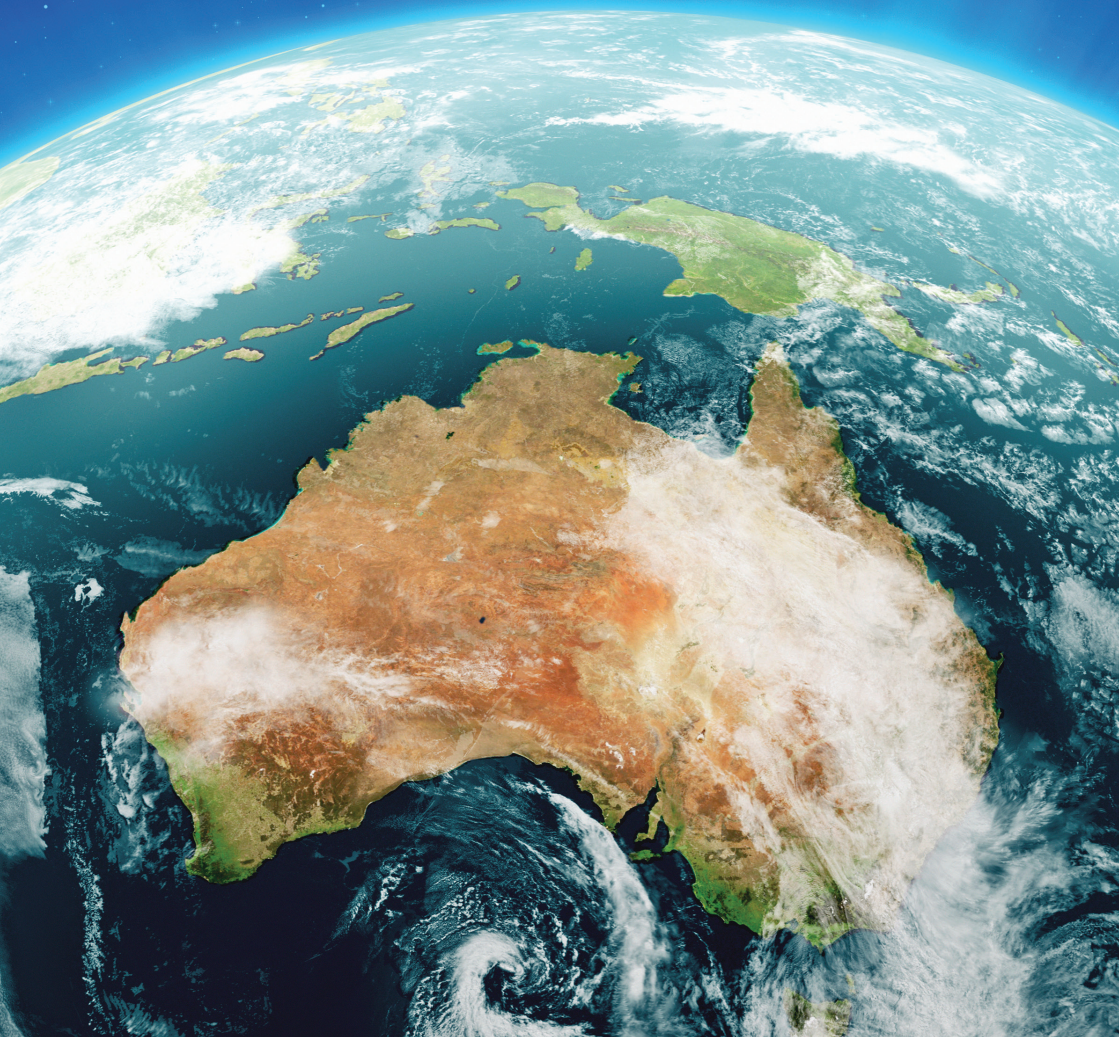
Volume 2

Negotiating our future: Living scenarios for Australia to 2050

Australian Academy of Science



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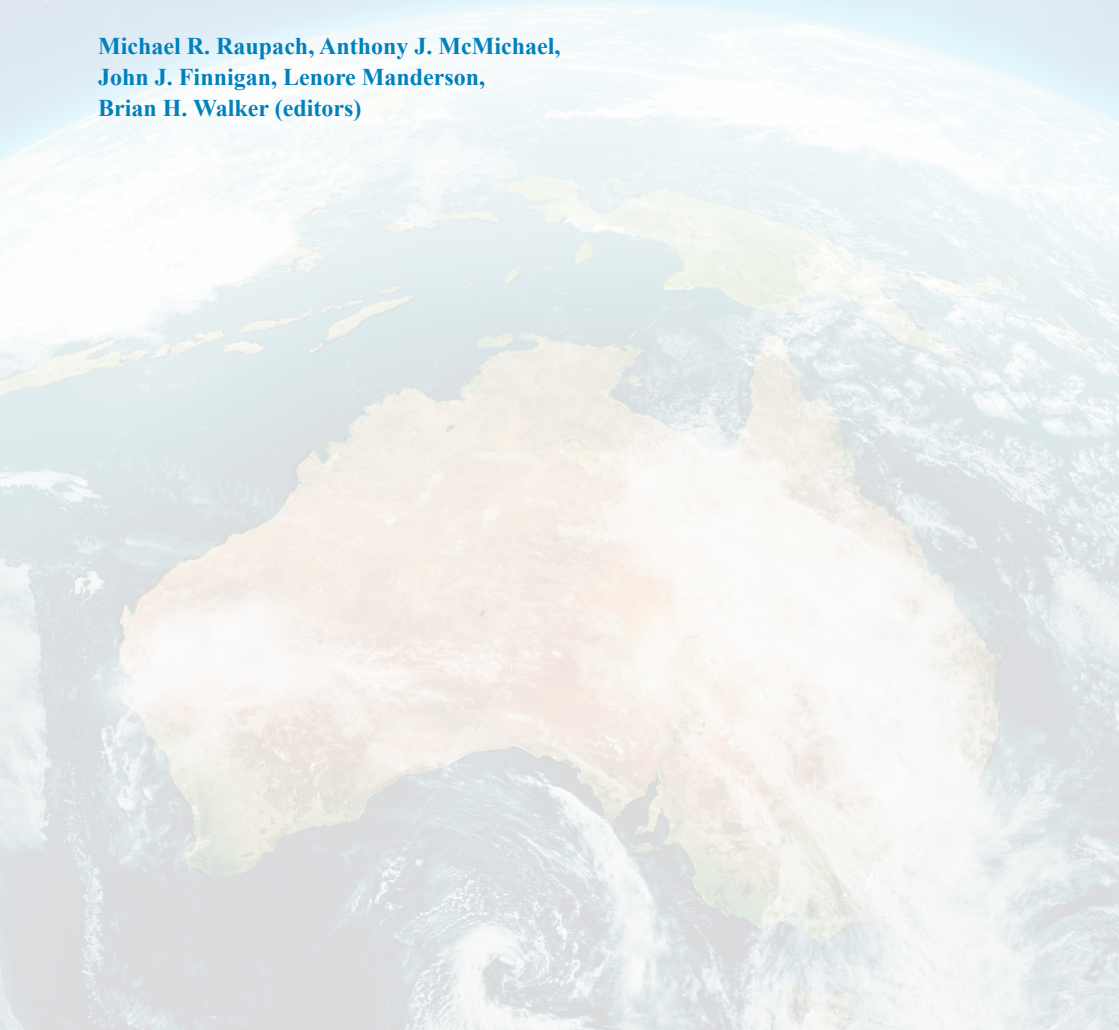
Michael R. Raupach, Anthony J. McMichael,
John J. Finnigan, Lenore Manderson,
Brian H. Walker (editors)



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Chapter 10

Science to inform and models to engage

Pascal Perez
SMART Infrastructure Facility, University of Wollongong

Scientific evidence and evidence-based reasoning are likely to face epistemological challenges when brought into societal debate if their foundational assumptions generate cognitive dissonance among key elements of the community. The risk of dissonance is even greater when scientific demonstrations and models are concerned with the decisions and behaviours of people interacting with an environment of interest. In this case, scientific information is often perceived as distorted or biased due to the inherent uncertainties attached to human ecosystems

Human ecosystems are complex and adaptive, largely due to our individual cognitive capacities and communication skills. Complex systems science aims to track uncertainties attached to these systems by exploring metaphoric models of reality.

1 An old debate after all

Four centuries ago the English philosopher Francis Bacon classified the intellectual fallacies of his time under four headings, which he called idols. An idol was defined as an image held in the mind that received veneration despite its lack of a defining substance. Bacon did not regard idols as symbols but rather as fixations. In this respect he laid the foundations of modern psychology. For Bacon, knowledge was intimately mixed with the idols, hence prefiguring our present concepts of beliefs and mental models [1]. More importantly, Bacon drew visionary consequences from the existence of the idols for the communication of innovative ideas (*Nova organum* 1620: 346:35) [2]:

> Enter quietly into the minds that are fit and capable of receiving it; for confutations cannot be employed, when the difference is upon first principles and very notions and even upon forms of demonstration.

Individuals and groups exhibit varied responses when faced with new information. If such information is consistent with existing behaviours and beliefs, it can be readily accepted and integrated. However, if the new information conflicts with current behaviour and belief, the resulting state is described as cognitive dissonance [3]. According to the theory, one can reduce the inconsistency and psychological discomfort of cognitive dissonance by changing one's beliefs, values or behaviour. Another way to avoid dissonance is to reject or avoid information that challenges belief systems or to interpret dissonant information in a biased way. Elaborating on the conflicting views upon 'uncertainty' between scientists and policymakers to explain the science–policy gap, Bradshaw and Borchers (2000: 30) [4] outlined the complexity of cognitive dissonance:

> Dissonance between existing beliefs and new information may be shaped by a host of factors, all of which inhibit the rate at which scientific findings are assimilated into policy. In what we have called the 'volition' phase of the science-policy gap, public debate around an emerging scientific consensus may derive from a combination of cultural, psychological, and economic interests threatened by the policy inferences of dissonant scientific findings.

Unlike scientific inquiries that use verification (modus ponens) and refutability (modus tollens) in an iterative and constructive way, folk-reasoning seems to use one or the other in ad hoc mental settings that try to minimise dissonance with socially and historically contingent beliefs. At the end of the 19th century Charles Sanders Pierce, a founder of modern semiotics, also suggested that we lacked direct access to reality and had to use 'signs' so as to mediate between our mind and the world [5]. Pierce hypothesised that as signs were socially

shared, it was society that established their meaning. Therefore, any truth was provisional and the truth of any proposition could not be certain but only probable. It follows from this preamble that scientific evidence and evidence-based reasoning are likely to face epistemological challenges when brought into societal debate if their foundational assumptions generate cognitive dissonance among key elements of the community. The risk of dissonance is even greater when scientific demonstrations and models are concerned with the decisions and behaviours of people interacting with an environment of interest. In this case, scientific information is often perceived as distorted or biased due to the inherent uncertainties attached to human ecosystems.

2 Human ecosystems are uncertain

Human ecosystems are characterised by very strong and long-term interactions between human communities and their environment; as such they constitute an expansion of the ecological concept of ecosystem. According to Stepp et al. (2003) [6] human ecosystems not only process matter and energy flows, but also—and more specifically—information flows. Therefore, they display very specific characteristics due to our ability to communicate and learn from others, creating the conditions for co-evolutionary processes in which chance gives a hand to necessity. Bradbury (2006) [7] argues that until recently human beings had been able to adapt to changes and to cope with co-evolution through rather simple heuristics. But human activities have gradually strengthened the links between loosely connected environments and societies—let's call it globalisation. More information, more interactions, and shorter communication paths tend to create intractable dependencies between events and to generate deeper uncertainties overall.

Batten (2000) [8] relates the uncertainty of human ecosystems to the idiosyncratic nature of human decision-making processes. As a matter of fact, we as cognitive beings constantly shift from deductive to inductive reasoning in order to solve daily problems or to assess complex, collective situations. Deduction is reasoning from the general to the particular. A perfectly logical deduction yields a conclusion that must be true provided that its premises are true. Inductive reasoning involves pattern formation and pattern recognition, aided by intuition and creativity. Clearly some people are more intuitive or creative than others. But we all share this capacity to adapt to complex situations through alternate inductive and deductive reasoning [9].

By admitting that most human ecosystems are highly complicated, we acknowledge their inherent uncertainty. Thus we also accept the fact that it may

not be possible to understand the intimate processes leading to well-established facts supported by social observations. For example, Durkheim (trad. 1979: 58) [10] in his famous study of suicide concluded that no matter how much a researcher knows about a collection of individuals 'it is impossible to predict which of them are likely to kill themselves. Yet the number of Parisians who commit suicide each year is even more stable than the general mortality rate'. A process that seems to be governed by chance when viewed at the level of individuals turns out to be strikingly predictable at the level of society as a whole. Hypothesising that most human ecosystems are complex and adaptive in nature, we need to accept the fact that they display these unexpected emergent properties, challenging our hopes of understanding the workings of causation [11].

3 Using metaphoric models to track uncertainty

During the late 1980s, research on complex and adaptive systems in biology or physics progressively permeated the social sciences. Concepts like emergence, path dependency, dynamic equilibrium or adaptation were directly transposed into studies on human ecosystems [12]. Here we need to stress that these concepts are only theoretical predicates imposed by complex systems science in its attempt to better describe reality: observed systems are complicated, only their theoretical representations ought to be complex and adaptive. As a consequence, scientists have developed computer-based metaphors called social simulations in order to identify and better understand emergent processes within real systems [13]. Most of these models rely on an atomistic vision of human ecosystems; these atoms—being called agents or nodes—are metaphoric representations of social entities and aim at reproducing plausible, if not realistic, behaviours [14]. Boundless attempts to simulate reality with these computer metaphors have sometimes resulted in erasing limits between simulated and observed systems. Lissack and Richardson (2001: 101 [15]) criticise some complex systems modellers for not recognising this duality:

> The act of interpreting differs from the act of observing, and both may differ significantly from the underlying phenomenon being observed. In their failure to respect this distinction, [these scientists] are implicitly suggesting that the interpretation is reality. However, while a good model of complex systems can be extremely useful, it does not allow us to escape the moment of interpretation and decision.

But a large majority of complex systems scientists safely use computer simulations as virtual laboratories where they can test, replicate and compare social theories in order to better understand reality. The types of uncertainties

they have to face can be separated into two classes: i) ill-defined predicates, and ii) nonlinear interactions. The first class includes cases where observed social patterns rely on unknown or largely implicit rules. Hence the modeller faces the challenge of inferring atomistic rules without calibrating observations in order to validate macrolevel patterns. For example, Dray and colleagues (2008 [16]) designed an atomistic model of illicit drug use and street markets in Australia. Despite the support of a transdisciplinary team of experts, the authors admit that, because of the illicit nature of the industry, several simulated processes are highly hypothetical, although macropatterns match epidemiological observations. Similarly, any attempt to simulate Durkheim's findings on suicide would have to rely on a series of speculative predicates. Often these are temporary limitations lifted by new inductive evidence or innovative deductive theories. Hence, from this perspective, one might see the uncertainty attached to simulated emerging phenomena as being an indicator of our incomplete understanding of social reality.

Unlike ill-defined predicates, uncertainty linked to nonlinear interactions stems from purely deterministic rules. Complexity is generated from a large number of iterative and conditional interactions between social entities (atoms). These outcomes become rapidly intractable, leading to unexpected emerging phenomena. This second class of uncertainty has attracted a vast amount of literature since the 1990s [17, 18, 11]. Within this literature the most striking evidence of the analytical value of atomistic simulations was given by Arthur (1994) [19] with his famous El Farol metaphor. One intriguing result of the simulation is that deterministic individual decisions, while totally unpredictable for an external observer, drive the entire system towards a stable state due to its self-referential conditions. Though fascinating, this emerging simplicity shouldn't be taken for granted. Indeed most of the time nonlinear interactions drive social simulations towards highly unstable grounds and emerging complexity. Nowadays the conditions under which simplicity emerges from complex atomistic interactions are at the core of research on complex systems [20].

4 A constructivist viewpoint upon uncertainty

So far we have asserted that human ecosystems are complex and adaptive, largely due to our individual cognitive capacities and communication skills. Complex systems science aims to track uncertainties attached to these systems by exploring metaphoric models of reality. One can feel the potential tension between grounded reality and artificial metaphors, social sciences and computer engineering, and constructivism and positivism. As a matter of fact, mainstream research on

artificial human ecosystems stems from distributed artificial intelligence, which has developed a very normative approach to human behaviour [21, 22]. The advantage of a normative approach is that it establishes a consistent analytical framework in order to create and validate scientific knowledge. Its main limitation is to acknowledge the fact that science is inherently objective and that scrutinised reality is unique. While suiting perfectly computer development principles, these assumptions become questionable when addressing issues related to human cognition or social interactions.

Is there an objective way to describe decision-making processes? Maturana and Varela (1980) [23] denounced the circular paradox that arises when scientists seek to address and explain human cognitive abilities by using those same cognitive abilities. They argued that the primary response to this paradox had been to ignore it and to proceed with respect to a fixed and objective reality external to our acts of cognition. The authors disputed the very concept of objective reality by considering: i) people operating in multiple 'worlds', particularly sociocultural one and ii) a 'world' being moulded by contextual factors intertwined with the very act of engaging it. Their autopoieitic (self-creating) theory considered living beings as living systems embedded into larger systems constituted by themselves and the environment they interact with. Unlike other more positivist approaches to human ecosystems [24], their constructivist theory included the observer himself into the analytical framework.

Despite its robust foundations, the autopoieitic theory has failed so far to translate into a pragmatic analytical framework. The main reason for this failure is that denouncing circularities is not sufficient for designing concrete methodologies that would overcome the paradox. Hence validating atomistic models of human ecosystems might face three types of uncertainties born from ignorance (ill-defined predicates), complexity (nonlinear interactions) and subjectivity (observer-dependent design). A way out was probably inferred by Reynolds (1987) [25], pioneer of atomistic computer metaphors, when asked about the validation of his Boids simulating flocks of flying birds:

> Success and validity of these simulations is difficult to measure objectively. They do seem to agree well with certain criteria and some statistical proportions of natural flocks and schools. Perhaps, more significantly, many people who view these animated flocks immediately recognize them as a representation of a natural flock.

Reynold's proposal is nothing less than accepting social validation as a major component of a scientific evaluation, through a collective and consensual construction of truth.

5 Towards postnormal analytical frameworks

Funtowicz and Ravetz (1993) [26], studying the relationship between applied research and environmental policy, proposed a new scientific posture they called 'postnormal science' From a postnormal scientific perspective, the inclusion of an adequate set of stakeholders in research development legitimates scientific inputs to the debate. Thus these participants perform a function analogous to that of peer reviewers in traditional science. Furthermore, Funtowicz and Ravetz (1993: 745 [26]) challenge the commonly admitted rationality of decision and action:

> Until now, with the dominance of applied science, the rationality of reductionist natural scientific research has been taken as a model for the rationality of intellectual and social activity in general. However... this ideal of rationality is no longer universally appropriate. The activity of science now encompasses the management of irreducible uncertainties in knowledge and in ethics, and the recognition of different legitimate perspectives and ways of knowing.

We also have to accept the fact that social simulations, even the more sophisticated ones, will always be pale copies of the original, subjective and partial representations of a dynamic and uncertain reality. But recognising this very peculiar fact doesn't mean that these models are useless. Even Lissack and Richardson (2001: 105) in their criticism of computer-based atomistic models admit that:

> There is no need for the models in question to have predictive power, despite the strong desire of both consultants and their clients those models 'work'. The pedagogical value of exploring the interactions of complex relations through the manipulation of models is more than enough to justify the efforts that go into model development and proliferation. Clearly, it is easier to manipulate a computer model than a fully-fledged 'in reality' laboratory experiment, but the limitations of such models must be remembered.

Nowadays a growing community of scientists tend to accept a postnormal scientific posture and engage in collective design of their atomistic models with experts and stakeholders. This co-construction process doesn't intend to provide normative models of reality. Instead, it is meant to enhance discussion and collective decision around and about the mediating object [27]. In these models social entities (atoms) are designed according to the consensual information provided by the participants. Decisional rules and behaviours implemented in the simulations are the expression of participants' perceptions [28, 29]. Hence this constructivist and postnormal process deals with uncertainties in different ways:

- Ignorance (ill-defined predicates) is dealt with through individual contributions of experts on plausible atomistic features and processes (populating process).

- Complexity (nonlinear interactions) is dealt with through social consensus among participants on existing and plausible realities of the system under study (framing process).
- Subjectivity (observer dependency) is dealt with by fully acknowledging the inherent limitations of the designed model (embodiment process).

D'Aquino and colleagues (2003) [30] propose a formal approach of co-construction of social simulations aiming to support collective learning and decision-making. Acknowledging the complex and adaptive nature of human ecosystems, their c*ompanion modelling* (ComMod) approach requires a permanent and iterative confrontation between theories and field circumstances. ComMod deals with the dialectic confrontation between researchers, models and observed realities. The subjectivity and contextual nature of the models is fully acknowledged, as the observer is considered as part of the experiment. Furthermore, ComMod emphasises the modelling process itself rather than concentrating only on the model, embedding information gathering, model design and use of simulations into a collective process [9]. Incomplete knowledge, contrasted viewpoints and limited capacities of prediction are inherent and explicit weaknesses of this approach. But the legitimacy of the outcomes, through social validation of the whole process, supports a more effective use of such models by decision-makers [31]). Finally, ComMod might help to reduce the epistemological gap between science and policy described by Bradshaw and Borchers (2000) [4]: far from reducing uncertainties (policy standpoint) or relentlessly exploring them (scientific standpoint), co-constructed social simulations tend to 'domesticate' uncertainty through the populating, framing and embodiment processes described above. But it must be clear that decision-makers have to satisfy themselves with 'what if' scenarios, which are inherently limited and uncertain. Hence decision-making has to become again what it would have never ceased to be: a risky business for professional and responsible gamblers. Under this condition only, a new kind of complex systems science can bring in reality-connected and fast-evolving support systems.

Global issues need large scale models

While participatory approaches to social modelling have demonstrated their effectiveness to deliver at local and mesolevel scales, global issues like responses to climate change or a global financial crisis need large-scale simulations to be meaningful. It is fair to recognise that constructivist and postnormal approaches to modelling aren't naturally suited to inform large-scale models. Direct upscaling of locally validated social models holds the risk of i) incorrect generalisation of

empirically validated decision-making processes or behavioural patterns, and ii) missing essential explanatory factors that wouldn't have been revealed in the local context being studied. Consequently, statistical demographic models developed by quantitative sociologists or general equilibrium models developed by macroeconomists tend to dominate the world of large-scale social simulations. Shortcomings attached to both approaches have long been documented: the latter relying on unrealistic state equilibrium and economic rationality conditions, while statistical demographics provide a succession of causal snapshots without knowledge of the social dynamics at work. These models have proven to be reliable as long as local actors display expected behaviours. Simulated outcomes will prove to be utterly wrong whenever unexpected behaviour occurs.

In the field of population health research Galea and colleagues (2009) [32] have proposed to overcome the current shortcomings of epidemiological models by integrating ethnographic information into their analytical and modelling framework. Their approach, called social epidemiology, uses complex system dynamic models to integrate local and global levels of information. In Australia, Moore and colleagues (2009) [33] provide a case-based illustration of such an integrative process whereby epidemiology, ethnography and modelling engage in an iterative and recursive dialogue in order to develop a generative sociological framework [34].

Population synthesis techniques have been widely used in conjunction with activity-based models applied to health, transport or housing research [35]. Based on large-scale statistical demographics (often drawn from census data), these microsimulations tend to generate mechanistic and repetitive local behavioural patterns. An obvious way forward would be to bring together population synthesis and social epidemiology paradigms to create richer more dynamic pictures of the social fabric under study. Though intuitively attractive, this proposal imposes significant constraints on the research framework: i) creation of long-term transdisciplinary research teams; ii) maintenance and regular updating of statistical demographics and ethnographic information; as well as iii), a need to socially validate the content of the model and its outputs. Under such a framework, large-scale simulation models would mediate between scientists, local actors, domain experts, practitioners and policymakers. While conceptually attractive, this approach would probably face overwhelming challenges if these core models were to be used as interactive media for targeted audiences. As a matter of fact, computational requirements, development timelines and relevant skills associated with large-scale models are often incompatible with agile, intuitive and interactive uses. Instead, we suggest the creation of 'shuttle models' that would encapsulate simplified or limited versions

of the core model in order to engage with specific stakeholders on a given set of issues. For these shuttle models to be useful and consistent with the core model they would need to respect the integrity of a common ontological architecture. Each interactive model could use a subset of ontological components, or simplified versions of some of them, as long as their space of local solutions doesn't violate the boundaries of the overall space of solutions generated by the core model. The development of these highly interactive and visually intuitive instances of the core model could be used as 'flight simulators' with specific targeted audiences, taking the pioneering work of Meadows (2001) [36] to the next level.

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Author

Pascal Perez (pascal_perez@uow.edu.au) is Professor of Modelling and Simulation at theSMART Infrastructure Facility, University of Wollongong, NSW.