Chapter 5
Remote Sensing and Modeling of Coral Reef Resilience

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Abstract A new paradigm has emerged for management of coral reefs in an era of changing climate – managing for resilience. A fundamental need for such management to be effective is our ability to measure and map coral reef resilience. We review the resilience concept and factors that may make a coral reef more or less resilient to climate-driven impacts, and focus on recent advances in a trio of technologies – remote sensing, spatial distribution modeling, and ecosystem simulation – that promise to improve our ability to quantify coral reef resilience across reefs. Remote sensing allows direct mapping of several ecosystem variables that influence reef resilience, including coral and algal cover, as well as a range of coral reef stressors, as exemplified by three case studies. Spatial distribution modeling allows exploitation of statistical relationships between mappable environmental variables and factors that influence resilience but which cannot be mapped directly, such as herbivore biomass. Ecosystem simulation modeling allows predictions to be

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made for the trajectories of reef ecosystems, given their initial state, interactions between ecosystem components, and a realistic current and future disturbance regime. Together, these technologies have the potential to allow production of coral reef resilience maps. We conclude with a fourth case study that illustrates integration of resilience maps into a multi-objective decision support framework. Implementation of the managing for resilience paradigm is still in its infancy, but the rapidly advancing technologies reviewed here can provide the resilience maps needed for its successful operationalization.

5.1 Introduction

Global climate change is widely recognized as a major threat to tropical coral reefs, primarily due to an increase in the frequency and magnitude of thermal stress events leading to coral mortality from bleaching and disease outbreaks (Eakin et al. 2010). Climate change is also predicted to increase the frequency of severe storms and the acidity of ocean water that can cause physical damage to reef structure and reduce coral growth rates (Hoegh-Guldberg et al. 2007; van Hooidonk et al. 2014; Manzello et al. 2013). These broad-scale threats interact with more local stressors, such as exposure to materials from land that reduce water quality and fishing that removes functionally important species from the ecosystem (Hughes and Connell 1999; Wilson et al. 2006; Ban et al. 2014), to degrade reefs. The ecological consequence for coral reefs from multiple stressors operating at multiple scales will depend on the structural and functional attributes of the coral reef ecosystem, as well as the type, magnitude and duration of stress (Carilli et al. 2009; McClanahan et al. 2014). In many locations, interacting stressors have undermined the resilience of coral-dominated communities, resulting in a phase-shift to a less desirable algal-dominated community, with impaired provisioning of ecosystem goods and services (Moberg and Rönnbäck 2003; Hughes et al. 2010; Pratchett et al. 2014).

Although the functional integrity of coral reefs is likely to be impacted more where multiple severe stressors exist, the complex spatio-temporal heterogeneity of environmental systems causes coral reefs and associated organisms to exhibit a spatially complex stress response (Mumby and Steneck 2008; Elmqvist et al. 2003). This presents a major challenge for management of coral reef ecosystems where the identification of areas with different levels of resilience to stressors is required to prioritize actions and design place-based conservation strategies (Game et al. 2008; McClanahan et al. 2009; McLeod et al. 2008).

A new *resilience* paradigm has thus emerged for coral reef management, with conservation objectives that aim to enhance or sustain the resilience of coral reefs to the range of stressors they face (Nyström et al. 2008; McClanahan et al. 2012). A major challenge for conservation ecology has thus become the provision of information on resilience at spatial and temporal scales relevant to management. Typically, indicators of resilience are measured through in-water surveys, yet management domains are geographically broad and therefore in-water surveys alone are of limited utility and prohibitively expensive for agencies to conduct. Rapid and cost-effective techniques are therefore required to provide detailed and ecologically relevant spatial information on coral reef resilience across broad and structurally complex geographical areas. Advances in spatial technologies such as remote sensing and spatial modeling show great potential to address this challenge (Maina et al. 2008; Rowlands et al. 2012; Knudby et al. 2013a). For example, ecological studies have demonstrated that the diversity and abundance of herbivores (fishes and invertebrates) are important indicators of coral reef health through their function in controlling algal biomass (Burkepile and Hay 2008; Cheal et al. 2010). Models estimate that increased herbivory by parrotfish after protection from fishing may increase reef resilience sixfold (Mumby et al. 2013b). While little is known about the geography of herbivory and its implication for predicting resilience, spatial modeling has shown that it is possible to map herbivore species distributions, biomass, and the functional richness of herbivores across the seascape (Pittman and Brown 2011; Knudby et al. 2013a; Pittman and Knudby 2014). Research is now urgently required to determine the utility of mapping indicators of resilience as a functionally meaningful spatial proxy for reef resilience. To support science-based decision making in marine conservation, this chapter presents a review of how remote sensing and spatial distribution modeling can be used to map resilience indicators and how such maps can be integrated through simulation modeling to provide spatially explicit estimates of coral reef resilience. Finally we outline an approach for integrating such information through a spatial decision support framework that uses local expert knowledge, remote sensing data and in-water surveys to identify and prioritize coral reef ecosystems for conservation action.

5.2 Coral Reef Ecosystem Resilience and Indicators of Resilience

The concept of resilience and stability in ecology are not new. Holling (1973) defined resilience as “*a measure of the persistence of systems and their ability to absorb change and disturbance and still maintain the same relationships between populations or state variables*”. Stability was defined as “*the ability of a system to return to an equilibrium state after a temporary disturbance*” with a more rapid return indicative of greater stability. Holling (1996) differentiated between *ecological resilience* and *engineering resilience*, two aspects of a system’s stability that have different consequences for evaluating, understanding, and managing complexity and change. *Engineering resilience* assumes that the system in question has a single stable state that it will return to in the absence of disturbance, and is typically quantified as the magnitude of deviation from, and speed of return to, the stable state following a disturbance. *Ecological resilience*, on the other hand, assumes that multiple stable states exist, each bounded by a domain of attraction. It is thus considered the amount of disturbance the system can be exposed to without moving beyond its current domain of attraction and transitioning to another stable state (Holling 1996). Other authors have also considered ecosystem characteristics such as durability and robustness (Dawson et al. 2010). Clarification and debate on the use of terminology for both conceptualization and operationalization of resilience is dealt with elsewhere in the literature (Gunderson 2000; Levin and Lubchenco 2008; Mumby et al. 2014).

The spatial and temporal scales at which the system is considered influences our understanding of stability and resilience (Holling 1992). Although the relevant spatial and temporal scales are rarely specifically defined, it is broadly accepted that multiple stable states exist for coral reef ecosystems (Knowlton 1992; Mumby et al. 2013a, but see Dudgeon et al. 2010). Typically these include a desired coral-dominated state that, given a combination of press and pulse disturbances, can be replaced by an undesired macroalgae-dominated state. Ecological resilience has thus been broadly adopted as the relevant resilience concept by the coral reef community, however, it is difficult or impossible to measure in the absence of observed transitions between stable states, and thus not practical as a basis for resilience assessment or management. Engineering resilience, on the other hand, can be assessed by focusing on its two components, often termed "resistance" (to disturbance) and "recovery" (from disturbance). In order to manage for resilience, factors that influence resistance and recovery must be identified and protected. A recent survey of expert opinion and scientific evidence (McClanahan et al. 2012) identified 11 principal factors that influence the resistance and/or recovery of coral reef ecosystems to climate-driven disturbances – and are also feasible to assess from local field observations at relatively fine spatial scales. These include aspects of the coral fauna (presence of stress-resistant coral species, diversity of coral species, high levels of coral recruitment, and absence of coral disease) and competition for space (low presence of macroalgae), as well as moderators of competition (herbivore biomass), the physical environment (high annual temperature variability, low nutrient and sediment levels), and direct human impacts (physical impacts and fishing pressure). These 11 factors can thus act as resilience indicators and may function as a list of mapping targets that combined have the potential to characterize the resilience of a coral reef ecosystem to climate-driven disturbance. For coral reefs, resilience has also been linked to connectivity through consideration of the movement of organisms across the broader seascape within which coral reefs are embedded (Mumby and Hastings 2008; Olds et al. 2012; Melbourne-Thomas et al. 2011). This landscape ecology approach is still in its infancy, but offers a pragmatic and ecologically rational way that remote sensing and mapping can be used to identify coral reefs that vary in their connectivity to neighboring habitat types (Pittman and Olds 2014).

5.3 What Remote Sensing Can Map on Coral Reefs

Remote sensing from water-, air- and space-borne platforms is now a core tool for the mapping, monitoring and management of coral reef ecosystems (Mumby et al. 2004a; Knudby et al. 2007). Sensor technology and the analytical tools for

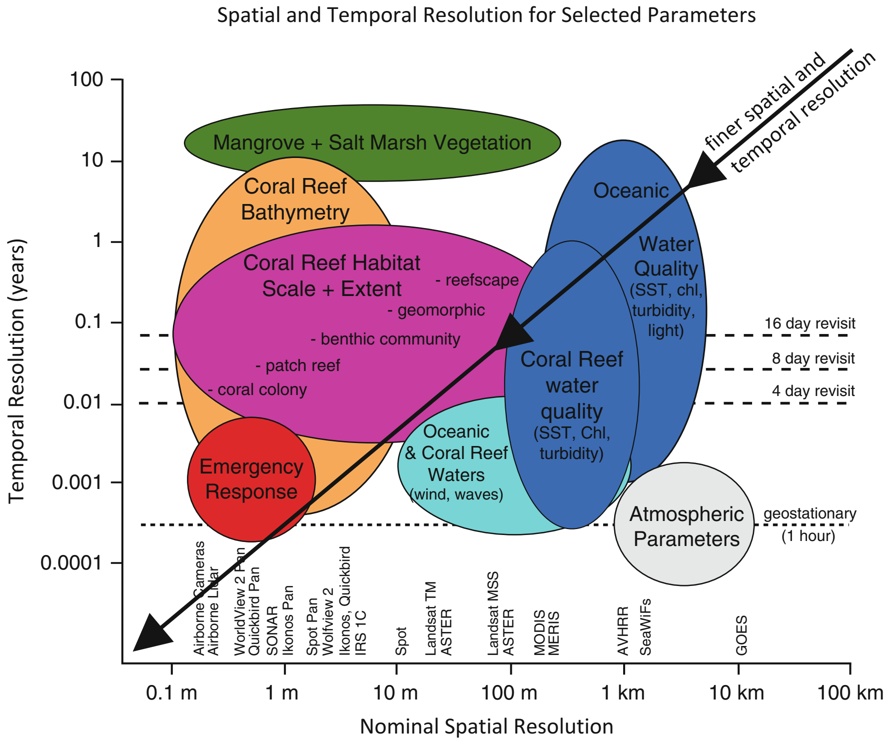

Fig. 5.1 Spatial and temporal scales for mapping and monitoring coral reefs and their environment (Reproduced with permission from Jupiter et al. (2013))

interpreting marine remote sensing data have advanced significantly in the past decade, and now provide reliable, repeatable and cost-effective quantitative assessments of habitat distributions and conditions over spatially extensive areas (Goodman et al. 2013). Remote sensing can provide a synoptic view of coral reef ecosystems by mapping a wide range of biological and physical variables from the water column to the seafloor, as well as on adjacent terrestrial areas that are required to characterize coral reef resilience, all at a wide range of spatial and temporal scales (Fig. 5.1). The diversity of information that can now be provided by remote sensing using passive sensors such as aerial photography, multispectral and hyperspectral sensors, or active sensors such as acoustic and lidar instruments, thus allows complex scientific and management-related questions to be addressed. Mapping the 11 resilience indicators identified by McClanahan et al. (2012), however, remains a significant challenge. Here we describe the capabilities of acoustic and optical sensors for mapping characteristics of the seafloor, the waters above, and the seascape context that is relevant to understanding and mapping reef resilience (Table 5.1).

Table 5.1 List of the 11 resilience indicators identified by McClanahan et al. (2012), and their potential for begin mapped either directly using remote sensing or indirectly through spatial distribution modeling

Resilience indicator	Potential for direct mapping with remote sensing
Stress-tolerant coral taxa	Coral taxa can generally not be mapped with remote sensing (Hochberg et al. 2003). Local mapping of distinct and prominent taxa is occasionally possible (Purkis et al. 2006)
Coral diversity	Coral diversity can generally not be mapped with remote sensing, although general measures of habitat diversity can be derived (Mumby 2001; Harborne et al. 2006; LeDrew et al. 2004)
Historical temperature variability	Historical SST variability can be directly derived from the long record of global SST data products (McClanahan et al. 2007)
Nutrients (pollution)	Derivation of near-surface concentrations of chlorophyll-a, CDOM and CDM is possible for Case I waters using ocean colour data, but is unlikely to be effective for coral reefs where RTM inversion algorithms must be used to derive nutrient concentrations (Giardino et al. 2007). The combination of airborne lidar and hyperspectral data is also promising for direct observations of nutrient concentrations on coral reefs (Aitken et al. 2010)
Sedimentation	Derivation of suspended sediment concentration has been demonstrated using airborne lidar and hyperspectral data (Epps et al. 2010) and acoustics (Hoitink and Hoekstra 2005), while limited progress has been made to derive this variable from passive optical data in coral reef environments (Ouillon et al. 2008)
Herbivore biomass	Several case studies show that the biomass of herbivorous fish can be mapped from lidar or multispectral data (Purkis et al. 2008; Pittman et al. 2009)
Physical human impacts	While natural physical impacts on reefs can be derived from models and historical observations, anthropogenic physical impacts on coral reefs cannot generally be mapped with remote sensing
Coral disease	Coral disease can generally not be mapped with remote sensing. However, remotely sensed SST can be used to predicted disease outbreak risk (Heron et al. 2010)
Macroalgae	Macroalgal cover can be mapped either with spectral unmixing techniques (Goodman and Ustin 2007) or using benthic cover classification techniques (Mumby et al. 1997; Roelfsema et al. 2013)
Coral recruitment	Coral recruitment can generally not be mapped with remote sensing. However, factors that influence coral recruitment and post-settlement survival, and which can be mapped with remote sensing, include suitable settlement substrate (Mumby et al. 2004b), suspended sediment concentration (Hoitink and Hoekstra 2005) and others
Fishing pressure	While fishing pressure cannot be directly mapped using remote sensing, proxy variables such as distance to settlements, port infrastructure or markets may provide quantification of relative fishing pressure between locations (Rowlands et al. 2012)

5.3.1 Mapping the Seafloor

Both the three-dimensional structure of the seafloor and the biological composition of benthic coral reef habitats can be mapped accurately and at high spatial resolution using active sensors, including ship-based acoustic systems (single-beam, side-scan, multi-beam) and airborne lidar, as well as passive optical (multispectral, hyperspectral) remote sensing. The basic principle employed in acoustic systems is that a transmitter emits a sound pulse and measures the time until its reflection off the seafloor is registered by a receiver. Using an estimation of the speed of sound in water (Chen and Millero 1977), the two-way travel time of the pulse (from the emitter to the seafloor, then back to the receiver) is then converted to a one-way vertical distance that equals water depth (Riegl and Guarin 2013). Airborne lidar operates using a similar principle. A short laser pulse is emitted, and the time until its reflection off both the sea surface and the seafloor is measured. The two-way travel times are then converted to one-way vertical distances, and the difference between the distances to the sea surface and the seafloor equals water depth (Purkis and Brock 2013). Given the positional accuracy obtainable with kinematic GPS and the timing accuracy of laser pulse emission and return registration, airborne lidar can achieve typical positional accuracies of seafloor points of 15 cm vertically and 1 m horizontally (Purkis and Brock 2013). The energy contained in the laser pulse is lost through refraction and backscattering at the sea surface, as well as absorption and scattering at the seafloor and in the water column, thus limiting the depth to which a signal reflected off the seafloor can reliably be detected to 60 m even in exceptionally clear water, and much less in more turbid conditions. This stands in contrast to the energy in the sound wave emitted by acoustic instruments, the attenuation of which is largely determined by frequency while being relatively insensitive to turbidity, and which can easily reach the seafloor at any depth relevant to studies of coral reefs (Tolstoy and Clay 1966). Typical positional accuracies of seafloor observations from multi-beam acoustic instruments are in the order of a few centimeters vertically and ~0.5 m horizontally (Ernstsen et al. 2006).

As an alternative to active sensors, the use of multi- or hyperspectral data to derive maps of bathymetry also has a long history (Lyzenga 1978; Jupp 1988; Bierwirth et al. 1993; Stumpf et al. 2003; Dekker et al. 2011). The most commonly used empirical methods rely on field observations for local calibration of model coefficients, and apply simplifying assumptions to constrain what is an inherently underdetermined problem (Lee et al. 1998). More recently, methods that do not require coincident field data for calibration have been developed for hyperspectral remote sensing data. Pioneered by Lee et al. (1998, 1999), these methods use radiative transfer models (RTM) to simulate the above-water spectral reflectance that would be observed in atmospherically corrected satellite data, given a set of inputs that include (or can be used to derive) water depth, water optical properties, and seafloor spectral reflectance (Mobley et al. 2005). The use of these methods with multispectral data is a promising but little explored approach to bathymetry mapping (Hedley et al. 2012), with typical vertical accuracies of ~1–2 m in optically shallow waters (Dekker et al. 2011). Although bathymetry per se is not an important factor determining coral reef resilience, it may influence several of the identified resilience indicators such as coral diversity and recruitment through its influence on local current patterns. Thus, bathymetry and its derivatives can serve as useful spatial proxies for a range of variables that cannot be reliably mapped (Pittman and Knudby 2014). For example, measures of seafloor structural complexity, derived from seafloor terrain models, have repeatedly been shown to function as a key predictor of several reef resilience indicators such as herbivore biomass and coral abundance (Pittman et al. 2009; Knudby et al. 2010a, b; Pittman and Brown 2011).

Although acoustic and lidar-based methods are also rapidly developing to provide more detailed information on benthic cover (Park et al. 2010; Foster et al. 2013; Pittman et al. 2013), derivation of information on coral reef biota primarily relies on passive optical remote sensing, from which reef geomorphological zonation (Smith et al. 1975; Andréfouët and Guzman 2005; Purkis et al. 2010) and benthic cover types (Ahmad and Neil 1994; Green et al. 1996; Mumby et al. 1997; Newman et al. 2007; Phinn et al. 2012) can be mapped. The number of benthic cover types that can reliably be distinguished using passive optical remote sensing methods depends on the platform and the sensor type, the depth and optical properties of the water, as well as the inherent spectral separability of the benthic cover types in question. Collectively research in this field suggests that high sensor spatial resolution (Andréfouët et al. 2003; Mumby and Edwards 2002), high sensor spectral resolution (Capolsini et al. 2003), and the presence of one or more bands operating in the 400–500 nm (blue) spectrum (Hedley et al. 2012), in addition to suitable environmental conditions (limited specular reflection off the sea surface, clear and shallow water) are important for production of detailed and accurate map products. Notable recent methodological developments have included object-based (Roelfsema et al. 2013) and semi-automated (Suzuki et al. 2001) delineation of geomorphology, a shift from per-pixel to object-based classification of benthic habitat (Leon and Woodroffe 2011; Phinn et al. 2012; Roelfsema et al. 2013), and multi-image approaches to improve map accuracy (Knudby et al. 2014). For example, to overcome limitations of any one technique, Costa and Battista (2013) developed a novel, semi-automated object- and pixel-based technique to map coral reefs in the Caribbean from multibeam echo sounder imagery. They produced maps with high accuracy (74–97 %) for geomorphological types, detailed biological cover types and live coral cover.

Due to the widespread use of fractional live coral cover as an indicator of reef health, methods have also been developed to map this biological variable (Hochberg et al. 2003; Goodman and Ustin 2007; Joyce et al. 2013; Mumby et al. 2004b). These methods typically rely on spectral derivative or unmixing approaches applied to airborne hyperspectral data, and are most successful in clear shallow water with few spectrally similar non-coral benthic cover types (Dekker et al. 2011). Individual coral species cannot generally be distinguished with remote sensing (Hochberg and Atkinson 2000; Hochberg et al. 2003), except in rare circumstances (Purkis et al. 2006). As a result, coral diversity or the presence of stress-resistant corals can also not be directly inferred from remote sensing data. Although it has been demonstrated that corals affected by disease have distinct spectral reflectance characteristics when measured in-situ (Anderson et al. 2013), coral disease is also unlikely to be detectable with existing remote sensing instruments, as is coral recruitment. As such, remote sensing is not capable of directly mapping any of the four aspects of the coral fauna identified as important resilience indicators. Estimates of macroalgal cover, on the other hand, can be derived from the same spectral unmixing approaches used to map live coral cover (Goodman and Ustin 2007; Lee et al. 1999; Hedley 2013).

5.3.2 Mapping the Water Column

In addition to mapping the seafloor, remote sensing can be used to characterize the physical environment surrounding a reef ecosystem. Applications of satellite remote sensing have been demonstrated for mapping surface layer concentrations of chlorophyll (Morel and Prieur 1977; Moses et al. 2009), coloured dissolved organic matter (CDOM) (Morel and Gentili 2009) and suspended sediment (Globcolour 2008), as well as sea surface temperature (SST) (Maina et al. 2008; McClanahan et al. 2007; Strong et al. 2000). SST has routinely been mapped from satellite data since the early 1970s, with a globally consistent temperature records available from 1981 (Casey et al. 2010). The accuracy of temperature estimates has improved through time with development of increasingly sophisticated sensors (e.g. MODIS, AATSR). The long global SST data record allows remote sensing to directly map the historical temperature variability of coral reef sites, one of the factors identified as important for coral reef resilience. Surface layer chlorophyll concentration was first mapped on a global scale by the CZCS sensor (1978–1986), and has been continuously mapped since first operation of the SeaWiFS sensor (1997–2010), with additional products available from the MERIS (2002–2012) and MODIS (2000–present) sensors. Derivation of near-surface chlorophyll concentration is based on observations of ocean colour, with algorithms for chlorophyll concentration retrieval differing between sensors, and as a result of regional optimization (O'Reilly et al. 2000; Curran and Dash 2005). Ocean colour is similarly the basis for operational algorithms used to derive concentrations of CDOM (Morel and Gentili 2009) or CDM (which includes CDOM as well as coloured detrital materials) (Siegel et al. 2005), as well as suspended sediment (Globcolour 2008). While ocean colour and SST algorithms are now routinely applied to data from several satellite sensors, producing freely available data with daily near-global coverage at 4 km spatial resolution (NASA 2014), it is important to note the algorithms employed were developed and calibrated for Case I waters (Jerlov 1968), oceanic waters where ocean colour is negligibly influenced by terrigenous particles, and where the spectral radiance recorded by satellite sensors is not influenced by seafloor reflection. Application is thus questionable for coral reef environments (Ouillon et al. 2008), where RTM inversion algorithms hold the greatest promise for mapping water optical quality (and constituents) from space (Giardino et al. 2007). Combinations of airborne lidar and hyperspectral data have also shown great promise for direct derivation of water quality parameters including chlorophyll (Aitken et al. 2010) and suspended sediment concentrations (Epps et al. 2010), the latter of which can also routinely be mapped with acoustic methods (Bunt et al. 1999; Hoitink and Hoekstra 2005).

5.3.3 Mapping and Modeling the Seascape Context

The ability of a coral reef to recover after disturbance and the rate and trajectory of that recovery will be influenced by its connections with the surrounding seascape (Mumby and Hastings 2008; Jones et al. 2009). Connectivity is critical for replenishment of corals, fishes and other species that form coral reef ecosystems, but can also be linked to the spread of pollution, invasive species and diseases (Hughes et al. 2010). In coral reef ecology, connectivity is usually studied with particle dispersal models where the focus is on identifying the distribution and movement pathways of larval transport. Progress in larval connectivity modeling has been thoroughly reviewed in the existing literature (Jones et al. 2009). Here we focus on how remote sensing data can help to identify coral reefs that are structurally connected to other benthic habitat types by the movement of post-settlement fishes.

The knowledge of ecological connectivity between coral reefs and neighboring habitat types such as seagrasses and mangroves is not new (Parrish 1989), yet it is only recently that this inter-habitat connectivity has been linked to reef resilience (Mumby and Hastings 2008; Olds et al. 2013). Underwater observations of the spatial patterns of fish distributions on coral reefs near and far from ‘nursery seascapes’, such as mangroves and seagrasses, have highlighted the importance of structural connectivity (Grober-Dunsmore et al. 2009; Nagelkerken et al. 2012). For example, in Belize, Mumby et al. (2004c) found that mangroves strongly influence the community structure of fish on neighbouring coral reefs and boosted biomass of some reef-associated fish species. Subsequent simulations indicated that enhanced herbivory by parrotfishes on deeper reefs near mangroves resulted in greater coral recovery from intense hurricanes, whereas reefs without ecosystem connectivity had lower capacity for recovery (Mumby and Hastings 2008). In the Bahamas, high levels of parrotfish herbivory led to a twofold increase in coral recruitment (Mumby et al. 2007a, b). Thus, for some reefs, connectivity to mangroves infers greater resilience to disturbance. A similar mangrove-enhanced trophic cascade that reduced algal cover and enhanced coral recruitment and reef resilience was identified in eastern Australia (Olds et al. 2013).

In landscape ecology, structural connectivity is measured by the spatial arrangement of patches in the seascape using a wide range of spatial pattern metrics from simple proximity measures (i.e. nearest neighbor distances) to more complex graph theoretic approaches (Calabrese and Fagan 2004). Although rarely applied to coral reef ecosystems, these metrics can be readily applied to benthic habitat maps to calculate a spatial proxy for functional connectivity (Grober-Dunsmore et al. 2009; Wedding et al. 2011). Very little is currently known about the relevance of seascape pattern for reef resilience or the ecological consequences of movements on populations and ecosystem patterns and processes. The landscape ecology approach, with its focus on spatially-explicit pattern-process analysis, offers great potential to support ecologically effective strategies for restoring and optimizing connectivity. For example, when marine reserves are placed to protect well connected habitats then the rate of recovery will likely be enhanced (Olds et al. 2013). Landscape ecology concepts and tools together with remote sensing data are set to make major contributions to the new study of spatial resilience (Nyström and Folke 2001; Cumming 2011a). Spatial resilience focuses on the importance of location, connectivity, and context for resilience, based on the idea that spatial variation in patterns and processes at different scales both impacts and is impacted by local system resilience (Cumming 2011b).

5.3.4 *Mapping Threats and Stressors*

Natural physical impacts on the reef environment include long-term wave exposure as well as extreme events such as hurricanes. Long-term wave exposure can be derived at coarse resolution (~25 km) directly from wind wave models (Tolman and Alves 2005) or extracted from climatological reanalyses (Caires and Sterl 2005), while hurricane exposure can be depicted statistically from historical hurricane data (Edwards et al. 2011). However, the anthropogenic physical impacts identified as an important factor influencing reef resilience (McClanahan et al. 2012) include damage from reef trampling and diving, ship groundings and coral mining, all of which are difficult or impossible to map directly using remote sensing. While these may correlate with proxies such as the distance to human settlements, data from interviews or field observations are more likely to provide spatial information on anthropogenic physical impacts. Similarly, fishing pressure, another important resilience indicator, cannot be mapped directly using remote sensing, although proxies such as distance to settlements, port infrastructure or markets may be used to provide quantification of relative fishing pressure between different sites (Rowlands et al. 2012).

5.4 Direct Monitoring

An alternative to mapping resilience indicators is to map and monitor relevant reef state variables such as the fractional cover of corals and macroalgae through a period before, during and after a major disturbance, to assess the state changes caused by the disturbance (resistance), as well as the time taken to reach the pre-disturbance state (recovery), thus providing a direct measure of engineering resilience to the specific disturbance event. In-situ hyperspectral measurements have shown that significant differences in spectral reflectance exist between corals and macroalgae (Holden and LeDrew 1998; Myers et al. 1999; Hochberg and Atkinson 2000), and studies employing airborne hyperspectral data have shown the potential to utilize these differences for monitoring. However, the limited availability of hyperspectral data means that any operational monitoring of live coral and macroalgal cover must rely on multispectral satellite data, at least until the launch of EnMAP expected in 2015. Encouragingly, a few studies using time series of Landsat TM/ETM+ data (Dustan et al. 2002; Phinney et al. 2002; Palandro et al. 2003) have demonstrated correlations between measures derived from multi-spectral satellite data and transitions from coral- to algal-dominated reef benthos over a ~15 year period for two reef sites in Florida. Although no remote sensing-based coral reef monitoring system exists and successful replication of these studies elsewhere is needed, these studies suggest that monitoring of live coral and macroalgal cover may be possible both retrospectively and operationally. The potential of this approach will be further improved by availability of data from sensors with improved spatial and spectral resolutions such as Landsat 8 OLI and Sentinel-2 MSI (launch expected 2014).

5.5 Spatial Distribution Modeling

For resilience indicators that cannot be mapped directly, spatial distribution modeling can be used to predict distributions across geographical space by extrapolating the statistical relationship between remotely sensed environmental variables and georeferenced field observations (Franklin 2009; Pittman and Brown 2011; Knudby et al. 2013a). Spatial distribution modeling relies on a two-step process. In the first step, a predictive model is calibrated based on an observed statistical relationship between the resilience indicator in question and one or more environmental variables with known spatial distribution. For example, several studies have demonstrated statistical relationships between fish herbivore biomass and environmental variables such as geomorphologic zone (Friedlander and Parrish 1998), seafloor structural complexity (Pittman et al. 2009), and habitat heterogeneity (Purkis et al. 2008). Model calibration requires georeferenced field observations of the resilience indicator in question, as well as maps of the environmental variables thought to structure its spatial distribution. In the second step, the predictive model is applied to the environmental variable maps to produce per-pixel predictions of the resilience indicator (Franklin 2009; Knudby et al. 2013a). Spatial distribution modeling has been extensively used to map distributions of species and habitats in both terrestrial (Guisan and Thuiller 2005; Elith and Leathwick 2009) and marine environments (Cheung et al. 2008; Pittman et al. 2009; Knudby et al. 2013b). Even when maps of the relevant environmental variables are not available or possible to derive from remote sensing, spatial interpolation/extrapolation methods can be used to predict the spatial distribution of resilience indicators (Knudby et al. 2013a; Mumby et al. 2013b). Spatial predictive modeling has also been used to forecast changes to the quality of fish habitat due to declines in the topographic complexity of coral reef terrains (Pittman et al. 2011). Such scenario modeling can be used to investigate the potential impact of multiple stressors such as thermal stress, ocean acidification, storms and land-based sources of pollution that can adversely influence the structural complexity of coral reefs through coral mortality, mechanical breakage, reduced growth and survival and erosion (Graham and Nash 2013). These questions address crucial knowledge gaps in our understanding of climate impacts on coral reef fish, fisheries and coastal livelihoods in a changing world (Wilson et al. 2010). Linkages between remotely sensed measures of reef complexity and the structure and function of coral reefs may provide a rapid and cost-effective way to assess the spatial complexity of reef resilience and predict impacts to a wide range of goods and services provided by coral reefs (Pratchett et al. 2014).

5.6 Case Studies

With a combination of remote sensing and spatial distribution modeling, it is possible to map biological, physical and human factors known to influence coral reef resilience, albeit with varying and often unknown degrees of accuracy. In addition to factors related to resilience (resistance and recovery), remote sensing has successfully been used to map the exposure to climate-driven disturbance experienced at different reef sites. Few examples of such resilience-related mapping exists for tropical coral reefs, here we present three case studies that represent the leading edge of this new frontier in marine spatial ecology.

5.6.1 High-Resolution Mapping of Selected Resilience Indicators in Fiji

In their study of the traditional fisheries management area of Knudby et al. (2013a) used spatial predictive modeling to map four of the resilience indicators listed in Table 5.1: stress-tolerant coral taxa, coral diversity, herbivore biomass, and coral recruitment (quantified as the density of juvenile corals), as well as herbivore functional group richness and the live cover of corals and coralline algae, both of which may also influence reef resilience. The range of resilience indicators mapped in this study was limited by available field data, and focused on indicators that could not be mapped with existing methods but were thought to exhibit significant small-scale variability within the study area, a >260 km^2 complex reef system. Georeferenced field observations of the resilience indicators were derived from the Wildlife Conservation Society's reef monitoring program, from which data for 66–72 sites were available depending on resilience indicator. IKONOS and QuickBird satellite images were used to derive maps of bathymetry, geomorphology and reef benthos (Knudby et al. 2011), which in turn were used to map a coral cover index, seafloor structural complexity and habitat richness, all of which were calculated at spatial scales ranging from the smallest possible (individual 16 m^2 pixels) to those incorporating large parts of the neighbouring landscape (>3 km^2). Spatial layers quantifying distances to land, nearest seagrass bed, and nearest mangrove stand were also derived, as was a layer describing the conservation status of different areas (unprotected, tabu, no-take reserve). Two types of spatial predictive models were then used to produce maps of each resilience indicator. Regression modeling was conducted with random forest (Breiman 2001), a non-parametric tree-based ensemble classifier that predicts per-pixel values for each resilience indicator based on their statistical relationship with the

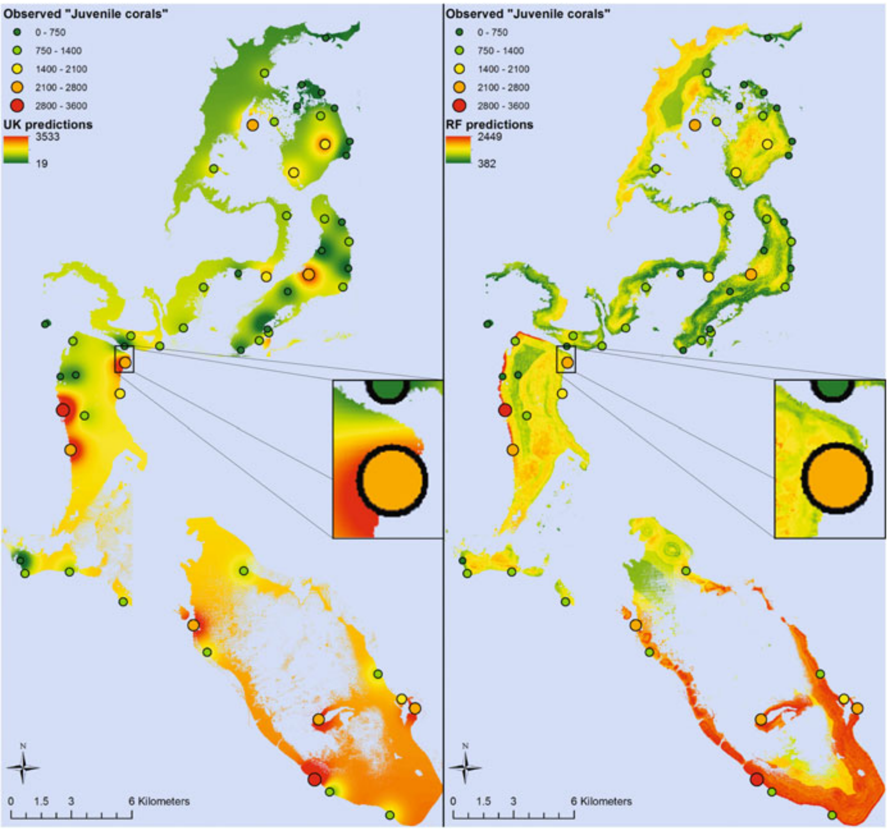

Fig. 5.2 Predictions of the spatial distribution of juvenile coral density across the Kubulau traditional fisheries management area, Fiji (Knudby et al. 2013a). *Points* indicate field observations while the coloured background illustrates the model predictions. Universal Kriging (*UK*) predictions are shown on the *left*, Random Forest (*RF*) predictions are shown on the *right*

spatial data layers. Spatial interpolation/extrapolation was conducted using universal kriging (Krige 1951), a geostatistical method that does not utilize the spatial data layers but rather fits a deterministic trend to the large-scale spatial variation in the value of each resilience indicator, and then uses locally optimized spatial interpolation of the residuals to account for small-scale spatial variations (Goovaerts 1997).

The results from Knudby et al. (2013a) suggested that, based on the data available, the spatial distribution of stress-tolerant coral taxa and herbivore biomass could be reasonably well predicted using the random forest model, while the density of juvenile corals could only be poorly predicted using the universal kriging model and coral diversity was essentially unpredictable. An example output, the predicted spatial distribution of juvenile coral density from each of the two models, is provided in Fig. 5.2. Numerous factors contribute to limited predictability of field-measured resilience indicators in this study, including mismatch between the spatial scale of field sites (belt transects, point intercept transect and quadrats, all covering different areas) and that of the satellite data (4 m for IKONOS, 2.4 m for QuickBird), imperfect georeferencing of both field sites and satellite data, limited sample distribution for both resilience indicators and environmental predictors, and, importantly, inability to incorporate information on past disturbance history, direct human impacts from fishing and other reef use, the influence of source populations and ocean and tidal currents on coral and fish recruitment, and the direct influence of wave exposure on post-settlement coral survival and growth. Some of these limiting factors can be easily addressed in future studies, while others will require substantial effort in data collection and analysis.

In addition, the results illustrated that the choice of modeling method, beyond producing different estimates of prediction error, also produced markedly different mapped predictions for each resilience indicator. As would be expected, predictions based on the random forest model tightly matched distributions of influential environmental predictors and thus changed quickly across steep environmental gradient such as reef edges, while predictions based on universal kriging varied more smoothly through space but were also better able to account for spatial clustering of high or low resilience indicator values when these were unrelated to the reef environment. The relative strengths of the two modeling methods suggest a potential for error reduction with hybrid models such as regression kriging (Hengl et al. 2004).

5.6.2 High-Resolution Mapping of a Coral Reef Resilience Index in Saudi Arabia

Focusing on coral reefs in the Saudi Arabian Red Sea, Rowlands et al. (2012) mapped aspects of coral reef resilience using a geographic information system (GIS) approach. A novel metric termed the *Remote Sensing Resilience Index* (*RSRI*) was developed that quantified and mapped important factors influencing reef resilience in the Saudi Arabian Red Sea (Fig. 5.3). *RSRI* was calculated at 1 km^2 ground resolution across a geographic extent of 20,000 km^2. The spatial resolution and extent are appropriate for addressing both local and regional management concerns. *RSRI* maps three key spatial gradients: (1) human use gradients; (2) physical gradients; and (3) biological and sediment gradients. These were considered within two classes of resilience indicators: (1) those which positively affect the reef community, termed *landscape indicators* and incorporated into the Coral Resistance Index (*CRI*); and (2) indicators that negatively impact reef communities, termed *stress indicators* and incorporated into the Coral Stress Index (*CSI*) (see Box 5.1).

Meter-scale habitat and water depth mapping, satellite derived SST, night time imagery, and spatial modelling were all used to develop map-based indices of

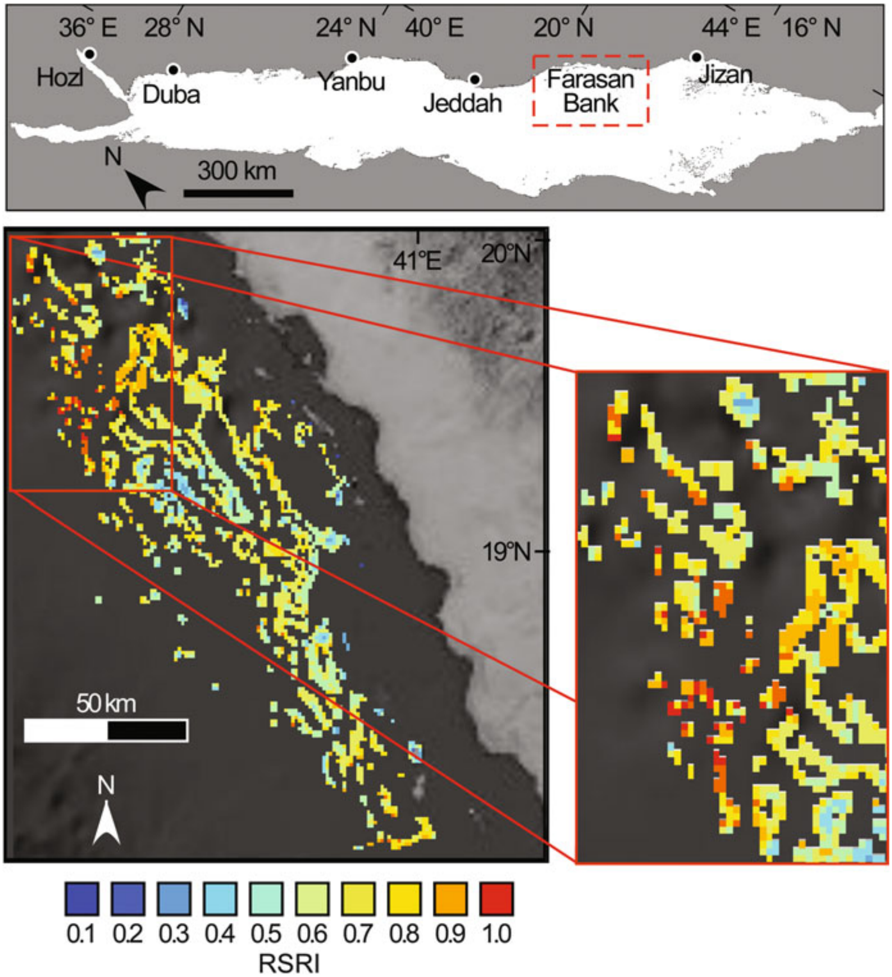

Fig. 5.3 The remote sensed resilience index (*RSRI*) mapped for the outer Farasan Banks in the Saudi Arabian Red Sea. The inset image to the right highlights a region with many high RSRI grids (Adapted from Rowlands et al. 2012)

important resilience indicators. Data sources included both freely available satellite data (NASA, Google Earth), and archived and tasked QuickBird satellite (DigitalGlobe Inc.) imagery funded by the Khaled bin Sultan Living Oceans Foundation. In the original formulation of *RSRI* three landscape indicators were considered: (1) live coral abundance; (2) framework abundance; and (3) water depth variability, and three stress indicators were considered: (1) fishing; (2) industrial development; and (3) temperature stress. Subsequent analysis by Rowlands (2013) used a more refined approach, using maps of water depth and wave exposure to incorporate the vulnerability of sites to coral bleaching events and modelling the distribution of high coral sites with greater certainty.

Box 5.1. Equations used to calculate the Remote Sensing Resilience Index (RSRI)

The remote sensed resilience index (*RSRI*), is calculated according to Eq. 5.1 to be:

$$RSRI = \frac{CRI_n - CSI_n}{\max(CRI_n - CSI_n)} \tag{5.1}$$

Positive influence is provided within the coral resistance index (*CRI*) shown in Eq. 5.2, while negative influence is provided by the coral stress index (*CSI*) shown in Eq. 5.3. All indices are normalized to a 0–1 scale.

$$CRI_n = \frac{((Lw_1 \cdot LF_1) + ...(Lw_n \cdot LF_{\mathrm{n}}))}{\max((Lw_1 \cdot LF_1) + ...(Lw_n \cdot LF_n))} \tag{5.2}$$

$$CSI_n = \frac{((Sw_I \cdot SF_1) + ...(Sw_n \cdot SF_n))}{\max((Sw_1 \cdot SF_1) + ...(Sw_n \cdot SF_n))} \tag{5.3}$$

LF and *SF* represent the map-based landscape and stress resilience indicators. *Lw* and *Sw* represent weighting factors, attributed to each resilience indicator and adjusted to model a range of resilience scenarios.

By adjusting the weight attributed to each input index, a number of resilience scenarios are considered for Saudi Arabia. Noting that resilient reefs can act as both repositories and also sources of reef organisms enabling recovery after a chance mortality event (Nyström and Folke 2001; Pinsky et al. 2012), several scenarios were modeled to explore the role of local feedback. Changing the relative importance of input indices, and calculating with or without local feedback produced nonlinear responses in *RSRI*, emphasizing the need to understand spatial dynamics when assessing spatial resilience.

The study showed that seascape morphology exerts a strong controlling role on reef resilience through the abundance of habitat, topography, and exposure to anthropogenic and physical stress. Understanding of the processes creating morphology in the Saudi Arabian Red Sea and elsewhere will therefore be helpful in targeting research and management towards the most resilient reef sites.

5.6.3 Mapping Exposure of Coral Reefs to Climate-Driven Environmental Stress

In addition to spatial information on the factors that enable coral reefs to resist and recover from climate-driven impacts, managing for coral reef resilience requires a better understanding of the magnitude and spatial distribution of threats, their interactions, and respective roles they play in impacting coral reefs. Threats maps and ecosystem vulnerability studies in historical and future time scales and at multiple spatial scales have therefore become an important research focus (Bruno et al. 2007; Maina et al. 2008, 2011; Selig et al. 2010; Burke et al. 2011; Gove et al. 2013; van Hooidonk et al. 2013, 2014). Often these regional and global scale models utilize modelled and remotely sensed data as inputs, highlighting the increasingly important role of remote sensing in decision support. Among these, multivariate stress models (Maina et al. 2008, 2011) have used a relatively more complicated multivariate approach including fuzzy logic techniques of integrating multiple variables and stress proxies derived from remote sensing data (Logan et al. 2014). Fuzzy logic provides a platform for translating the absolute values of environmental variables into indices that represent the exposure of coral reefs to the respective threats. Such procedures are informed by the perceived role of the environmental variable on coral health, as supported by empirical findings or expert knowledge. Fuzzy logic models are also easy to apply as they allow for use of fuzzy operators, which are useful in synthesizing the partial exposures into an overall exposure or vulnerability metric. Moreover, this modeling framework is relatively flexible for modifications to accommodate any lurking variables and new science.

In their global analysis, Maina et al. defined three broad categories of environmental stressors. These included: (1) radiation stress indicators which are considered to be the primary climatic drivers of coral reef exposure (temperature, UV light and doldrums); (2) stress-reinforcing indicators (sedimentation and eutrophication) which have been shown to reinforce radiation stressors; and (3) stress-reducing indicators (temperature variability and tidal amplitude) which act to reduce or balance thermal stress. Following these definitions, a systems analytical approach and fuzzy logic functions were used to represent the interactions among radiation stress variables, stress reinforcing variables and stress reducing variables. For each of these broad stress categories, constituent variables were derived from various sensors within the ocean realm.

SST time series from 1982 to 2010, produced using data from NOAA's Advanced Very High Resolution Radiometer (AVHRR) sensors, were used to produce global maps of mean absolute temperature, mean maximum temperature, and temperature variability. Thermal stress metrics, including time series of weekly SST anomalies (WSSTAs), defined as the weekly averaged temperature in excess of 1 °C or more above that week's long term average value, and thermal stress anomalies (TSAs), defined as the temperature excess of 1 °C or more above the climatologically warmest week of the year were computed. Cumulative estimates of TSAs and WSSTAs were calculated from annual averages in the 27 year time series. Further, for each year, a maximum duration (in weeks) that WSSTA and TSA were greater than or equal to 1 °C were computed and averaged over 27 years. These two cumulative metrics, the mean annual cumulative and mean yearly maximum duration, represent the characteristic magnitude and duration of the anomalies at a given location, which are important predictors of coral stress (Bruno et al. 2007; Selig et al. 2010). UV-erythemal (biologically damaging) irradiance at the Earth's surface was mapped in a 1 by 1.25° grid using data from 1996 to 2001 from the total ozone mapping spectrometer (TOMS) (Herman et al. 1999; Vasilkov et al. 2001). Doldrums (i.e. wind conditions with a daily mean of less than 3 ms^{-1}) were computed using daily averaged wind speeds (2000–2009) and the averaged 10-year mean monthly wind speeds (1995–2004). To estimate the magnitude and consistency of wind regimes in a given location, a doldrums metric was computed by taking the annual average maximum number of days that wind speeds were greater than 3 ms^{-1} over 10 years (2000–2009) and multiplying this by the 10-year mean monthly average. To represent tidal conditions, modelled tidal data (Le Provost et al. 1998) was used where tidal ranges were computed as the long term averaged difference between the weekly maximum and minimum simulated tidal heights.

As outlined earlier, concentrations of nutrients and suspended sediment are operationally mapped from ocean colour data, but algorithms are calibrated for Case I waters and fail in turbid coastal waters (Morel and Bélanger 2006) as well as in shallow areas where sunlight reflected off the seafloor increases the reflectance of the water/seafloor system, leading to overestimations of suspended particles (Boss and Zaneveld 2003). Given these problems, until special algorithms that take into account the complexity in coral reef areas (e.g. Ouillon et al. 2008) are developed and incorporated in the standard processing chains of the current ocean color satellites, the usefulness of ocean color data for coral reef applications will remain limited (Boss and Zaneveld 2003; Mumby et al. 2004a). To overcome this, Maina et al. (2011) analyzed the global ocean color data such that appropriate algorithms were applied in the respective water types. Further they applied a depth flag of 30 m to remove shallow water before extrapolating values from nearby deep-water pixels into the shallow areas. While this product avoided the problems associated with high reflectivity of complex coastal areas, optical properties estimates in highly turbid coastal areas such as river mouths were underestimated (Gove et al. 2013).

Based on the above data sets, modeling of coral reef stress exposure involved two key steps. First, summaries of environmental layers comprised within each of the three categories of stressors were converted into partial exposures using fuzzy logic equations. Second, exposure layers for each of the three categories were synthesized using fuzzy-logic operators. The resulting multivariate exposure model provided estimates of coral reef exposure to climate stress worldwide where coral reefs are found.

The multivariate stress model by Maina et al. (2011) found high within-region variability, and spatial heterogeneity of exposure to radiation and both reinforcing and reducing stress categories. Furthermore, the magnitudes of radiation and reinforcing stressors were analyzed in order to facilitate appropriate management decisions. For instance, while reduction of climate-driven stress is impossible in the short term, management can act to reduce reinforcing stress on corals through a pollution reduction strategy. Findings from the analysis of the exposure model advanced coral threat mapping by providing evidence of spatial differences in exposure to multiple stressors, highlighting potential utility of the spatial adaptive management approach to coral reef conservation, and developing a frame work for exposure analysis applicable at local scales for implementation purposes. While the model has found application in social vulnerability analyses Cinner et al. (2013), its implementation for local scale coral reef management is yet to be realized. Ideally, application of the model at the local scale would require downscaling where in situ measurements of the constituent variables in the model would be used. Furthermore, other useful information not currently incorporated in the model, for example habitat typologies and socio-economic indicators, would improve the models performance and its utility in aiding management decisions.

5.7 Spatially Explicit Resilience Modeling

Informative as they may be, maps that quantify either exposure to stress and disturbance or factors that influence resilience do not by themselves allow quantification of coral reef resilience. Engineering resilience can be quantified as the magnitude of deviation from, and speed of return to, the stable state following a disturbance, while ecological resilience can be quantified as the amount of disturbance the system can be exposed to without moving beyond its current domain of attraction and transitioning to another stable state (Holling 1996). To properly quantify resilience we thus need mechanistic models that allow simulation of how key ecosystem state variables (e.g. coral and algae cover) through interaction with other components of their ecosystems respond to both chronic stress and periodic disturbances through time (Mumby and Hastings 2008). Parameters used in such models should at a minimum include the critical state variables, factors they interact strongly with and which therefore are important for determination of resilience, and realistic stress and disturbance regimes that the ecosystems can be subjected to in model simulations.

An early example of a coral reef ecosystem simulation model was developed by McClanahan (1995). Although not explicitly developed to study coral reef resilience, the model quantifies a set of core ecosystem state variables and their interactions using an energy-circuit diagram (Odum 1983). Model coefficients that quantify development of individual ecosystem components and interactions between different components are derived from field observations. Using fixed time steps the model can be run until negligible change in state variables is seen and a *stable state* has emerged, using either a business-as-usual scenario or one of several simplified management scenarios (e.g. allowing fishing activity to remove all piscivores, or both piscivores and herbivores). Although results were demonstrated by McClanahan (1995) to broadly match field observations from a number of Kenyan reefs, the model suffers from several limitations, including fixed instantiation (the starting values of all state variables), no inclusion of large-scale disturbance events, no inclusion of information on recruitment, and a lack of spatiality that prevents modeling of connectivity.

A more recent model developed by Mumby et al. (2007a, b) similarly allows simulation of states and interactions between core ecosystem variables, focusing on coral-algal dynamics. Allowing variable instantiation this model illustrates how, in the absence of an external disturbance regime, the initial state of the system determines whether it will gradually develop toward a coral-dominated or an algal-dominated stable state. The model also allows introduction of a stochastic disturbance regime (e.g. hurricanes causing 20 % coral mortality occurring on average every 20 years) as well as chronic stresses (e.g. annual removal of a certain amount of fish herbivore biomass) to examine the effect of pulse disturbances and chronic stresses on coral-algal dynamics. The use of a stochastic disturbance regime additionally allows multiple model runs with identical instantiations to produce different results, which in turn enabled Mumby et al. to define a useful measure of coral reef resilience – the probability that the reef would be in a coral-dominated state after a given time period. This model was recently applied to the Belize Barrier Reef System (Mumby et al. 2013b), with a spatially explicit disturbance regime defined on a 16 km^2 cell-by-cell basis using information on hurricane tracks from 1909 to 2008 and predictions of future sea surface temperatures derived from two climate scenarios. Reef state variables were derived from interpolation of field observations. This spatially explicit model instantiation and disturbance regime definition allowed exploration of differences in resilience between different parts of the studied reef system, and also allowed spatially explicit evaluation of potential management interventions (e.g. protection of parrotfishes was shown to be important for reef resilience in parts of central Belize, but less so in southern Belize where reef resilience was already high).

Another model, developed by Melbourne-Thomas et al. (2011) specifically as a decision-support tool, provides a core of ecosystem variables and interactions similar to the previously discussed models but is inherently spatial in nature and also specifically incorporates connectivity by larval transport (though not by movement of adults). Larval dispersal is simulated using lower-resolution hydrodynamic and particle-tracking modules and includes basic larval behavior (i.e. coral, fish and urchin larvae behave differently). Once arrived at a sink reef location, larval settlement is limited by availability of settlement habitat and mortality of recruits is modeled differently than adult mortality during the first year after settlement. A simulation applied to the Meso-American Reef System, using the Millennium Coral Reef Mapping Project (IMaRS 2004) to define reef locations and spatially distributed field observations of reef state (Garcia-Salgado et al. 2006) to define initial values of state variables, showed that the model realistically captures ecosystem dynamics and reproduces known historical trajectories of state variables. This simulation illustrates the current state-of-the-art in resilience mapping and modeling, relying on a combination of spatially explicit data on state variables and disturbance regime parameters, and modeling of ecosystem dynamics through time to assess likely future ecosystem states, including the likelihood that part of or all of the reef ecosystem will flip to an alternate stable state.

5.8 Management Applications

In many parts of the world resource managers are operating with limited funds, and therefore require cost effective, reliable, spatially-explicit and easily interpretable information to help prioritize coral reef sites for risk assessments and conservation actions. Managers may be required to develop a conservation investment portfolio that prioritizes management actions to coral reefs of highest conservation status or exhibiting greatest resilience to stressors, or they may wish to spread investments over a wider range of risks that include reefs with low resilience but high importance to local industry. Reefs with lower resilience may have potential to rapidly regenerate to their former status if targeted action is taken to reduce stressors i.e. reducing runoff through watershed restoration. The great problem for current coral reef conservation is to operationalize our understanding of ecosystem resilience and apply it for management. Here we illustrate one approach to addressing this challenge with a decision-support framework for prioritizing coral reef units for conservation action, currently under development in the U.S. Virgin Islands (USVI).

Coral reefs across the USVI vary geographically in their diversity, structure, resilience and economic and aesthetic importance to people. To prioritize actions, effective management requires knowledge of the locations of the ecologically and economically most important coral reefs, their resilience to stressors and expectations for rapid recovery when management action is taken to reduce stressors. Interdisciplinary research is underway in the USVI as a collaboration between NOAA, The Nature Conservancy, University of the Virgin Islands, USVI government, local professional dive industry (dive operators and scientific divers) and other local partner agencies to develop a decision-support tool that integrates environmental data (remote sensing, ocean models and in-water biological surveys) with local expert knowledge from underwater observations, maps of stressors, and predictions of the locations and attributes of resilient reefs. To quantify structural connectivity, NOAA's benthic habitat maps are being used to rank reefs based on their proximity to seagrasses and mangroves. In addition, sites of ecological and biological significance are identified using spatial predictive models of fish species richness and known locations of fish spawning aggregations. Sites with high biodiversity have been associated with high topographic complexity. For unsurveyed areas, predictive modeling used bathymetry data as a proxy by classify the seafloor terrain into high, medium and low topographic complexity. These patterns will be combined with locations identified as important to local professional SCUBA divers (scientific and commercial dive industry).

The decision support framework (Fig. 5.4) will identify and rank the most important reefs for conservation concern in USVI. By evaluating resilience metrics and incorporating a resilience index into a comprehensive and transparent spatial matrix of site importance this project will objectively rank sites into several categories that will identify: Class A Reefs) the most important and best examples of coral reefs in the USVI; Class B reefs) coral reefs that have high potential to become Class A reefs with strategic conservation actions; Class C reefs) coral reefs

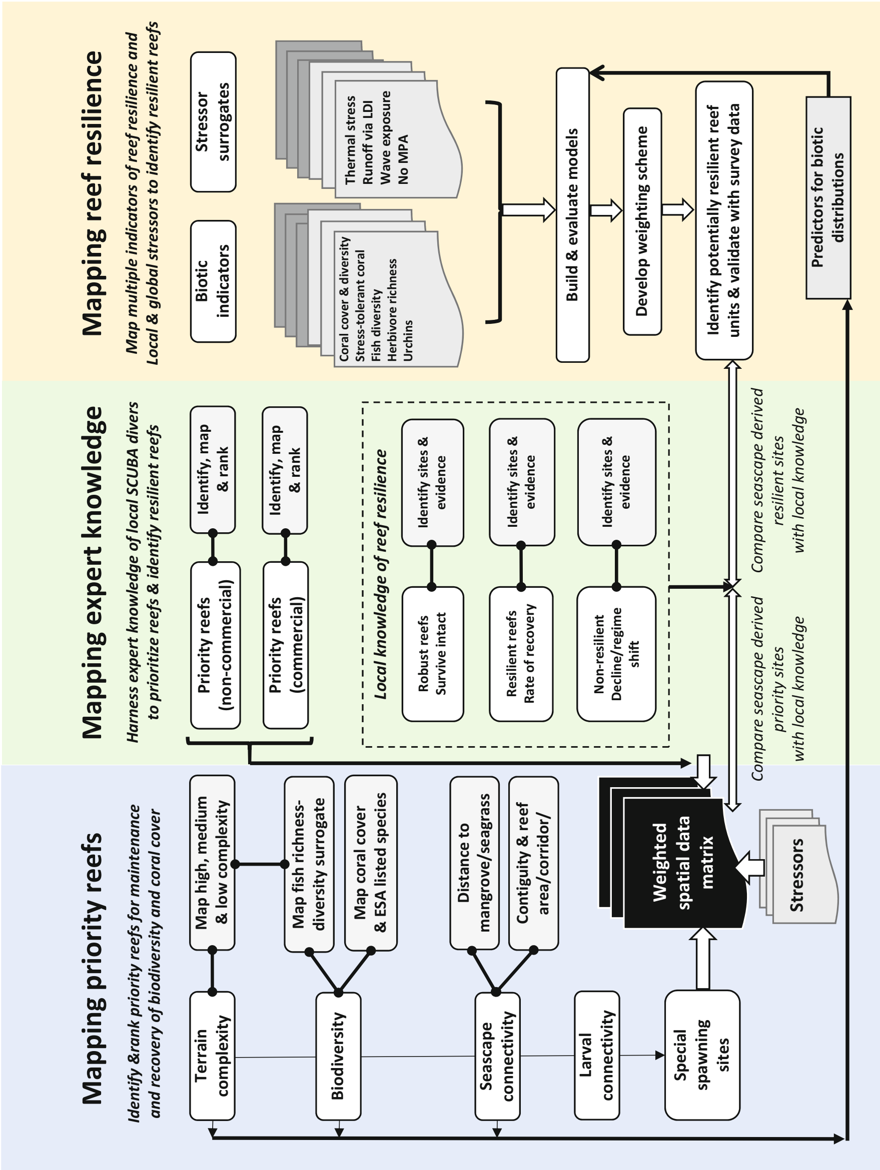

Fig. 5.4 Schematic illustrating the decision-support framework being developed to support resilience-focused coral reef management in USVI

that have some importance, but have low potential for recovery even with considerable conservation effort.

The framework is being designed to address multiple management objectives with a greater understanding of the spatial heterogeneity of reef resilience being a central objective. Data will feed the USVI government permitting system, enhance risk assessments, support management plans for MPAs, lay foundations for regional ocean governance and begin to map resiliency to identify and rank “reefs of hope”. This synoptic product ensures that management processes and strategic planning decisions are guided by best available information.

5.9 Conclusion

A new paradigm has emerged for coral reef management – managing for resilience. This approach aims to sustain and enhance the ability of coral reefs to resist and recover from periodic disturbances made increasingly frequent and severe by a changing climate, while simultaneously being subjected to chronic stress from more direct human impacts. Managing for resilience requires, first and foremost, an understanding of what contributes to or detracts from the resilience of a coral reef, and secondly information on the spatial distribution of resilience across management areas of varying size. Remote sensing, spatial distribution modeling and ecosystem simulation modeling combine to form a trio of rapidly developing technologies that can be employed to provide such information. Although in its infancy, this combination of technologies is already being explored for regional-scale mapping of coral reef resilience, producing the kind of spatially explicit information demanded. Through decision-support frameworks this information can be translated into management action. Maps of reef resilience will show improvement as: (1) research sheds new light on the influence of a wider range of environmental factors on aspects of coral reef resilience; (2) remote sensing technology improves and distribution modeling matures; 3) ecosystem simulation models become increasingly adept at incorporating a wider range of species or functional groups as well as information on larval and adult connectivity, seascape context, disease and invasive species. Improved maps of resilience will enable better management on coral reefs.

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