workflows, and can produce standardized habitat maps at multiple scales that are also suitable for use in ecosystem risk assessment.

Although trends in area are important indicators of the status of an ecosystem, varying map accuracies (typically classification errors) or the direct comparison of maps developed at different spatial resolutions can substantially influence estimates of area across a time-series and cause incorrect inferences about ecosystem change (Fuller et al., 2003; Olofsson et al., 2014). Therefore, regardless of the mapping method employed, a clear focus of an ecosystem mapping protocol for risk assessment must be to produce accurate and consistent maps over time, with a robust method for estimating accuracy and associated uncertainty. Comparing classifications to independent reference data—confirmed observations of a focal ecosystem—is the most common approach for estimating accuracy and can be used to quantify uncertainty around area change estimates (Olofsson et al., 2014). New model-based approaches for map classifications provide useful diagnostics that can inform better choices of mapping units and can propagate uncertainty from training data acquired *in situ* through to corresponding ecosystem maps (Lyons et al., 2016). These new approaches to mapping and classification should help produce better ecosystem maps and estimates of area change for use in ecosystem risk assessments.

3. Ecosystem processes and function

The disruption of biotic and abiotic ecosystem processes can also be key pathways towards ecosystem collapse. For those protocols that integrate functional changes into risk assessment, identifying variables to monitor and matching these with remote sensing indicators remains a challenge. Some ecosystem risk assessment protocols provide a useful framework for conceptualizing processes that lead to ecosystem degradation, helping to isolate specific components of ecosystems that could be monitored with satellite data (Nicholson et al., 2015). The IUCN Red List of Ecosystems, for instance, requires assessors to identify the most important functional symptoms of risk, such as declines in particular biota that perform critical roles in ecosystem function or changes in particular components of the abiotic environment that cause reductions in those biota (Fig. 1; Keith et al., 2013). Examples of the latter include a loss of connectivity, interrupted nutrient cycling or increased disturbance regimes (Keith et al., 2013; Pettorelli et al., 2017). Contrasting ecological drivers and threats across different terrestrial, marine and freshwater ecosystems therefore result in extremely diverse expressions of functional decline, which can only be tracked accurately with carefully selected data and analytical methods (Keith et al., 2013).

Most ecosystem risk assessment protocols offer guidance on the selection and use of time-series data for monitoring ecosystem dynamics. However, substantial error can be introduced into risk assessments as a result of variation in data processing streams (Morton et al., 2014), particular start and end-points of a time-series (Wessels et al., 2012), data biases in remote sensing data (Smit et al., 2013), varying severity and extent of change (Keith et al., 2013) and natural temporal fluctuations in ecosystem properties (e.g., seasonal; Ferrari et al., 2012). Consequently, it is necessary to take care in choosing indicators variables for use in risk assessment by first clearly resolving the relationship between remotely sensed data and key mechanisms of ecosystem change (03–05, Fig. 2). Conceptual models that represent the pathways and mechanisms of change in key ecosystem features are often the best way to describe these relationships (Bland et al., in press). For example, a conceptual model of the Antarctic shallow invertebrate-dominated ecosystems illustrated the critical role of sea ice cover in maintaining its geographic distribution and key biotic and abiotic elements (Clark et al., 2015). The process of developing a conceptual model for the ecosystem allowed transparent selection and use of remotely sensed sea ice distribution data to estimate future risk of collapse, ultimately indicating that the ecosystem qualified as Near-Threatened to Vulnerable under the IUCN Red List of Ecosystems (Clark et al., 2015).

To support identification of variables suitable for ecosystem risk assessments that can be monitored with satellite remote sensing, we reviewed 17 published case studies that have conceptualised or described the relationship between satellite remote sensing data and specific ecosystem responses that contribute to elevated risk of ecosystem collapse (Table 1). Cases were selected to illustrate different uses of remote sensing data for monitoring symptoms of ecosystem collapse across a range of ecosystem types. The review indicated that a wide variety of variables that can be monitored with satellite remote sensing, including area loss, biomass change, and disease stress, have been used successfully to quantify spatial, biotic and abiotic degradation in a manner directly suitable for ecosystem risk assessment. For example, Tebbs et al. (2015) used reflectance data obtained from the Landsat Archive to analyse cyanobacterial biomass, suspended sediment and extent of cyanobacterial scum in a system of 15 connected alkaline-saline lakes ('flamingo lakes') in the East African Rift Valley. These data enabled an assessment of the changing ecological states of the

Fig. 2. Framework for identifying and using remote sensing data in ecosystem risk assessment. A preparation stage is required to evaluate the risk assessment protocol and define the assessment unit (01 — 02). Developing a conceptual ecosystem model and identifying indicators variables to monitor with remote sensing follows (03–06), with opportunities to incorporate with field data and ecosystem models (purple). The ecosystem is then evaluated against risk assessment criteria (demonstrated here with the IUCN Red List of Ecosystems criteria; 07–09), before summarizing and reviewing the results (10 — 12). The ecosystem is then formally listed (13). Ideally, the assessment is repeated with new data on a regular basis.

lakes system over a 13 year period (Tebbs et al., 2015). Such analyses can be incorporated into ecosystem risk assessments by generalising these measurements to an index of 'relative severity' of lake degradation over the time frame of the assessment, obtained as the ratio of observed change of one of these variables to the amount of change that would lead to ecosystem collapse (Keith et al., 2013).

To provide practical guidance on the use of satellite remote sensing data for risk assessments of specific ecosystem types, we have identified remote sensing products that have been used for monitoring degradation of 21 ecosystem types spanning in eight sub-realms (Table 2). Surprisingly, the underlying drivers of ecosystem degradation are often similar across functionally related ecosystem types, and several remote sensing products are particularly useful for assessing ecosystems with similar characteristics (Table 2). For instance, because of the strong functional relationships between sea surface temperature (SST), coral death and loss of coral cover, SST is a frequently used variable for assessing risks to coral reef ecosystems (Bland et al., 2018). Indeed, SST has been used to assess the likelihood of bleaching of Australia's Great Barrier Reef (Ainsworth et al., 2016) and the Meso-American Barrier Reef (Mumby et al., 2014), and enables real-time bleaching alerts *via* NOAA's Coral Reef Watch (Liu et al., 2014). Near-shore kelp forest ecosystems are also sensitive to changes in SST, and remotely sensed estimates of SST have been used to monitor functional decline of those systems (Table 2; Vergés et al., 2016). Sedimentation is a qualitatively different process of degradation in aquatic ecosystems. In this case, satellite-derived water turbidity data (Table 2) has been be used to infer environmental degradation of both near-shore marine ecosystem types such as coral reef (Fabricius et al., 2014; Herzfeld et al., 2016) and seagrass (Kilminster et al., 2015), as well as freshwater ecosystem types (e.g., lentic ecosystems; Tebbs et al., 2015).

Table 1
Case studies that were used to identify the types of remote sensing data used to estimate spatial or functional declines of a wide diversity of ecosystem types. These studies were selected to illustrate different uses of remote sensing data for monitoring symptoms of ecosystem collapse. The reference list supporting this table is located in Table A.1.

Ecosystem response	Ecosystem type	Remote sensing indicator	Reference
Area loss	Intertidal flat	Ecosystem distribution	Murray et al. (2015)
	Tropical forest	Vegetation cover	Hansen et al. (2013)
	Cloud forests	Cloud dynamics	Ponce-Reyes et al. (2013)
Biomass change	Alkaline-saline Lakes	Chlorophyll *a*	Tebbs et al. (2015)
	Kelp forest	Normalized Difference Vegetation Index	Cavanaugh et al. (2010)
	Savanna	Above ground biomass	Levine et al. (2016)
Bleaching	Coral reef	Sea surface temperature	Ainsworth et al. (2016)
	Coral reef	Rugosity	Ferrari et al. (2016)
Decline in relative abundance	Coral reef	Coral cover	Palandro et al. (2008)
Desertification	Arid shrubland	Vegetation cover	Kefi et al. (2007)
Disease stress	Temperate rainforest	Reflectance ratios	Leckie et al. (2004)
Diversity decline	Coral reef	Spectral signal	Mellin et al. (2012)
Drought stress	Forest ecosystems	Vegetation indices	See Norman et al. (2016)
Eutrophication	Aquatic ecosystems	Vegetation cover	See Zhang et al. (2016)
Migration	Mangrove forest	Water cover dynamics	Asbridge et al. (2016)
	Mangrove forest	Land surface temperature	Cavanaugh et al. (2014)
Vegetation loss	Grasslands	Normalized Difference Vegetation Index	Hilker et al. (2014)

4. Threatening processes

Many ecosystem risk assessment protocols require extensive assessments of threatening processes. These include information on the location of threats, their extent, and their impacts on ecosystems and their component biota (Nicholson et al., 2015). Landscape- and seascape-scale perspectives on threats (e.g., deforestation, coastal development, pollution, fire, invasive species, disease, extreme weather events) are crucial to the application of risk assessments (Keith et al., 2017). The spatial distribution of threats that alter the extent of an ecosystem can be used to derive area change estimates as a result of their impact (Fig. 3), parameterise models that simulate the impact of such threats (Murray et al., 2017a), or evaluate ecosystem degradation by assessing loss or disruption of key processes (e.g., fragmentation; Bland et al., 2017a; Ferrari et al., 2016a). Some risk assessment protocols also require assessments of 'plausible threats' (Nicholson et al., 2015). In these cases, remote sensing data can be used to develop disturbance histories that can help estimate the likelihood and extent of these types of threats (Rodríguez et al., 2015). Finally, spatial data on the distribution of observed threats can be used to formulate threats scenarios and parameterize conceptual or quantitative ecosystem models.

Many attempts to quantify the impacts of threats to species and ecosystems have been limited by a lack of suitable data (Joppa et al., 2016), a poor understanding of how threats influence specific ecosystem processes (Keith et al., 2013), subjective judgments about the nature of threats (Hayward, 2009), and the cumulative or synergistic impacts of threatening processes (Tulloch et al., 2015). However, as the frequency of satellite data acquisition increases, the spatial resolution of the data decreases, and data processing pipelines improve, the utility of remote sensing for rapidly identifying and responding to threatening processes is beginning to live up to its potential. For example, the development of near real-time alert systems (e.g., Hansen et al., 2016; Liu et al., 2014) are useful for identifying ecosystems at risk, enable rapid response to threats by governments and land managers, and for reducing risks to ecosystems over shorter time frames than previously possible. Remote sensing data is also becoming increasingly accessible to non-experts through the development of user friendly methods and online applications that allow straightforward access to remote sensing datasets (e.g., Ferrari et al., 2016b; Gorelick et al., 2017; Murray et al., 2017b).

5. Integrating remote sensing into ecosystem models

Ecosystem models that elegantly represent salient ecological processes deliver the capacity to monitor and predict change, estimate risks of ecosystem collapse and explore alternative future management scenarios (Bland et al., 2018). Such models can be parameterised, initiated, or validated with remote sensing data. The *eReefs* model of the Great Barrier Reef, for example, consists of 1 km and 4 km resolution models that integrate three-dimensional hydrodynamic, sediment, biogeochemical and ecological data obtained across a spatial domain of several thousand square kilometres. *eReefs* utilises satellite remote sensing data (such as SST) to predict >40 biotic and abiotic variables across space and throughout the water column in near real-time and at high spatial resolution (Herzfeld et al., 2016). Stochastic land-use models such as the 'SimAmazonia' model can produce maps of estimated future land-use change (including deforestation) using satellite-derived historical deforestation maps (Soares-Filho et al., 2006). This type of model, which often includes a stochastic process, is particularly suitable for assessing the risk of collapse by averaging results over a large number of stochastic simulations (e.g., Bland et al., 2018; Bozec and Mumby, 2015). Remote sensing data therefore has great potential for parameterizing a wide variety of ecosystem models, and is increasingly being used to assess the skill of models at reproducing ecosystem dynamics. The continued development of ecosystem models, particularly those designed to directly ingest relevant remote sensing data and that account for environmental stochasticity, allow risks to ecosystems to be estimated for a range of future scenarios and greatly enhances our ability to formulate environmental and conservation policies.

6. Conclusions

Utilising data from existing remote sensing platforms, and integrating these with *in situ* monitoring programs, expert knowledge, clear conceptualization of ecosystem processes, and quantitative ecosystem models will be crucial to support the global deployment of ecosystem risk assessment protocols. We have suggested a structured pathway for the selection and use of remote sensing data for use in ecosystem risk assessment (Fig. 2), which is founded upon a basic understanding of each ecosystem to be assessed. Ideally, remote sensing data should have spatial resolution and temporal resolutions that are fine enough to represent ecosystem dynamics and allow for the detection of rapid changes, correlate closely with appropriate *in situ* indicators of ecosystem degradation, and be capable of delivering deep time-series that allow ecosystem monitoring over several decades. Influencing the development of future satellite sensors through direct engagement with private and public space agencies and rapidly employing novel technologies as they become available will also enhance our ability to estimate risks to ecosystems. Rapid degradation of ecosystems is occurring in nearly all biomes, and compiling a global list of threatened ecosystems as soon as possible will better enable an international response to global

Table 2
Potential remote sensing indicators for assessing symptoms of increasing risk of collapse for functionally similar ecosystem types. For simplicity 'vegetation indices' here includes indices such as Leaf Area Index (LAI), Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI); refer to the cited studies for further details. The full reference list supporting this table is located in supplementary Table A.2.

Ecosystem type	Main pressures	Example symptoms of increasing collapse risk	Potential indicators
Tropical & sub-tropical forests			
Moist montane	Warming, drying, cloud stripping (Auld and Leishman, 2015; Ponce-Reyes et al., 2013)	Replacement of mesic vegetation	Cloud cover, precipitation
Tropical	Deforestation, land use change, drought, climate change (Hansen et al., 2013; Levine et al., 2016)	Declining extent, change in above ground biomass	Vegetation height & structure, land cover change, vegetation indices, dry season length
Temperate & boreal forests & woodlands			
Boreal	Timber harvest, drought, stand-replacing fires, climate change (Bond-Lamberty et al., 2014; Chapin III et al., 2004; Delpierre et al., 2016)	Skewed stand structure, forest cover thinning, tree mortality	Burned area, vegetation height & structure, land cover change
Temperate evergreen	Deforestation, land use change (Hansen et al., 2013)	Declining extent	Vegetation height & structure, land cover change, vegetation indices
Cool temperate	Fire, invasive species, climate change (Anderson et al., 2006; Bergstrom et al., 2015; Payette et al., 2001)	Tree mortality, replacement by grassland, reduced productivity	Burned area, net primary productivity, vegetation indices, land surface temperature
Shrublands & shrub-dominated woodlands			
Shrubby woodlands	Desertification, drying, over-grazing (Vicente-Serrano et al., 2012)	Stunted vegetation, reduced biomass, phase shifts to alternative overgrazed desert state	Vegetation height & structure, land cover change, vegetation indices
Tropical & subtropical savannas			
Savanna	Predator persecution, trophic cascades, CO_2 fertilization, changed fire regimes (Van Langevelde et al., 2003)	Woody thickening, diversity decline	Vegetation height & structure, land cover change, vegetation indices
Polar/alpine			
Subantarctic megaherb	Invasive species, over-grazing, climate change (Bergstrom et al., 2015; Bergstrom et al., 2009)	Vegetation mortality	Vegetation indices
Tundra	Climate change, reduced snow persistence, fire (Stow et al., 2004)	Species replacement	Vegetation indices, burned area, snow cover
Temperate & montane grasslands			
Temperate grassland	Plant invasions, drought, fire, land use change (Villarreal et al., 2016)	Changed productivity and phenology	Vegetation indices, land cover change
Wetland			
Bogs, marshes, fens, peatland	Eutrophication, land use change (Koh et al., 2011; Torbick et al., 2012)	Mortality of water-dependent vegetation, altered flood regimes, declining extent	Surface water extent, hydroperiod, vegetation indices
Freshwater springs & oases	Aquifer change, water extraction (Stromberg et al., 1996)	Mortality of endemic flora and fauna	Surface water extent, land cover change, hydroperiod
Freshwater lakes	Eutrophication, water extraction (Tebbs et al., 2015)	Algal bloom, declining extent, altered flood regime	Photosynthetically active radiation, hydroperiod, surface water extent, turbidity
Permanent rivers, streams, creeks	Water extraction, river regulation (Nilsson and Berggren, 2000; Pisanu et al., 2015)	Mortality of water-dependent vegetation, altered flood regimes	Surface water extent, hydroperiod
Marine & coastal			
Coral reef	Acidification, warming (Ainsworth et al., 2016; Ferrari et al., 2016; Graham et al., 2015)	Bleaching, macroalgal dominance, changing structural complexity	Sea surface temperature, chlorophyll *a*, structural complexity, turbidity
Intertidal flat	Land reclamation, changing sediment regimes, relative sea level rise (Murray et al., 2014; Murray et al., 2015)	Declining extent, erosion, subsidence	Land cover change, sea level altimetry, ground deformation
Kelp forest	Predator harvest, warming (Cavanaugh et al., 2010; Steneck et al., 2002; Wernberg et al., 2016)	Increasing urchin barrens, cover decline	Vegetation indices, sea surface temperature
Mangrove forest	Coastal reclamation, sediment declines, sea level rise (Kuenzer et al., 2011; Lovelock et al., 2015)	Tree mortality, declining extent	Vegetation height & structure, land cover change, vegetation indices, land surface temperature, hydroperiod
Salt marsh	Land reclamation, relative sea level rise, changing sediment regimes (Deegan et al., 2012; Kirwan and Megonigal, 2013; Kirwan et al., 2016)	Erosion, drowning, vegetation loss	Land cover change, sea level altimetry, ground deformation
Seagrass	Eutrophication, habitat loss, sea level rise (Kilminster et al., 2015; Saunders et al., 2013)	Changes in extent, loss in cover, reduced biomass	Sea surface temperature, ocean color, vegetation indices
Tidal marsh	Eutrophication, habitat loss, sea level rise (Deegan et al., 2012; Kirwan and Megonigal, 2013; Kirwan et al., 2008)	Changes in extent, loss in cover, reduced biomass	Vegetation indices, land cover change.

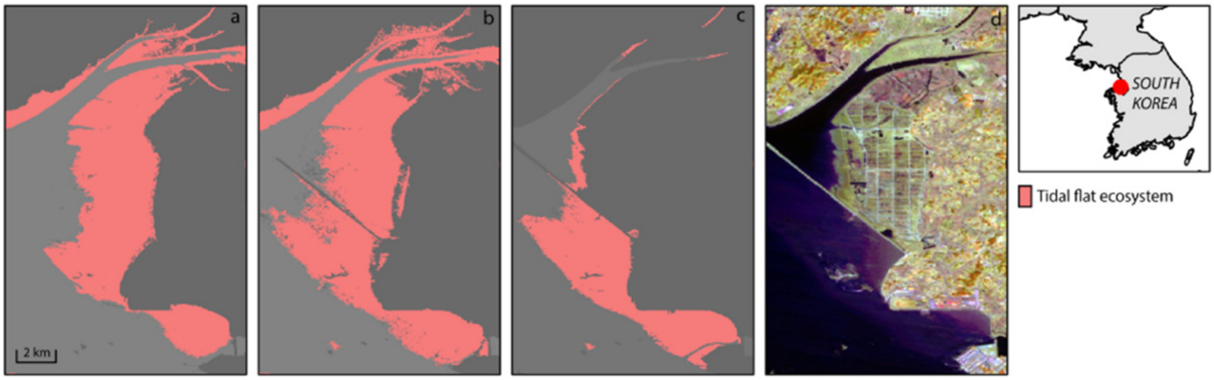

Fig. 3. Time-series classified maps of the Yellow Sea tidal flat ecosystem indicate a decrease in extent over 32-years due to land reclamation and the construction of a sea wall, Gyeonggi Province, South Korea. Maps were developed with random forest classifications of Landsat TM (a; 1985), ETM+ (b; 2000) and OLI (c; 2015) image composites (d; 2015 composite).

change and ensure the persistence of natural ecosystems into the 22nd century.

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Appendix A

Table A.1
References for example case studies cited in Table 1.

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Table A.2
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