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SCIENTIFIC CONCEPTS FOR AN INTEGRATED ANALYSIS OF DESERTIFICATION

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ABSTRACT

The Global Drylands Observing System proposed in this issue should reduce the huge uncertainty about the extent of desertification and the rate at which it is changing, and provide valuable information to scientists, planners and policy-makers. However, it needs careful design if information outputs are to be scientifically credible and salient to the needs of people living in dry areas. Its design would benefit from a robust, integrated scientific framework like the Dryland Development Paradigm to guide/inform the development of an integrated global monitoring and assessment programme (both directly and indirectly via the use of modelling). Various types of dryland system models (e.g. environmental, socioeconomic, land-use cover change, and agent-based) could provide insights into how to combine the plethora of monitoring information gathered on key socioeconomic and biophysical indicators to develop integrated assessment models. This paper shows how insights from models can help in selecting and integrating indicators, interpreting synthetic trends, incorporating cross-scalar processes, representing spatio-temporal variation, and evaluating uncertainty. Planners could use this integrated global monitoring and assessment programme to help implement effective policies to address the global problem of desertification. Copyright © 2011 John Wiley & Sons, Ltd.

KEY WORDS: Global Drylands Observing System; modelling degradation; desertification; UNCCD; Dryland Development Paradigm; slow variables; drylands; thresholds; integrated assessment; ecosystem services

INTRODUCTION

Governments regard desertification as such a serious threat (38 per cent of the 6·8 billion people of the globe live in drylands) that they have agreed on an international convention to address it. Yet, 14 years after the United Nations Convention to Combat Desertification (UNCCD) came into effect, its Parties have no accurate estimates of the extent of desertification. A system for monitoring and assessment of land degradation and desertification[1] is needed if the Parties to the UNCCD are to have the reliable information they need to implement the Convention and to monitor the effectiveness of their activities (Grainger, 2009b) and to identify national and global priorities for action (MA, 2005). This lack of reliable monitoring information, based on robust empirical data, also perpetuates differing interpretations, methodologies and assessments of desertification among arid lands scientists, encumbering efforts to integrate knowledge for promoting the sustainable development of drylands (Verstraete *et al.*, 2011).

During the past several years a general consensus has emerged among scientists and the Parties to the UNCCD that a comprehensive monitoring and assessment programme is needed. Verstraete *et al*. (2011) have proposed the Global Drylands Observing System (GDOS), a global monitoring

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[1]In this paper we follow the definitions of land degradation and desertification as given in Vogt *et al.* (2011).

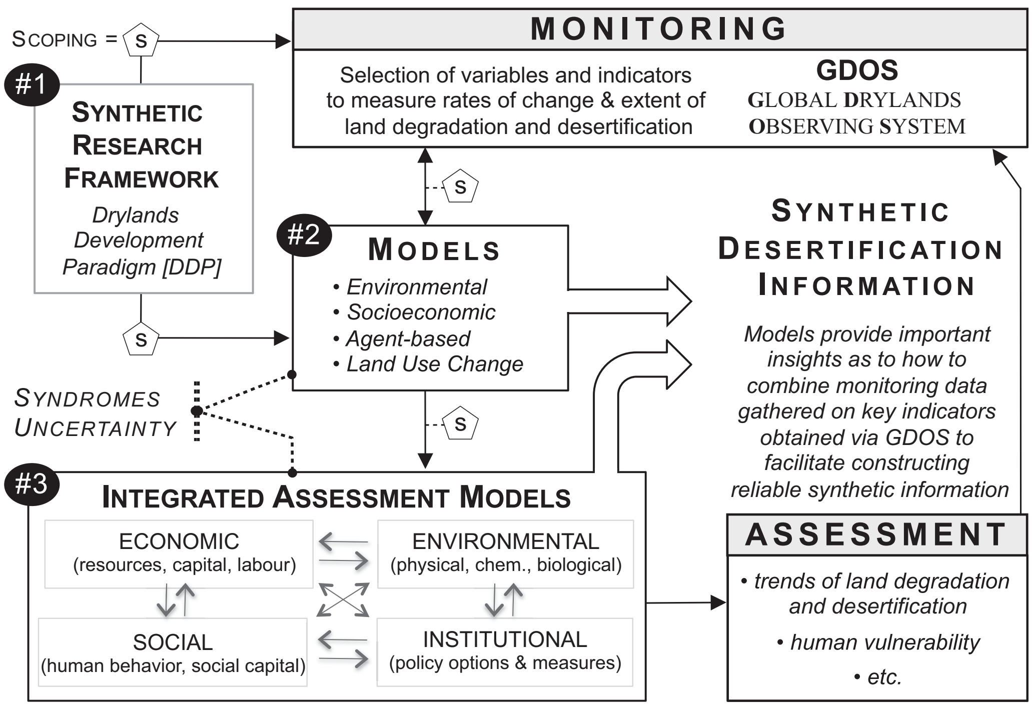

Figure 1. Recommended three-pronged scheme for formulating action policies on desertification relevant to the UNCCD and to facilitate communication between diverse stakeholders from different sectors and disciplines. A robust, integrated scientific framework (#1, the Dryland Development Paradigm) is needed to guide/inform the development of a global monitoring and assessment programme (both directly and indirectly via models). The diversity of dryland system models (#2) could provide insights into how to combine the plethora of monitoring information gathered on key socioeconomic and biophysical indicators (e.g. via the GDOS) to develop integrated assessment models (#3). The latter models serve to facilitating the testing and implementation of scientific- and policy-relevant concepts following a rigorous scientific framework (#1). See text for explanation of the scoping process.

system for desertification to fill this gap. GDOS would facilitate repeatable and harmonized measurements to meet standardized objectives; enable the archiving and availability of resulting information to support research and development; and help in formulating policies and monitoring their implementation. However, numerous practical questions must be answered before GDOS becomes operational, e.g. which set of indicators to use and how to measure them (Sommer *et al.*, 2011).

Here, we consider two broader questions that are also vital to an operational GDOS, each of which is multifaceted and hence eschew simple answers:

(1) How should a monitoring programme be structured to facilitate input from different sources of stakeholder expertise, across different spatial and temporal scales, institutions, scientific disciplines and development sectors?
(2) How should the plethora of monitoring information gathered on key socioeconomic and biophysical indicators be synthesized to formulate policy-relevant assessments?

Ideally, the answers to these questions should inform an improved understanding of the causation of desertification relevant to identifying remedial action and economic costs, provide a pathway for integrated assessments to aid in the formulation of action policies relevant to the UNCCD, and facilitate communication between diverse stakeholders from different sectors and disciplines. We acknowledge this is a daunting challenge. Nevertheless, in this paper we recommend a three-pronged scheme (depicted in Figure 1) we believe is well suited to tackle these questions.

- #1 (Figure 1)*: Adopt a robust, synthetic research framework*. It is essential to have an integrated scientific framework—focused on the dynamics of coupled human (H)–environmental (E) systems—to guide the development of a global monitoring and assessment programme. Historically, the field of desertification research and policy-making has been dominated by a *linear* cause–effect epistemology. This must be replaced with a new archetype that frames coupled H–E systems as complex adaptive systems, where heterogeneity, variability, self-organization and nonlinearity are the norm (Levin, 1998; Gross *et al.*, 2006).
- #2 (Figure 1)*: Use the rich diversity of dryland models to support monitoring*. Obtaining meaningful land degradation and desertification information is a challenging task (Grainger *et al.*, 2000; Verstraete *et al.*, 2009). Dry-

land system models can provide insights into how to combine the plethora of monitoring information gathered on key H–E indicators (e.g. via the GDOS) to facilitate constructing reliable synthetic information on desertification. Here, we discuss four types of dryland models: environmental, socioeconomic, agent-based and land-use change.

- #3 (Figure 1): Monitoring data, in conjunction with other available information, should be converted into forms useful for decision makers through integrated assessment modelling. Integrated assessment models (IAMs) attempt to portray the social, economic, environmental and institutional dimensions of a problem. For decades IAMs have been at the forefront of climate change research (e.g. Schneider, 1997; Mastrandrea and Schneider, 2004). As opposed to advancing knowledge for its own sake, the adoption of integrated assessment modelling would provide a platform for the continuing evolution of desertification monitoring and assessment by facilitating the testing and implementation of scientific- and policy-relevant concepts following a rigorous scientific framework (#1, Figure 1).

A SYNTHETIC RESEARCH FRAMEWORK

An integrated scientific framework for dryland systems should provide guidance on likely causal hypotheses concerning the structure and functioning of coupled H–E systems and, hence, what indicators to monitor (#1, Figure 1). In essence, the framework itself becomes a model to test over time as data are gathered and information is refined.

DPSIR Framework

One approach to integration, widely used by governments and international organizations involved in desertification, is the Driving Forces-Pressures-States-Impacts-Responses (DPSIR) framework (Burkhard and Mueller, 2008; Ponce-Hernandez and Koohafkan, 2010; Sommer *et al.*, 2011). Although the DPSIR has been widely employed to structure monitoring of desertification (reviewed by Sommer *et al.*, 2011), it has been criticized for numerous shortcomings. It portrays land degradation in a circular fashion (Grainger, 2009a). It necessarily simplifies complex systems relations into one-to-one linkages (Burkhard and Mueller, 2008) although the connectivity between drivers, pressures and responses are much more complex than sequential causes and effects as depicted in the DPSIR (Dawson *et al.*, 2010). Grainger (2009a) observed that in the DPSIR schema, climatic variation is both a pressure that directly affects vegetation cover as well as a driving force that affects the type and intensity of land-use and that government policies can be both a driving force as well as a response (and hence are as much part of the problem as part of the solution). The DPSIR framework has also been criticized for applying a 'one-size-fits-all' approach to diverse human–environment phenomena (Berger and Hodge, 1998; Gobin *et al.*, 2004; Svarstad *et al.*, 2008).

In spite of these shortcomings, the DPSIR has proven very useful in desertification research (Sommer *et al.*, 2011). Nevertheless, it is evident that it fails to capture the nature of complex–adaptive interrelationships between coupled human (H) and environmental (E) systems in drylands that are crucial to monitoring and assessment.

DDP Framework

Drylands possess a set of attributes that distinguish them from other regions, including an unpredictable climate, resource scarcity, sparse populations and remoteness from global markets and from centres of political power (Amiran, 1973; Stafford Smith, 2008). The close dependency of human livelihoods on the environment in drylands means we must focus on coupled H–E systems. As depicted in Figure 2, the interrelationships between H–E systems are dynamic, and include external drivers and constant changes in the internal functioning of each subsystem. In other words, complexity is the key characteristic of coupled human–environment systems (Liu *et al.*, 2007). Notice the critical linkages between the H and E subsystems,

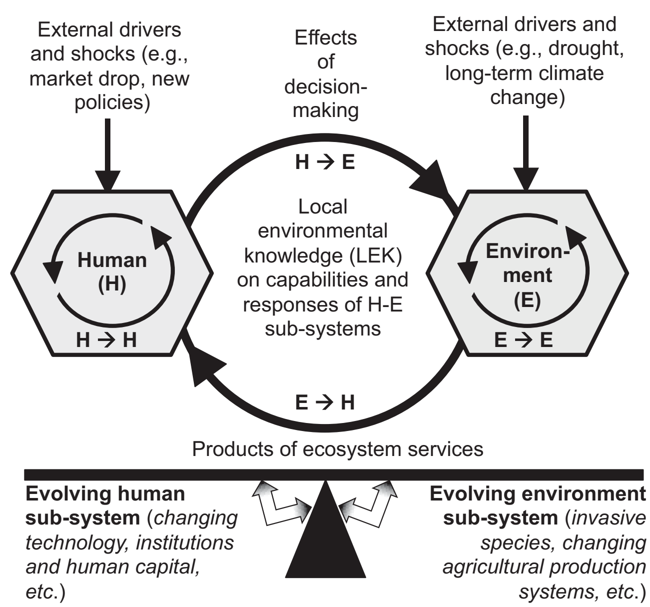

Figure 2. Schematic depicting interactions between human (H) and environmental (E) components of the land system. These systems co-evolve as balanced networks of feedbacks and interactions between H–E components in spite of constantly changing external drivers. Decision making (H → E) and ecosystem services (E → H, e.g. grazing land, clean air) are key linkages between components (moderated by an effective system of local and scientific knowledge; LEK).

created by human decision making on the one hand (H → E) and the flow of ecosystem services on the other (E → H). As a result, ecosystem goods and services vital to local populations are constantly changing over time (MA, 2005).

This complexity must be structured if we are to grapple with monitoring, forecasting and assessing the coupled dynamics of social, economic, political and environmental systems (AC-ERE, 2009). Synthesizing these attributes from the diverse knowledge gleaned from studies of vulnerability, community development, poverty alleviation and ecosystem science, Reynolds *et al*. (2007b) proposed the Dryland Development Paradigm (hereinafter 'DDP') as a framework of five principles. The DDP has extensive, practical implications for deciphering the complexity of coupled H–E dryland systems.

Pertinent implications of the DDP (see Table I for further details) are as follows:

- Principle 1: As already argued, the dynamics (or balance) of coupled H–E systems are invariably a function of *both* human and ecological changes; the essential implication is that monitoring and assessment systems must consider both.
- Principle 2: Focusing on 'slow' variables (Carpenter and Turner, 2000) for monitoring and modelling is

Table I. Five principles of the Drylands Development Paradigm (DDP). From Reynolds *et al*. (2007b)

Principles	Why significant in drylands	Key implications for research, management and policy
P1: H–E systems are coupled, dynamic and co-adapting, so that their structure, function and interrelationships change over time	The close dependency of most drylands livelihoods on the environment imposes a greater cost if the coupling becomes dysfunctional; variability caused by biophysical factors as well as markets and policy processes, which are generally beyond local control, means that the tracking of the evolving changes is relatively harder and understanding the effects on functionality more important in drylands	Understanding dryland desertification and development issues always requires the simultaneous consideration of both human and ecological drivers, and the recognition that there is no static equilibrium 'to aim for'
P2: A limited suite of '*slow*' variables are critical determinants of H–E system dynamics	Identifying and monitoring the key 'slow' H and E variables is particularly important in drylands as high variability in 'fast' variables masks fundamental change indicated by slow variables[a]	A limited suite of critical processes and variables at any scale makes a complex problem tractable
P3: Thresholds in key slow variables define different states of H–E systems, often with different controlling processes; thresholds may change over time	Thresholds particularly matter in drylands because the capacity to invest in recovering from the impacts of crossing undesirable thresholds is usually lower per unit (area of land, person, etc.); and, where calls must be made on outside agencies, the transaction costs of doing so to distant policy centres are usually higher	The costs of intervention rise nonlinearly with increase in land degradation or the degree of socioeconomic dysfunction; yet high variability means great uncertainty in detecting thresholds, implying that managers should invoke the precautionary principle
P4: Coupled H–E systems are hierarchical, nested and networked across multiple scales	Drylands are often more distant from economic and policy centres, with weak linkages; additionally, regions with sparse populations may have qualitatively different hierarchical relationships between levels	H–E systems must be managed at the appropriate scale; cross-scale linkages are important in this, but are often remote and weak in drylands, requiring special institutional attention
P5: The maintenance of a body of up-to-date local environmental knowledge (LEK) is key to functional co-adaptation of H–E systems	Support for LEK is critical in drylands because experiential learning is slower where monitoring feedback is harder to obtain (more variable systems, larger management units, in sparsely populated areas); and secondarily where there is relatively less research	The development of appropriate hybrid local and scientific knowledge must be accelerated both for local management and regional policy

[a]There are instances where fast variables can be reasonable indicators of underlying slow variables. In mesic pastures, for example, annual grass production is quite stable and a reasonable indicator of the status of soil properties. In rangelands, however, inter-annual variability in annual grass production does not permit the detection of change in underlying productivity measures such as grass basal area or soil water holding capacity. There may be a case for monitoring fast variables for some specific purposes, but this should not be the primary focus in a desertification monitoring system. For example, instantaneous food availability may be important for detecting where a famine is going to occur but longer-term measures of food productivity and household income levels (slow variables) are more stable indicators of which regions are more or less resilient to future drought shocks.

particularly important in drylands; not only are these the state variables that ultimately determine the flows of ecosystem goods and services that people need (Walker *et al.*, 2002), as in all H–E coupled systems, but also fast variables can be misleading in variable dryland environments.

- Principle 3: Significant changes in these state variables occur at more-or-less sudden thresholds (Walker and Meyers, 2004); these thresholds are important both for understanding degradation, and for intervening to recover the state of a system. Though difficult to identify other than after the event, in recent years thresholds have been the subjects of hundreds of studies (see Walker and Meyers, 2004, for on-line database documenting thresholds). For example, Samhouri *et al*. (2010) introduced a method for identifying 'utility thresholds', defined as the level of human-induced pressure at which small changes produce substantial improvements in protecting an ecosystem's structural (e.g. diversity) and functional (e.g. resilience) attributes.
- Principle 4: Cross-scale linkages are common in H–E coupled systems, but are particularly important in drylands, for reasons noted in Table I. Care is thus needed not to focus only at one scale. In the context of UNCCD, stakeholders occur at all scales from local households to international like the Convention itself. International donors, for example, are contributing funding to on-ground action within the context of a national action plan; supporting all scales with models and monitoring that are both compatible but sensitive to the needs at particular scales is essential. The nature and identity of slow variables and their thresholds depend on the scale of interest (Carpenter *et al.*, 1999).
- Principle 5: The flows of ecosystem goods and services in Fig. 1 that link the H and E sub-systems are mediated by local and scientific knowledge. However, all of this is scale-dependent. For example, the policies of distant decision-makers about how to influence land management is as important as actions farmers take to manage grazing at a particular location (Stafford Smith *et al*., 2007).

These principles can underpin and draw out conversations about how particular dryland systems function and thus contribute to informing the monitoring process.

SYSTEM MODELS OF DRYLANDS

The goals of a carefully planned, holistic, multi-scalar monitoring and assessment regime must be aimed at how to best prioritize and interpret monitoring data in terms of future investments to counter desertification, and how to measure the success of such investments in future adaptive learning cycles. To this end, rather than using fixed indicator sets alone, the UNCCD community must take advantage of the full range of methodologies available, including the use of modelling (#2, Figure 1). Although models are simplifications of reality, they have proven extremely useful tools in improving our understanding of the potential vulnerability of both H and E systems and the causes and potential consequences of desertification (e.g. Lambin, 1997; Farajzadeh and Egbal, 2007).

Importantly, there are no simple 'one-size-fits-all' explanations for desertification (Geist and Lambin, 2004), which is due to many factors, including stakeholder interests, scale-specific factors, local socioeconomic and biophysical conditions and a multiplicity of cause–effect interactions. Equally, long shopping lists of undifferentiated possible causes are also not helpful (Geist, 2004). In this section we describe the potential of modelling as a means to frame hypotheses formally, synthesize results, make assessments to support policy and management and to provide a basis for on-going improvements in monitoring, thus enabling a more flexible and insightful use of indicators attuned to the aims of the UNCCD (Sommer *et al.*, 2011).

We present four types of dryland models—environmental, socioeconomic, agent-based and land-use cover change[2]—to illustrate the diversity of modelling approaches. These types partly overlap and differences tend to blur as elements of two or more of these are combined into a single model. For example, Parker *et al*. (2003) explored the utility of a multi-agent system model of land-use/cover change for decentralized, autonomous decision-making; Walker and Janssen (2002) constructed a coupled agent-based, socioeconomic and environmental model to examine management options for commercially operated rangelands; and land-use change models are typically process-oriented economic and/or agent-based and focus on land managers' decisions and/or behaviour (Veldkamp and Lambin, 2001; Lambin *et al.*, 2003; Entwisle *et al.*, 2008).

Environmental Models

Because of the importance of drylands globally, hundreds of agricultural and ecological simulation models have been developed. We posit four generalities about these models: (1) the objectives often focus on either the effects of environmental drivers (precipitation, fire, etc.) or grazing (implicit or explicit) on ecosystem structure and function; (2) aboveground net primary production (ANPP) is a key

[2]Wind and water soil erosion models are outside the scope of this paper (for an overview of desertification-related erosion models, see Kirkby, 1995; Grau *et al.*, 2010).

variable of interest; (3) spatially, they centre on small-scales or patch-level and temporally, on short periods (days, weeks, months, years) and (4) include elements of the following processes: (i) soil moisture (infiltration, storage, uptake via transpiration, surface evaporation, etc.); (ii) energy budgets (e.g. soil, surface, canopy); (iii) plant growth (ANPP, phenology, physiological characteristics of plant functional types such as grasses, shrubs, trees, etc.) and (iv) nutrient cycling (decomposition, soil carbon sequestration, etc.).

Examples of models, and principal drivers of interest to desertification monitoring and assessment, include grazing (Filet, 1994; Dunkerley, 1997), fire (Boer and Stafford Smith, 2003; Mata-Gonzalez *et al.*, 2007) and the effects of elevated carbon dioxide concentrations on ANPP (Osborne *et al.*, 2000; Shen *et al.*, 2008). Given that arid and semiarid ecosystems are considered to be highly sensitive to climatic change, many models have been developed to explore impacts of extreme climatic events, including droughts (e.g. Seligman *et al.*, 1992; Mulligan, 1998; Marlon *et al.*, 2009; Dougill *et al.*, 2010). Of course, many environmental models consider interactions between drivers (see review by Tietjen and Jeltsch, 2007 of 41 patch-level arid and semiarid ecosystem models published between 1995–2005 for numerous examples).

Ecohydrology modelling in drylands has seen tremendous growth in recent years (Wilcox and Thurow, 2006). By coupling patch-scale environmental dryland models to spatially explicit hydrological models, researchers are able to study landscape-scale interactions between climate, soils and vegetation (e.g. Turnbull *et al.*, 2008; Urgeghe *et al.*, 2010). Using such a model, Ludwig *et al*. (1999) found that the rehabilitation of degraded, dysfunctional landscapes in Australia could be achieved only by restoring vegetative patches, which serve as physical structures to trap and store soil resources (water, nutrients, etc.). Ecohydrology models have been used to study the susceptibility of dryland systems to abrupt shifts of state as a result of climate change or anthropogenic disturbances (Borgogno *et al.*, 2009), e.g. the encroachment of woody plants into areas that have been historically dominated by grasses, which is an important type of land degradation globally (Schlesinger *et al.*, 1990). Gao and Reynolds (2003) conducted spatially explicit simulations in the northern Chihuahuan Desert of grass-shrub interactions and concluded that increases in the number of large precipitation events during the past 100 years favoured shrub establishment. Jeltsch *et al*. (1997) used a grid-based spatial simulation model to examine if cattle grazing in southern Africa would lead to shrub encroachment and to determine a threshold grazing pressure. Jeltsch *et al*.'s simulations showed that the answers to these (and other questions of land degradation) were related to the quantity and timing of rainfall (for example, thresholds in grazing pressure only existed in wet years).

The susceptibility of a landscape to changing drivers and hence desertification has been explored using spatial models that consider the distribution of vegetative patches (or stripes) separated by bare ground (Ludwig *et al.*, 1999; Svoray *et al.*, 2007). The resulting patterns, which can be quantified by connectivity indices, determine flowpaths (Woodmansee, 1988) whereby water, soil sediment, organic matter (plant litter, dung), plant seeds and nutrients are transported across a landscape. The underlying factors that lead to certain vegetation pattern formations in global drylands has been extensively investigated and vary depending upon local conditions (see Klausmeier, 1999; Tongway *et al.*, 2001; Kéfi *et al.*, 2007). For example, based on a modelling analysis HilleRisLambers *et al*. (2001) found that pattern formation in semi-arid areas was a function of positive feedbacks between plant density and local water infiltration coupled with the spatial redistribution of runoff water; other factors such as herbivory, seed dispersal, precipitation and physiological traits of plants, were significant only in so far as dictating under what conditions pattern formation was likely to occur.

This brief summary raises an issue highly germane to a GDOS monitoring system: the role of vegetation patterns. There has been a plethora of studies on the description and significance of vegetation pattern in global drylands (Tongway *et al.*, 2001) inspired by its ubiquitous occurrence and potential for inferring how temporal changes or shifts in the mosaic of patches (termed a 'patch dynamic landscape' by Wu and Loucks, 1995) can be used as a sensitive indicator of underlying ecosystem dynamics. For example, Kéfi *et al*. (2007) concluded that 'patch-size distributions may be a warning signal for the onset of desertification'. In fact, a number of studies have used shifts in patch mosaics as the basis for desertification indicators (e.g. Kepner *et al.*, 2000; Ludwig *et al.*, 2002; Kéfi *et al.*, 2007; Sun *et al.*, 2007; Danfeng *et al.*, 2008; Ravi and D'odorico, 2009). Similarly, models have been used to map potential 'desertification hazard' (e.g. Kirkby *et al.*, 2000; Shi *et al.*, 2007; Salvati *et al.*, 2009). Farajzadeh and Egbal (2007) successfully developed a desertification hazard map for the Lyzad Khast Plain of Iran using a modified version of the MEDALUS model (originally developed for Mediterranean regions) by adding two additional regionally specific indicators (ground water and wind erosion).

Socioeconomic Models

As is the case for environmental systems models, many socioeconomic models for drylands have been developed in recent decades. They consist of entities such as demographics, human consumption, production, institutions (government, corporations, etc.), emigration and migration and resource extraction (Gault *et al.*, 1987). Examples include modelling human vulnerability to droughts (e.g.

Vörösmarty *et al.*, 2000; Acosta-Michlik *et al.*, 2008), impact of climate warming (Liverman, 1992) and extreme climate events (Patt *et al.*, 2010) on H–E systems in arid zones, and the economic consequences of warming on food security (Nordhaus and Boyer, 2000). Stahel (2005) reasons that the economic and ecological value of ecosystem goods and services (Figure 2 and related text) must be assessed within a particular spatiotemporal context, which is recognized as an important aspect of a desertification monitoring programme (see Sommer *et al.*, 2011; Verstraete *et al.*, 2011).

Socioeconomic models often consist of (i) a decision making component and (ii) a socioeconomic impact component (Letcher *et al.*, 2007). The decision-making component may, for example, represent key land and water use and management decisions such as agricultural production decisions and industrial versus urban water use, which are crucial factors in dryland H–E systems. The specific decisions simulated and the types of models employed are a function of the spatial and temporal scales at which these decisions are relevant whereas the impact component may consist of the relevant social and economic changes. In the case of land degradation this may include impacts on farm profits and its financial viability, impacts on the regional economy, and on individuals, households and communities (Letcher *et al.*, 2007). Local impacts can be aggregated into a regional-scale model (e.g. an input–output model) to obtain second order impacts, but this depends upon the scale and range of impacts and the type of modelling approach used.

In a review of paradigms of ecological economics, Stahel (2005) notes that when considering interactions between human (H) and natural (E) systems, (i) 'we have to enlarge the scope of economic evaluation procedures assuming not only unpredictability, incomplete control and a plurality of legitimate perspectives ... (*but also*) ... dynamic and changing conditions' and (ii) 'that any economic system is an emergent complex system'. This perspective is consistent with the principles of the DDP framework, which considers H–E system as complex adaptive systems.

Land-use Cover Change Models

Land-use change emerges from interactions among and between components of a coupled H–E system and these changes then feed back to subsequently impact future H–E interactions (as illustrated in Figure 2). Socioeconomic systems can be linked to environmental systems by expressing land-use cover change (LUCC) as a function of multi-scale drivers and proximate factors driving land degradation, i.e.:

Land-use Cover Change $= f$ [pressures, opportunities, policies, vulnerability, social organization, environmental drivers, etc.]

Typical proximate (or immediate) causes of land degradation, and the underlying causes that drive these, are summarized in Figure 2 (also, see Sommer *et al.*, 2011). Such dynamics are increasingly included in LUCC models in the form of agents (see following section).

LUCC models address two separate questions: (1) location (where changes are likely to take place); and (2) the quantity and the rates of change, wherever and whenever they are occurring (Veldkamp and Lambin, 2001). The first question requires identification of the natural and socioeconomic landscape attributes, which are the spatial determinants of change, i.e. local proximate causes directly linked to land use changes (Figure 3). The latter are often described in terms of land cover change. The question about the rate or quantity of change is usually answered by demands for land-based commodities and is often modelled as a commodity demand (van Meijl *et al*., 2006). So we observe that the 'where' question is often answered with a land cover pattern, while the 'how much' question is answered as a land-use commodity quantity.

LUCC models often link land cover information on spatial patterns to potential drivers and extrapolate into the future using a variety of methodologies (Parker *et al.*, 2003 summarize the properties of seven broad categories of LUCC models: mathematical equation-based, system dynamics, statistical, expert system, evolutionary, cellular and hybrid). Finally, LUCC models often rely on land cover data derived from satellite imagery (e.g. Palmer and van Rooyen, 1998; Hill *et al.*, 2008; Karnieli *et al.*, 2008). Unfortunately, a common limitation of all such models is the lack of quantitative empirical data to calibrate and validate them (Veldkamp and Verburg, 2004), again underscoring the need for a global monitoring system.

Agent-based Models

Agent-based modelling (ABM) is a powerful approach for modelling coupled human–environment (H–E) systems (Janssen *et al.*, 2000; Grimm *et al.*, 2005; Entwisle *et al.*, 2008). Agent-based modelling is the computational study of social systems to analyse the aggregated behaviour of many autonomous interacting agents (e.g. individual humans, households, communities, regions and their environment, depending upon the application, Janssen and Ostrom, 2006). Autonomous agents 'sense' the world, which consists of other agents and the environment, and make independent decisions (see Figure 3). Based on these perceptions, and their goals and attributes, the agents decide which actions to perform. Agents can have only reactive behaviour, such as when a farmer selects a specific crop to sow. More comprehensive ABMs include goal-directed behaviour where agents aim to satisfy or maximize some goal, such as pastoralists determining the amount of livestock on their property.

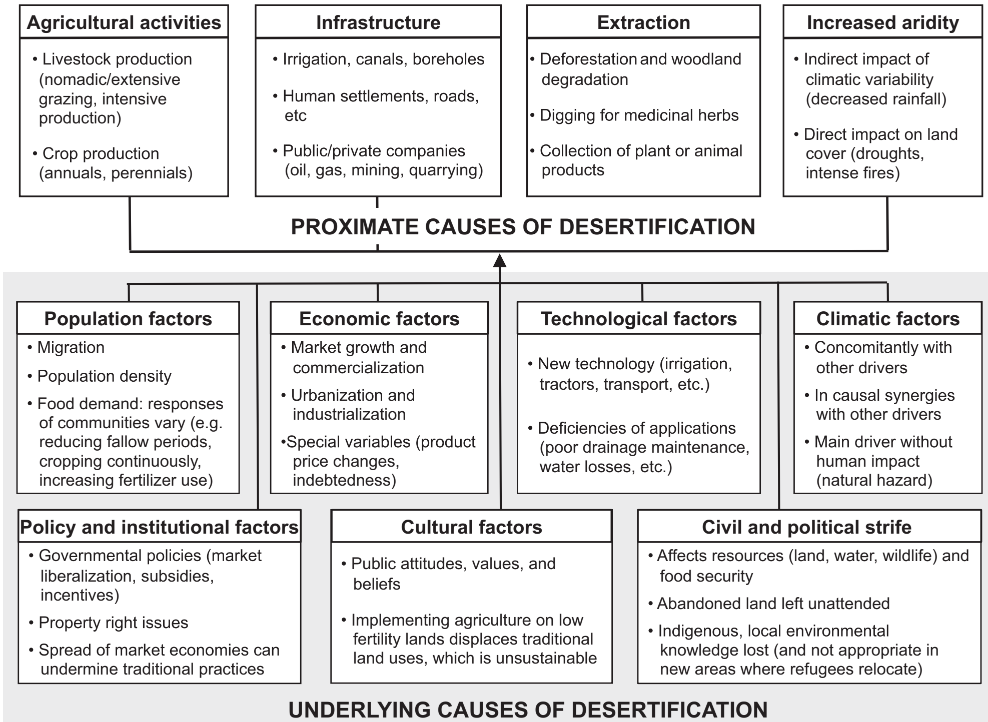

Figure 3. In a global survey of 132 case studies of desertification, Geist and Lambin (2004) found repeating causal patterns, which resolved into four major proximate causes explained by six major underlying drivers. They found that only 10 per cent of the case studies were driven by a single cause (*ca.* 5 per cent due to increased aridity and *ca.* 5 per cent to agricultural impacts), *ca.* 30 per cent of the case studies were attributable (primarily) to increased aridity and agricultural impacts, and the remaining cases were combinations of three or all of the proximal causal factors. Modified from Geist and Lambin (2004).

Agent-based modelling has been applied to rangeland management since 2000. Early papers focused on managing rangelands with multiple stable states (Janssen *et al.*, 2000; McAllister *et al.*, 2006), where the agents were pastoralists who made decisions on grazing pressure, fire suppression, buying and selling livestock and the location of grazing (including movement to other properties). Decision making took into account the possible effects on future returns based on precipitation patterns, and the prices of livestock products (e.g. wool and meat). Even in the same environmental context, different groups of pastoralists could make different decisions reflecting their risk preferences, abilities and motivations (e.g. life-style or profit orientation).

Le *et al*. (2010) review the use of multi-agent simulation (MAS) modelling for spatiotemporal simulation of coupled H–E systems, where human populations and the environment are self-organized interactive agents. Multi-agent simulation modelling has proven to be an excellent tool for modelling land-use change, including land degradation phenomena, as it explicitly includes interactions between human actors and their environment (e.g. Dearing *et al.*, 2006; Castella *et al.*, 2007; Schreinemachers *et al.*, 2007; Lobianco and Esposti, 2010). In an MAS setting, models of highly diverse H and E processes are incorporated as agents that are able to autonomously react to ever-changing conditions (as depicted in Figure 2), which captures both localized interactions as well as emerging landscape-scale changes and thus overcoming the limitations of conventional approaches used to model land-use change (Le *et al.*, 2010).

INTEGRATED ASSESSMENT MODELS

Integrated Assessment

Integrated assessment (IA) is the process of combining information and understanding from diverse scientific disciplines in order to achieve an accurate representation of complex, real world problems (like land degradation and desertification). In the context of this paper, IA has the following goals (modified from Weyant *et al.*, 1996):

(i) to prioritize research needs, e.g. global monitoring, in order to better support our ability to conduct assessments;
(ii) to develop insights into key questions of policy relevance and
(iii) to explore potential (plausible) future trajectories of coupled H–E systems in drylands.

Following Rotmans and Dowlatabadi (1998), an IA should produce added value (as compared to a single disciplinary assessment); provide information of relevance to policy- and decision-makers; and consist of an iterative, *participatory* process that links knowledge (science) and action (policy). Achieving this requires engaging all stakeholders (managers, farmers, business and community leaders, policy-makers, etc.), a process known as 'scoping' (see Figure 1, Costanza, 1999; Sandker *et al.*, 2008).

National Action Programmes (NAPs) are a cornerstone of the UNCCD, emphasizing stakeholder input at local and community levels to 'redress and inhibit land degradation' (Thomas, 2003). Stakeholder input is needed to identify schemes to control and monitor desertification in ways that make sense to them, though at times there will be sufficient previous experience for science to construct an initial set for debate. Undoubtedly, we would expect engaging stakeholder input via the scoping process to take multiple iterations since a diverse stakeholder base will hold differing perspectives and biases regarding both the drivers and consequences of land degradation. All stakeholders (including scientists) hold (often, unconsciously) strong mental models as to what factors are most important (Schwilch *et al.*, 2009). However, these mental models have many hidden assumptions, their internal consistency is untested, their relationship to data is unknown, and complex systems (e.g. coupled H–E systems) are noteworthy for exhibiting counterintuitive behaviour and complexities beyond our mental capacity to grasp (see Epstein, 2008, for more on this topic). Even at relatively small spatial scales, e.g. a household, an overwhelming number of complex interactions exist between and within human (H) factors (e.g. social networks, out- and return-migration, remittance behaviour, deaths, marriages, kin networks and so forth, Entwisle *et al.*, 2008) and environmental (E) ones (drought, livestock diseases, soil and wind erosion, crop production, insect outbreaks, etc., Geist and Lambin, 2004).

Scoping is another example that illustrates the need for a robust scientific framework for desertification. In a series of case studies conducted in Latin America[3] (via the ARIDnet programme; see Reynolds *et al.*, 2003, 2005), we found that filtering desertification issues through the lens of the five principles of the DDP provided a strong channelling of information into better understanding of local H–E dynamics by helping stakeholders eliminate ambiguities and logical inconsistencies and to focus attention on those processes and variables most crucial to monitoring and assessment.

Dowlatabadi *et al*. (2000) noted that there are no simple solutions to the complex problems facing humankind and thus IA is needed because it aims to convey innovative and (often) counterintuitive insights into real world problems rather than necessarily attempting to 'predict the future'. Logically, IA is not a single methodology or model type (Rotmans and van Asselt, 2003) but, rather, it is akin to a toolbox from which a very broad spectrum of approaches can be drawn upon in creative ways, depending on the question at hand. One of these tools is the development of integrated assessment models (IAMs).

Integrated Assessment Models

Integrated assessment models are computer simulators composed of linked submodels that represent different socioeconomic and environmental disciplines. IAMs are used to study whole-system dynamics in the context of the relationships of the submodels with each other, and with other systems, rather than in isolation. As depicted in Figure 1, in the case of desertification the whole-system is a coupled H–E dryland system and the submodels are environmental, social, economic and institutional variables. The interactions between these variables govern the co-evolutionary trajectory (and ultimate balance) of the networks of feedbacks and H–E drivers that impact ecosystem services (Figure 2). Land degradation and desertification occur when the H–E system becomes unbalanced. An IAM can be used to explore potential future states of the system given a specific set of assumptions and uncertainties (such as the resilience of the H–E system to differing degrees of drought, implementation of alternative land management schemes, and so forth) rather than focus on accurate predictions *per se* (as discussed previously).

IAMs are an effective means to link scientific research to policy (Rotmans and Dowlatabadi, 1998; Sutherst, 1998; Dowlatabadi *et al.*, 2000). In the Fourth Assessment Report of the IPCC, for example, IAMs were used to assess the range of uncertainty in the environmental, economic and social consequences of climate change (including human vulnerability); explore adaptation options; evaluate cause-and-effect chain of events in complex climate systems, and facilitate participatory engagement (Schneider *et al.*, 2007). The use of IAMs in the field of desertification (#3, Figure 1) has expanded in recent years (for examples, the reader is referred to Mouat *et al.*, 1997; Schellnhuber and Tóth, 1999; Desanker and Justice, 2001; Mulligan, 2009; Vogt *et al.*, 2011).

In the next section we discuss *syndromes*. Syndrome analysis is considered to be one of the most promising approaches to scale-dependent integrated assessments (Hill *et al.*, 2008).

Syndromes

Desertification is caused by a large number of factors (Figure 3), which vary from region to region, often acting in concert with one another. Combined with the need that it is

[3]Examples include Mexico (Huber-Sannwald *et al*., 2006), Bolivia (Reynolds *et al.*, 2008) and Honduras (Ayarza *et al.*, 2010).

imperative that *consequences* as well as *causes* of desertification be addressed at multiple scales (Stafford Smith and Reynolds, 2002), this presents a daunting challenge. However, Petschel-Held *et al*. (1999) proposed that land degradation could be systematized into a limited number of driving factors, variables and scales as *syndromes* or 'archetypical, dynamic, co-evolutionary patterns of civilization–nature interactions'. A syndrome seeks to capture H–E dynamics using clusters of symptoms rather than focusing on hundreds of isolated variables (Hill *et al.*, 2008). As shown by Geist and Lambin (2004; Figure 3) desertification is a prototype syndrome, whereby general patterns of causes and consequences of land degradation manifest themselves in repeatable ways in different parts of the world (Schellnhuber *et al.*, 1997; Manuel-Navarrete *et al.*, 2007).

Researchers at the Potsdam Institute for Climate Impact Research developed 16 global syndromes (Schubert *et al.*, 2009), seven of which Downing and Lüdeke (2002) singled-out as relevant to land degradation and desertification (we group these as 'desertification-type' syndromes):

(1) Sahel: overuse of marginal land;
(2) Dustbowl: environmental degradation through non-sustainable agro-industrial use of soils and water;
(3) Overexploitation: overexploitation of natural resources;
(4) Rural Exodus: environmental degradation through abandonment of traditional agricultural practices;
(5) Katanga: environmental degradation through depletion of non-renewable resources;
(6) Scorched Earth: environmental destruction through war and military action and
(7) Aral Sea: environmental damage of natural landscapes through large-scale projects.

Downing and Lüdeke (2002) proposed that these global desertification-type syndromes could be applied to assess *local* vulnerability to land degradation and desertification. The 'syndrome contexts' approach (reviewed by Manuel-Navarrete *et al.*, 2007) similarly supports applying the syndrome concept to local circumstances if clusters of environmental, social, and economic problems or symptoms reappear in different areas or regions. Lastly, Verstraete *et al.* (2009) reviewed case studies representing a variety of scales and desertification-type syndromes and concluded that they shared three characteristics in common: (i) all linked H-E drivers and outcomes via ecosystem services (Figure 2); (ii) regardless of scale they sought a moderate (not overwhelming) degree of complexity and (iii) they enabled generalizations to be made across diverse case studies at similar scales, which is vital for guiding policy-makers and managers.

Syndrome Analysis and Integrated Assessment

As part of an integrated global desertification monitoring and assessment programme (Figure 1), we recommend syndrome analysis be used to inform integrated assessment. Land degradation indices have limited utility in that they rarely combine biophysical and socio-economic variables and their applicability is usually limited to localized conditions (for an excellent example of both the potentials and limitations of such indices, see Salvati *et al.*, 2009). As a result they generally fail to elucidate the cause–effect relationships that need to be understood to guide changes in policy and management. Such limitations could be addressed if developed within the framework described by Verstraete *et al*. (2009) as a 'nested set of syndromes of dryland degradation at different scales, which could inform a systematic typology of causes, impacts, and responses relevant to different levels in dryland systems'. Excellent examples of the use of the syndrome analysis approach for vulnerability assessment are provided in Manuel-Navarrete *et al*. (2007); and an excellent example of the use of the syndrome analysis approach for monitoring land degradation is provided in Hill *et al*. (2008) who used remote sensing to monitor desertification in the Mediterranean region using a 'combination of symptoms' to describe 'bundles of interactive processes and symptoms that appear repeatedly and in many places in typical combinations and patterns'.

Syndromes and IAMs

We also recommend the syndrome analysis approach be used to inform the development of IAMs. Syndrome analysis provides a modelling paradigm for operationalizing desertification in the context of causes (multi-causal and cumulative stressors) and their consequences. Following the DDP any 'desertification-type' syndrome must be defined in terms of human and biophysical variables, their key slow variables and thresholds, and a unique scale of interest. Importantly, principle 2 of the DDP (Table I) posits that it is possible to focus effort on a *necessary but sufficient* set of key variables, which is not too large.

This is analogous to Schellnhuber's (1999) description of the need for models of *intermediate complexity*. On one hand, an over-simplified IAM would ignore crucial elements of a system and be of low value; but an over-complicated model would defy understanding and most likely be impossible to parameterize, especially for data-poor regions. A syndrome analysis, as envisioned as a part of our proposed three-pronged scheme (Figure 1), would help guide the development of IAMs to avoid both extremes. Although not referring explicitly to syndromes, Grimm *et al*. (2005) observed that if the 'process of model development is guided by multiple patterns observed at different scales and hierarchical levels' the resulting model is likely to end up as one of balanced intermediate complexity.

Uncertainty and IAMs

IAMs aim to provide information- and decision-support regarding complex, real world problems. Therefore, it is not surprising that *uncertainty* is one of the most difficult areas in IA modelling. Rotmans and van Asselt (2001a) and van Asselt and Rotmans (2002) identified the following issues:

(i) In addition to uncertainty in model structure, for each disciplinary science IA modelling must deal with both inherent uncertainties and lack of knowledge of the real world problem at hand. This is especially true for uncertainty due to societal and biophysical variability, value judgments, H–E diversity of all types, technological surprises, ignorance and indeterminacy, and so forth;
(ii) IA models are prone to an accumulation of uncertainties because of their ambition to cover numerous non-linear cause–effect chain of events;
(iii) Current methods of data gathering (such as desertification information as reviewed by Verstraete *et al.*, 2011) often give no indication of the magnitude and sources of underlying uncertainties and
(iv) Aggregated uncertainty due to the above sources (and others) is difficult to convey in a coherent, understandable way for decision makers and other audiences.

Many of these uncertainties cannot be adequately addressed with existing methods and tools. Hence, uncertainty remains one of the most problematic and challenging issues in the field of IA modelling (see van Asselt *et al.*, 1996; Rotmans and van Asselt, 2001a, 2001b; van Asselt and Rotmans, 2002; Liu *et al.*, 2007; Gabbert *et al.*, 2010; Le *et al.*, 2010).

INSIGHTS INTO CONSTRUCTING SYNTHETIC DESERTIFICATION INFORMATION

Models reviewed in the previous sections can provide important insights into how to combine the streams of information on key indicators monitored by a Global Drylands Observing System (GDOS) (Verstraete *et al.*, 2011) to construct reliable synthetic information on the extent and rate of change of desertification. This section discusses these insights, while ensuring that the practical feasibility of incorporating them in the design of an operational GDOS is clearly evaluated.

Selecting Indicators

The most common type of indicators employed in desertification monitoring so far have been state indicators (see Sommer *et al.*, 2011). These wholly or partially summarize the entire system, providing a broad, quick, and easily understood (but not comprehensive) overview of the current ‘state of the system’ being monitored. Two examples, vegetative cover per unit land area and degree of soil salinity, typify the two classes of biophysical state variables most often used to characterize desertification: vegetation and soils. These are surrogates to provide a quantitative measure of the condition and potential services of an ecosystem and, by extension, human well being.

Most of the models reviewed above include multiple socioeconomic and biophysical variables, implying that the set of desertification indicators should be equally diverse. The recent attention paid to ecosystem services in environmental systems models could inspire attempts to include more biophysical indicators. Yet, although it has long been acknowledged that desertification involves degradation of soil and vegetation, the last UN Environment Programme Desertification Atlas could only map soil degradation, owing to practical difficulties in vegetation monitoring (Middleton and Thomas, 1997). This is a fundamental problem (Lambin, 1999) constraining the modelling of dryland vegetation degradation generally (Grainger, 1999). Extending the operational set of biophysical indicators may therefore take time, but it could proceed in parallel with research aimed at translating ecosystem services from theoretical concepts to practical planning tools (Daily and Matson, 2008).

Integrating Indicators

Developing indicators that represent an integration of economic, social and environmental dimensions of dryland development is a major challenge, and requires a robust foundation (see Munoz-Erickson *et al.*, 2007; Salvati *et al.*, 2008). As the scientific basis for such foundations is still embryonic, options are limited.

Any integration should be undertaken with great care, giving scope for synthesis to provide policy-relevant information, while ensuring sufficient disaggregation that the research of scientific end-users is not compromised. For example, some land-use cover change modellers will require an index of the rate of desertification that is independent of socioeconomic driving forces so they can build regression models (one of the types of LUCC model described above). Early cross-sectional regression models of tropical deforestation found an excellent correlation between annual deforestation rates and population growth rates at national scale but scientists did not realize that many of the UN Food and Agriculture Organization (FAO) deforestation rate statistics they used had been estimated using population growth rates (Rudel and Roper, 1997). Similar problems should be pre-empted here.

Interpreting Synthetic Trends

Complex coupling between biophysical variables, evident in environmental systems models, has implications for how spatio-temporal trends in desertification are synthesized from trends in individual indicators. Ecological research on non-equilibrium dynamics and alternative states (e.g. Pickup *et al.*, 1998; Sullivan and Rohde, 2002) suggests that defining reliable measures of degradation from a robust standard will prove to be very challenging. Even determining the most appropriate year to use as a baseline for measuring change will be difficult, given the immense spatio-temporal variability in rainfall and vegetation growth. The classic study by Tucker and Choudhury (1987) using low-resolution satellite images showed that the boundary between the Sahara desert and the Sahelian region shifted south in 1981 but in 1985 moved north when rainfall returned. In 1984 alone, the area of the Sahara Desert expanded by 15 per cent compared with its value in 1980. This and similar studies did much to raise suspicions among arid lands scientists about the reality of 'desertification'. Of course, part of the reason for this was the misunderstanding of what desertification entails, but robust monitoring by a future GDOS will need sufficiently sophisticated procedures to adjust for such processes.

Complex coupling between multiple socioeconomic and biophysical variables (Figure 2), which underlies the Dryland Development Paradigm (and other coupled human–environment synthetic frameworks or conceptual models), makes this challenge even greater. The social and biophysical variables involved in dryland degradation are closely linked and constantly changing, both in the short-term (precipitation variability, changes in markets, population migration, etc) and in the long-term (population growth, land use change, climate change, etc). The resulting institutional and political systems, which also vary in time and space, are partly driven by such factors. While all these elements of variability are fundamental components of the desertification phenomenon, it is not possible to measure most of these linkages directly (Ayarza *et al.*, 2010) so we must rely on models.

Allowing for Cross-scalar Processes

Recognition in the DDP of cross-scalar processes (principle 4, Table I) in which, for example, socioeconomic driving forces in one area can ultimately lead to land degradation in another area, is another reason to be careful when integrating biophysical and socioeconomic indicators. Scrupulous reporting by GDOS of environmental state variables will enable scientists to use this information to identify such processes through subsequent analysis. GDOS may not have the time or resources to undertake such research itself.

Any monitoring system should therefore be nested by scale, with patterns at each scale a subset of those at higher scales. The design at each scale should address the needs of decision makers at that scale but be linked to the other scales by a common theme or goal (see Figure 4 in Verstraete *et al.*, 2009). This presents a challenge when selecting variables for monitoring, but if achieved it will facilitate meaningful comparisons by decision makers of information gathered at local, regional and national scales.

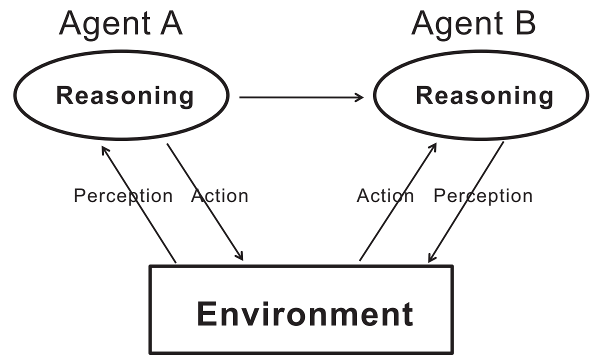

Figure 4. Scheme of cognitive interactions between two agents and their environment. See text for details.

Reynolds *et al*. (2007a) identified four scales of relevance for *human impacts* (farm/household, community, district/provincial, national/international) and *environmental impacts* (patch, landscape, regional and global) to illustrate how scale affects the role of processes, such as external drivers, and slow variables. For many pastoralists in Africa, for example, the human consequences are directly related to a decline in productivity or the capacity of the land to support plant growth and animal production (e.g. Mortimore and Turner, 2005).

In early stages of desertification such losses may be compensated by the social resilience of the local populations, especially in developing countries, or by financial inputs from government (Vogel and Smith, 2002). However, when *thresholds* are crossed (DDP principle 3), social resilience or government subsidies may not be enough to compensate for the loss of productivity, which fuels socioeconomic changes such as lower agricultural production to population migrations. Environmental consequences usually start with the loss of soil and vegetation, which have a 'cascading' effect leading to a progressive deterioration of the ecological structure and functioning of the system. Both H and E consequences may differ substantially between regions due to the intensity and number of driving forces at work; the extent of the impacted area; and the duration of the deterioration.

The definition of 'slow' or 'fast' variable (DDP principle 2) is also scale-dependent: debt to equity ratio and gross basal area of pasture are slow variables at the household scale, but fast variables at the national scale where they are nested within other related 'slower' variables, (e.g. interest rates or land use patterns, Stafford Smith *et al.*, 2007, see Table I). Many important issues arise from conflicts between scales, for example, when expectations or structures at provincial levels fail to provide suitable incentives at village level, or tenure systems instituted by national governments do not allow for appropriate local management.

All of the models described previously explicitly consider scale. Modellers have developed numerous 'laws' for simplification, aggregation and scaling (Levin, 1995; Rotmans and Rothman, 2003), which can aid in dealing with these concerns.

Representing Spatio-temporal Variation

Desertification is highly contextual and ill-suited to simplistic regional or national generalizations. Huge variations in the condition of land makes land degradation hard to map and nearly all drylands are characterized by extreme year-to-year fluctuations in precipitation, making it difficult to distinguish between short-term variability and long-term changes in ecosystem appearance, as well as between temporary and permanent changes. Resilience in human systems adds further lags to observed spatio-temporal trends that need correct interpretation. For example, variation in resilience between different groups of human residents, even in the same geographical area, highlights the need for discrimination when reporting and interpreting the degree of degradation in a particular area (see Bradley and Grainger, 2004, for an example involving two Senegalese ethnic groups).

Gross generalizations, whether by expert mapping or the interpretation of low resolution satellite imagery, have also contributed to scientific unease about the reality of desertification, when empirical studies fail to find it present in various locations to the same extent shown in regional maps. In such circumstances collecting contextual knowledge at local scale is indispensable. In view of the cross-scalar nature of desertification, also represented in the DDP, contextual knowledge is valuable at all scales and not just the local.

Evaluating Uncertainties and Sources of Variability

Uncertainty about desertification arises from many sources, including errors in interpreting socio-biophysical cause–effect relationships; variability in precipitation; dimensional mismatching of scales, including temporal, spatial or functional information; errors introduced when data are averaged over differing time scales; the inherent complexity associated with the presence of nonlinearities and thresholds and overly-simplified or too complex methodologies (including models). The great uncertainty about the extent of desertification and its rate of change is self-evident from the lack of empirical global measurement. Even if a GDOS is established, uncertainty will continue, owing to the complexity of the phenomenon. Therefore, it is imperative that in order to integrate modelling results into the broader monitoring and assessment process, and to increase the effectiveness of interpreting information that will be of use to policy-makers, uncertainty analyses must be an ongoing theme in the recommended three-pronged scheme depicted in Figure 1.

MAKING MONITORING INFORMATION USEFUL FOR PLANNERS

The UNCCD contains many positive elements (e.g. stakeholder participation) but the challenge of developing an integrated analysis of desertification processes—and turning policy discourses into concrete action plans—will require a convergence of insights and advances drawn from a diverse array of research and knowledge in the fields of desertification, vulnerability, poverty alleviation and community development. It is important to involve more scientific disciplines and facilitate ways for stakeholders to work across disciplines to produce more diagnostic, pragmatic explanations of the phenomenon of desertification. These are precisely the strengths of integrated assessment.

A big challenge in all types of environmental monitoring is to convert information outputs into a form useful for practical planning and policy-making. In the case of desertification, integrated assessment and integrated assessment modelling have great potential to support the formulation and implementation of National Action Programmes for the UNCCD. Integrated regional models that incorporate biophysical, economic and technological change will be needed to provide policy-makers with the tools necessary to examine the potential consequences of different management scenarios of complex systems (Ayensu *et al.*, 1999). Integrated assessment models devised to extend our understanding of desertification could provide insights into how to construct synthetic information from the outputs of monitoring systems (Figure 1); they could guide the selection and integration of indicators, the interpretation of synthetic trends, making allowances for cross-scalar processes, representing spatio-temporal variation, and evaluating uncertainty; and they could also provide a means to construct and test our understanding of the causes of desertification, in order to provide decision makers with greater confidence as to where to make investments in ameliorating desertification and whether those investments are having any effect.

Desertification is a complex phenomenon with much uncertainty. Throughout this paper we have emphasized uncertainty as related to understanding coupled H–E systems, implementing a monitoring system like GDOS, conflicting stakeholder interests, lack of predictability and developing various types of models. Because of the inherent uncertainty involved, framing an issue like desertification will not be neutral, nor will the resulting models. However, the value of integrated assessment modelling as a structuring device is that they embrace uncertainty (van Asselt and Rotmans, 2002). Of special relevance to GDOS is that integrated assessment modelling is a dynamic and recursive process, and improved scientific understanding gleaned from modelling can be continuously used to adapt modes of monitoring, refocus objectives, modify management options and so forth (Figure 1) (Dowlatabadi *et al.*, 2000; Levin *et al.*, 2009).

CONCLUSIONS

The numerous models devised to extend our understanding of desertification provide many insights into how to construct synthetic information from the outputs of desertification monitoring systems. They can guide the selection and integration of indicators, the interpretation of synthetic trends, making allowances for cross-scalar processes, representing spatio-temporal variation, and evaluating uncertainty.

Each of these issues will be a challenge when designing an operational Global Drylands Observing System (GDOS). Scientists, planners and policy-makers are all keen to gain a better understanding of the complex phenomenon of desertification, devise improved planning methods to facilitate sustainable use of drylands, and monitor implementation of the UN Convention to Combat Desertification and National Action Programmes linked to it. The information produced by GDOS, whether in the form of digital spatio-temporal databases or published statistics, will be of immense value in meeting these goals.

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