Limits to Planetary Fresh Water Use: A Multi-Model Investigation

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Abstract

There has been a renewed interest over the last few years in limits to various earth bound systems and processes. This has been instigated by the work of Rockström and colleagues on planetary limits. Essentially, the planetary limit concept can be understood as a modern update to the seminal system dynamics work on limits to growth. The central idea of planetary limits is to identify thresholds in various earth bound systems and processes that, if crossed, would push the earth system out of its Holocene state. This work has been criticized for overlooking key feedbacks between the various earth bound systems and the ignoring the uncertainty that is intrinsic to any assessment of these limits. In this paper, we address these issues by using integrated system dynamics models in an exploratory way. We demonstrate this approach by investigating limits to planetary fresh water use using two world water models, namely ANEMI and WorldWater. The initial results suggests that sever water shortage is driven by the need to dilute waste water, and food demand and production. We discuss directions for improving the overall methodology and the case specific application.

1 Introduction

In the *Nature* article ‘A safe operating space for humanity’, Rockström et al. (2009) introduce the concept of a safe operating space for humanity. A safe operating space is the space for human activities that will not push the planet out of the ‘Holocene state’ that has seen human civilizations arise, develop, and thrive.

The concept is inherently anthropocentric and excludes non-human events and processes that could push the planet out of the Holocene state. Rockström et al. have identified nine earth-system processes and associated thresholds which, if crossed, are expected to generate unacceptable environmental change. These include climate change, rate of biodiversity loss, interference with the nitrogen and phosphorus cycles, stratospheric ozone depletion, ocean acidification, global freshwater use, change in land use, chemical pollution, and atmospheric aerosol loading. For all nine earth-system processes identified associated preliminary boundaries are given by Rockström et al. (2009). However, for only three of them, notably, climate change, rate of biodiversity loss, and the nitrogen cycle, are these boundaries substantiated theoretically and methodologically. The thresholds for the other six, including the global fresh water cycle, are tentative 'best guesses' (Rockström et al. 2009). For water, Rockström et al maintain that the boundary must be set to safely sustain enough green water for moisture feedback while allowing for terrestrial and aquatic ecosystem functioning and as a first attempt propose runoff depletion in the form of consumptive blue water use as a proxy. Based on global fresh water cycle assessment studies, Rockström et al set the threshold for global fresh water use at a range of 4000 to 6000 cubic kilometers per year.

Although we do subscribe to Rockström et al.'s ambition and concepts, there are nevertheless several problems associated with the approach they advance. A first problem is the ambiguous treatment of reductionism versus holism. While the authors clearly recognize thresholds and threshold behavior as a systemic and emergent property, Rockström at al. embark on a reductionist approach by reducing the earth system to nine biophysical processes and define planetary boundaries internal to these subsystems. Such an approach is bound to overlook the impacts of the dynamic interactions between the subsystems. For example, climate change speeds up the hydrological cycle, thus changing the limits to planetary fresh water use. The concept of global limits as introduced by Rockström et al ignores these feedbacks. To further complicate the study of global limits, our understanding of the global system is rife with uncertainty: structural uncertainties exist in the relation between climate change and renewable fresh water resources (Oki and Kanae 2006); local conditions, regional variations, the role of management, and financial and institutional capacity are being ignored by focussing on the physical system only (Molden 2009).

The presence and potential crucial importance of feedbacks between the various earth systems and their associated limits, suggests that a system dynamics investigation could be fruitful. Central to system dynamics is the focus on the use of models to explore the link between the system structure and the evolutionary behaviour over time arising out of this system structure (Lane 2000). That is, the behaviour of a system is to be explained by offering a causal ‘theory’, or dynamic hypothesis, for the behaviour (Lane 2000; Sterman 2000). In turn, this causal ‘theory’ or dynamic hypothesis can serve as the basis for interventions in the structure in order to change the resulting behaviour. This causal theory of the dynamic behaviour should be endogenous. That is, it should explain how the dynamic behaviour arises within the internal structure of the system (Richardson 2011). This endogenous view addresses the critique of reductionism that has been levelled at the idea of global limits.

To cope with uncertainty, an exploratory modeling approach is necessary. As detailed by Bankes (1993), there are broadly speaking two main purposes for making models: consolidating known facts into a model for predictive use, and the explication of our uncertainty and encapsulation of the uncertainty in an ensemble of models for exploratory use. The aim of the exploratory use of models is to support reasoning under uncertainty. The presence of uncertainty implies that there are different plausible hypotheses about a system. Exploratory modeling support the construction of valid arguments by conducting experiments with ensembles of models that capture the set of plausible hypotheses about a system, and to explore the implications of the different possible combinations of these hypotheses (Weaver, Lempert et al. 2013). The predictive use hinges on the ability to validate in a strict sense (Hodges and Dewar 1992) the correspondence of the model to the real world. For many systems, like the earth system, this is next to impossible for reasons outlined by e.g. Sterman (2000). However, it is still possible to use the available information, knowledge, and existing models for exploratory purposes.

In order to address the combined challenge of studying limits to the planetary fresh water cycle in a non-reductive fashion in the presence of a wide variety of uncertainties, we combine system dynamics modeling with an exploratory modeling approach. In short, we use exploratory system dynamics modeling and analysis (Pruyt 2007). Rather than developing new models from scratch, we use existing integrated system dynamics models of the planetary fresh water cycle, and explore the dynamics of these models across a wide range of uncertainties. Specifically, we use ANEMI (Davies 2007; Davies and Simonovic 2008; Davies and Simonovic 2010; Davies and Simonovic 2011) and WorldWater (Simonovic 2002). These models are substantially different in their dynamic hypothesis; WorldWater is an extension to World3, while ANEMI brings together models of key earth subsystems (e.g. climate, the carbon cycle, and global economics). We analyze each world water model in isolation, in light of the literature identify uncertainties associated with the global water cycle, and explore the implications of these uncertainties for the behavioral dynamics of both models. By comparing these two analyses, we draw wider conclusions about limits to planetary fresh water use.

In section 2, we provide background material on the modeling of the global water system, focusing in particular on ANEMI and WorldWater. In section 3, we provide details on exploratory system dynamics. Section 4 contains the analysis of both models. In section 5, we discuss the results. Section 6 contains our conclusions.

2 Modeling the global water system

There are various modeling approaches that can be used to model the planetary fresh water cycle. Modeling choices depend on the purpose of the modeling exercise (global distribution of hydrological processes, global distribution of sectoral water use and availability, integrated assessment), model structure (grid based, grid based interaction, grid based processes, hydrological units based interaction, hydrological unit based processes, and all sorts of hybrids and cross-overs), data availability, format, and temporal and spatial specifications. Often these model characteristics interact and pragmatic choices are made that serve the specific purpose of the modeling exercise. Models that focus on the global characteristics of hydrological processes often use grid based approaches combined with a routing scheme for river discharges. Good examples of these macro-scale hydrological model (MHM) are PCR-GLOBWB (Weiland, van Beek et al. 2010), VIC (Nijssen, O'Donnell et al. 2001), Macro-PDM (Arnell 1999), WBM (Vörösmarty, Green et al. 2000) and WGHM (Alcomo, Döll et al. 2003). Models that in addition to the hydrological processes focus on water use mostly apply hydrological units like watershed as their smallest geographical units or apply hybrid approaches. For example the integrated water and food analysis model WATERSIM (de Fraiture 2007) uses river basins as its basic spatial unit for hydrological process, administrative units as the basic spatial units for policy and trade and their intersection as the basic spatial unit for the integrated model.

Next to these detailed models that primarily focus on the hydrological processed, there is a class of integrated dynamic models. At present, several integrated dynamic water cycle models exist at both global and regional scales. These models have been used to define global or regional limits to the use of blue water. On a global scale, AQUA (Hoekstra 1998) and WorldWater (Simonovic 2002) are the most relevant and best known models. ANEMI is a more recent model in this same tradition (Davies and Simonovic 2010; Davies and Simonovic 2011). These models deviate from other world water models such as WaterGap (Alcomo, Döll et al. 2003) in that the various feedbacks between the water cycle, water use, socio economic developments, the climate, etc. are endogenous to the model. In contrast, in WaterGap for example, scenarios for population development, GDP, and electricity production are necessary inputs. This implies that models like WaterGap cannot be used to investigate the impact of water shortages over time on how population or GDP evolves, nor can it cope with human adaptation to water shortage. For example, WaterGap will overestimate irrigation consumption in case of water shortage (Hunger and Döll 2008). This advantage of integrated dynamic world water models, however, comes at the price of not being geographically explicit. In this paper, we concentrate our effort on two integrated global water models: ANEMI and WorldWater.

2.1 ANEMI

ANEMI, an ancient Greek term for the four winds, heralds of the four seasons, links physical systems such as climate, the hydrological cycle and the carbon cycle with socio-economic systems, including economy, land use, population change and water use (Davies and Simonovic 2010). It was designed as an integrated assessment model that would permit the assessment both of socio-economic policies and uncertainties about the overall system (Davies and Simonovic 2010). ANEMI is a system dynamics model, focusing in particular on the importance of the feedback relations between the various physical and socio-economic subsystems, and the dynamics arising out of these feedbacks, rather than aiming at providing detailed predictions.

ANEMI is a system dynamics model. Central to system dynamics models is the endogenous point of view (Richardson 2011). According to this view, the dynamic behavior of a system arises within the internal structure of a model. This view implies a closed system boundary, where the behavioral dynamics of the system arise out of interacting feedback loops. Thus, in system dynamics, a system is viewed as an ongoing interdepended, self-sustaining, dynamic process. That is, the observed behavior of a system is to be understood as arising out of the internal structure of the system. This internal structure of a system is conceptualized using stocks and flows, and relations between them. System dynamics is a modeling method for understanding the behaviors of nonlinear, dynamic and complex systems and for policy analysis and design (Sterman 2000).

ANEMI is composed of nine subsystems: climate, carbon cycle, economy, land-use, population, agricultural production, natural hydrological cycle, water use, and water quality (Davies 2007; Davies and Simonovic 2008; Davies and Simonovic 2011). Fig. 1 shows the main feedback structure of the model. The positive or negative sign associated with each arrow indicates the direction of change one model component has on the other model component. The names next to each arrow indicate which aspect of the model component causes a change in the other model component. The closed loop structure of the model implies that model behavior emerges endogenous feedbacks (Davies and Simonovic 2010). The model has been validated through comparison with government statistics, scientific data, results from other models, and socio economic data (Davies 2007; Davies and Simonovic 2008; Davies and Simonovic 2010; Davies and Simonovic 2011).

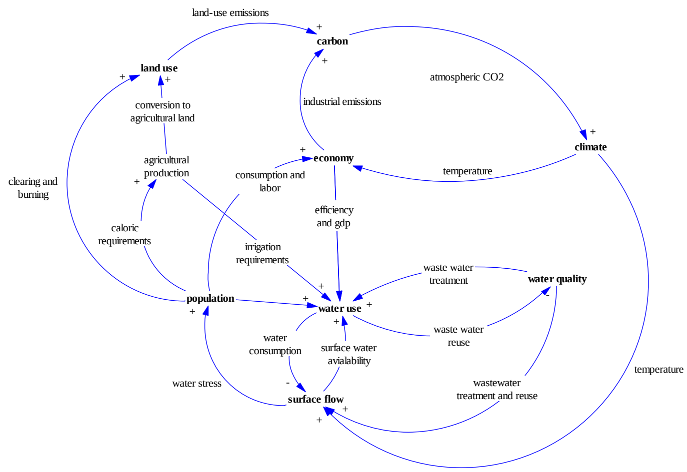

Fig. 1. Model components and their feedbacks (Davies and Simonovic 2011)

The climate sector is an upwelling diffusion energy balance model based on the box advection diffusion model of Harvey and Schneider (1985). The carbon cycle is based on Goudriaan and Ketner (1984), where the oceanic sector is modified based on Fiddaman (1997). The land use system is based on Goudriaan and Ketner (1984). The population component is based on Nordhause and Boyer (2000) and Fiddaman (1997). However, the dynamics are endogenous by including water stress (Davies and Simonovic 2010). The economic components is inspired by the updated DICE model (Nordhaus 2008)[1]. The three water parts and the agricultural production are unique to ANEMI, but build on earlier work (e.g. Shiklomanov 2000; Simonovic 2002). The water use model is similar to WaterGAP 2 (Alcomo, Döll et al. 2003). Water quality is comparable to how it is handled in WorldWater (Simonovic 2002). Surface flow, and the hydrological cycle are influenced by Chanine (1992), Shiklomanov (2000), and Simonovic (2002). The agricultural component is the latest addition to ANEMI and is based on Bouwman et al. (2005), Siebert and Döll (2010), and FAO data (Davies and Simonovic 2011).

2.2 WorldWater

The WorldWater model (Simonovic 2002) is based on the well-known World3 model (Meadows, Meadows et al. 1972; Meadows, Behrens III et al. 1974). World3 is a system dynamics model of world scope. It comprises five main sectors: population, agriculture, non-renewable resources, economy and persistent pollution. In WorldWater two new sectors are introduced: water quantity and water quality, together with various addition feedbacks between the two new sectors and the other parts of the model.

[1] We are well aware of the fact that there is an extensive critique in the SD literature on DICE. However, it is explicitly not the purpose of this research to develop new models. Rather, we start from the available models and explore the implications they hold for world water dynamics. In future work, the implications of the critique on DICE on world water dynamics might be investigated, for they arguably reflect different hypotheses, and thus are a source of uncertainty.

The total water stock in the model includes precipitation, ocean resources and non-renewable groundwater resources. The model also takes into account water recycling as a fraction of water use. The water use side is modelled in a traditional way to include: municipal water use for the needs of population, industrial, and agricultural water needs. However, the most important difference between the WorldWater and other global water models is in its ability to address the needs of freshwater resources for transport and dilution of polluted water. The original version of WorldWater is built on top of the world3 model that ships with Stella. We have re-implemented the model in Vensim. Full details on the model and model testing are provided in Simonovic (2002).

3 Exploratory System Dynamics

Exploratory system dynamics modeling and analysis has been receiving increasing attention over the last several years. Pruyt (2007) introduced the explicit combination of exploratory modeling and system dynamics under the label 'exploratory system dynamics modeling and analysis'. He argued that this ESDMA approach is particularly appropriate for (*i*) systematically generating, exploring, and analyzing all (sorts of) plausible dynamic behaviors over time, (ii) directly searching for tipping folds, vulnerabilities, leverage points, et cetera, and (iii) designing adaptive policies and testing the robustness of policies over the entire uncertainty space. ESDMA has been demonstrated with a variety of cases and for different purposes. Kwakkel et al (2013) use ESDMA for the identification of possible future undesirable behavior modes of the copper price. Kwakkel and Pruyt (2013) present three cases to demonstrate the benefit of ESDMA for foresight. Hamarat et al. (2013) use the approach for the development of a robust policy for realizing a transition towards more sustainable energy generation. Many more examples can be found in the proceedings of the last few International System Dynamics conferences (e.g. Pruyt 2010; Pruyt 2010; Pruyt and Hamarat 2010; Pruyt, Kwakkel et al. 2011; Pruyt and Kwakkel 2012)

The exploratory use of system dynamics models, however, is not something new. Rather, it goes back to some of the founding ideas of system dynamics.. In his earliest work, Forrester emphasized the experimental use of simulation models (Forrester 1961; Richardson 2011), and according to Lane (2010), experimentation is part of the analytical kernel of system dynamics. Similarly, Meadows and Robinson (1985: p. 394) already argue that it is "important to study deeply the model sensitivity with regard to these variables [about which there is lack of data and/or knowledge] and to present a spectrum of runs under different hypotheses, covering the range of their variation". In line with this, Moxnes (2005) has argued that traditional sensitivity analysis needs to be extended from judging the sensitivity of model behaviour to uncertain assumptions about model formulations and parameter values to testing the sensitivity of policy recommendations to uncertain assumptions. Ford and Flynn (2005) have proposed a simple statistical screening technique to identify the most influential uncertain inputs in a system dynamics model. Moreover, a long standing argument in the system dynamics literature is the need of computer simulation to rigorously deduce the consequences of the complex relationships with feedbacks and delays (e.g. Lane 2000). This same argument can be extended to apply to rigorous experimentation with computer models in the presence of uncertainty. Here too, we content that the capability of the human mind to correctly infer the joint consequences of the different uncertainties is deficient, and needs to be complemented by computer experimentation. In light of these considerations, we suggest that the combination of exploratory modelling and system dynamics is not a revolutionary new way of modelling, but rather an evolution of an idea from the earliest days of the field.

A system dynamics model offers a causal theory about a particular phenomenon (Lane 2000; Sterman 2000). This implies that a model is a concentration of assumptions or hypotheses about causal laws, that jointly offer a plausible representation and explanation of the phenomenon of interest. Uncertainty implies that one or more of these hypotheses are contested, and could be substituted for another hypotheses. We speak of two different models if the two models are not identical in all respects. So, changing a single parameter value for a given model results, according to this definition, already a different model. Admittedly, the difference between the two models in this case would be a difference in degree, rather than a difference in kind.

The aim of exploratory system dynamics is to systematically and comprehensively study the behavior of the system across the key uncertain factors. These uncertainties span a space of possible models. Each point in this uncertainty space represents one particular combination of uncertain hypotheses. The challenge of exploratory modeling is to design a search strategy for understanding the characteristics of this uncertainty space. A distinction can be made between two basic search strategies in EMA: open exploration and directed search. Open exploration can be used to systematically explore uncertainty space. That is, open exploration aims at generating a set of computational experiments that covers the uncertainty. This exploration relies on the careful design of experiments and can use techniques such as Monte Carlo sampling, Latin Hypercube sampling, or factorial methods. An open exploration can be used to answer questions such as “under what circumstances would this policy do well?”, “under what circumstances would it likely fail?”, and “what kinds of dynamics can this system exhibit?”. An open exploration provides insight into the full richness of behaviours of the ensemble of models.

Directed search, in contrast, is a search strategy for finding particular points in the uncertainty space that are of interest. Directed search can be used to answer questions such as “what is the worst that could happen?” What is the best that could happen?” “How big is the difference in performance between rival policies?”. A directed search provides detailed insights into the dynamics of specific locations in the full space of plausible models. Directed search relies on the use of optimization techniques, such as genetic algorithms and conjugant gradient methods. Active non-linear testing is an example of a directed search strategy (Miller 1998). Open exploration and directed search can complement each other. For example, if the open exploration reveals that there are distinct regions of possible dynamics, directed search can be employed to identify more precisely where the boundary is located between these distinct regions.

4 Cases

4.1 ANEMI

4.1.1 Uncertainties

Table 1 contains an overview of the parameters and their ranges that are to be explored. For this paper, we concentrated on parameters related directly to water use. The documentation of the model was reviewed and parameters that were either explicitly denoted as a guess or assumption, or for which divergent possible values were named were included in the analysis. The parameters include various time series that describe developments over the full runtime, such as the changing demand for food per person per year. These time series were replaced with sigmoid functions:

$$f(t) = \alpha \frac{1}{1 + e^{\frac{t-\gamma}{\delta}}} + \beta$$

Here, α, β, γ, δ, are uncertain parameters that can be explored; α and β control the upper and lower limit of the sigmoid, γ controls when the sigmoid is half way between the two limits, and δ controls the slope.

Table 1. The uncertainties and their ranges

uncertainty	description	range
Agricultural Blue Water Dilution Factor	factor for dilution of polluted agricultural blue water	5-10
Agricultural Polluted Fraction	percentage of return flow of agricultural blue water that is polluted	0.7-0.95
Average Virtual Water Content of Crops	virtual water in crops in m3/Gcal	400-500
Average Virtual Water Content of Fodder	virtual water in fodder in m3/Gcal	200-300
Base Specific Water Intake	base value for water intake in agriculture in	9000-12000

	m3/ha/year	
Base Returnable Water	base value for water return flow from agriculture in m3/ha/year	10-50
Base Precipitation Multiplier	increase of precipitation due to increasing global temperature in %/Celsius	3-4
Domestic Dilution Factor	factor for dilution of polluted domestic water	5-10
Domestic Polluted Fraction	percentage of return flow of domestic water that is polluted	90-100
Fractional Usage of Desalination Capacity	fraction of desalinization capacity that is being used	0.3-0.7
Fcl	simple area weighted cloud fraction	0.5-0.6
Gamma d	factor affecting increase in water demand per person due to gdp/capita increase	2.2e-10-2.2e-06
Industrial Dilution Factor	factor for dilution of polluted industrial water	5-10
Industrial Polluted Fraction	percentage of return flow of industrial water that is polluted	38-46
Max Groundwater Withdrawal	maximum amount of ground water withdrawal in km3/Year	7-10
Maximum Establishment of Desalination Facilities	maximum amount of desalinization capacity in km3/year	25-40
Percent Domestic Withdrawal	percentage of domestic withdrawal that is consumed	80-90
Stable and Useable Runoff Percentage	fraction of runoff that can be used, taking pollution dilution into account	30-40
Yield Ratio for rainfed to irrigated agriculture	yield fraction of rain fed agriculture as compared to irrigated agriculture	0.4-0.8
Wastewater Dilution Requirement	multiplier for dilution of polluted water	6-10
Technological Change for Consumption in Agricultural Sector lookup	transient scenario for technological change in agriculture affecting water consumption	sigmoid function
Technological Change for Withdrawals in Agricultural Sector lookup	transient scenario for technological change in agriculture affecting water withdrawal	sigmoid function
Crop Productivity Gains lookup	transient scenario for gains in crop productivity	sigmoid function
Percentage increase in irrigated area lookup	transient scenario for increase in irrigated area	sigmoid function
Global Per Capita Food Consumption lookup	transient scenario for increase in food consumption	sigmoid function

4.1.2 Open exploration

In order to investigate the consequences of these uncertainties on model behavior, we generated a Latin Hypercube sample of 10,000 experiments and explored the model behavior across these 10,000 computational experiments. As outcome indicators, we focused on water stress and the world population. Water stress is a proxy for the severity of water shortage. Formally, it is in this model defined as the water use per year divided by the yearly renewable flow. Thus, water stress is the fraction of the renewable flow being used. In the literature on water stress, values higher than 0.4 are considered to indicate sever water shortage.

Figure 1 shows the bandwidth, or envelope, of the results in shaded grey, with a set of example model runs imposed on top. On the right hand side, a Gaussian Kernel Density (KDE), which is like a continuous histogram, is shown. As can be seen, the behavior of the examples appears to be broadly similar for both outcome indicators. We can also see that the majority of runs results in a water stress of around 0.35 in 2100, while already climbing to this value around 2030. With respect to population, we see that the model project slow stabilizing growth. There is no indication of population collapse induced by water shortage across the 10,000 experiments.

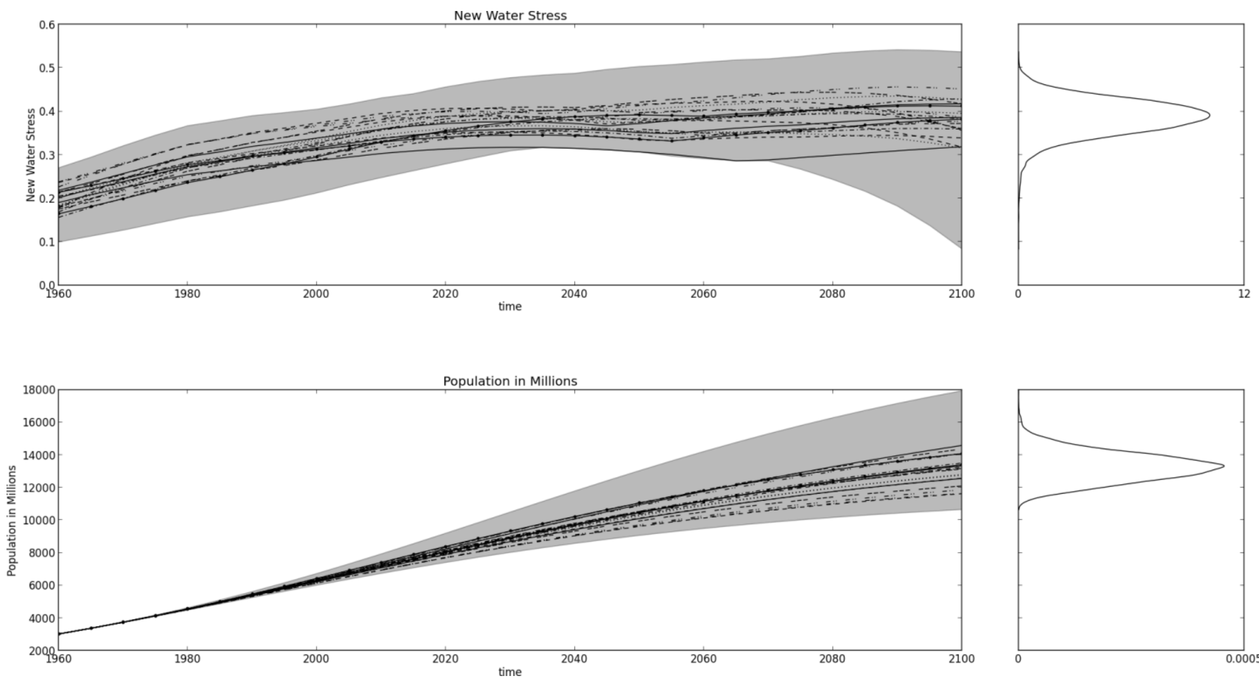

Figure 1: Envelopes and exemplar runs for water stress and population

The next question is to understand what drives model behavior, given the limited behavioral diversity generated by the model across the 10,000 runs, we concentrate on the runs that result in severe water stress. To this end, rather than looking at behavior, we concentrate on the maximum value for water stress encountered over the run. Figure 2 shows a histogram for this. As can be seen, the maximum water stress ranges from around 0.32 up to 0.55. There also appears to be a second 'hump' around 0.43.

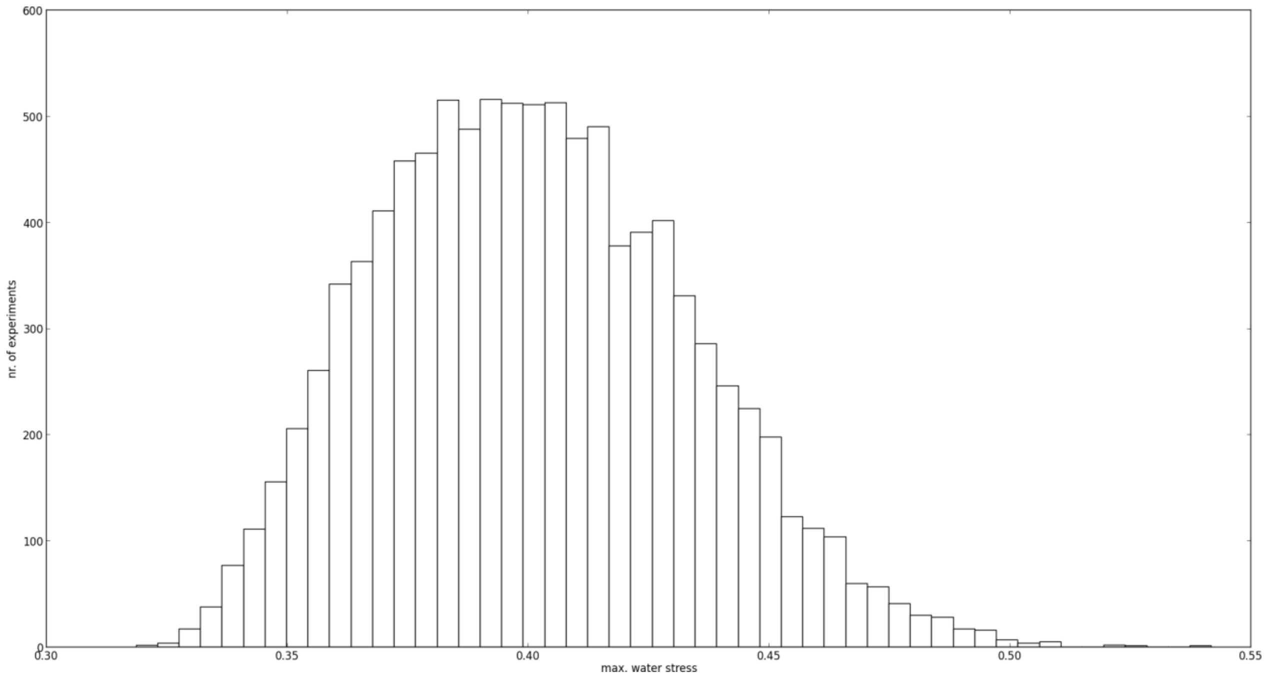

Figure 2: Histogram of the maximum value of water stress encountered for each experiment

In order to identify the experiments that produce high values of water stress, we concentrate on the cases in this second 'hump' and beyond. We use the Patient Rule Induction Method (PRIM) (Friedman and Fisher 1999) to identify the region in the uncertainty space that produces runs with high water stress values. Knowing the parameterizations under which high water stress occurs offers a starting point for identifying the dominant feedback mechanisms that drive water stress. PRIM is machine learning algorithm. More specifically, it is a rule induction algorithm that aims at finding hexagonal subspaces, or 'boxes' which contain a high concentration of the experiments of interest. PRIM is the most used machine learning algorithm for analysis exploratory modeling results (Lempert, Bryant et al. 2008). There are 1919 cases with a maximum water stress value higher than 0.43. Table 2 shows the identified boxes. We found two boxes that jointly contain around 50% of the high water stress cases. For comparison we also show the box limits of the full space.

By comparing the box limits of box 1 and box 2 with the rest box, one gains insight into the most important uncertainties that drive water stress. The more restricted an uncertainty is, the more it drives water stress. The dimensions are sorted based on their degree of restrictedness in box 1. As can be seen, the food consumption and the yield of rainfed agriculture as compared to irrigated agriculature are two main drivers for water stress. That is, a high demand for food, and a low yield from rainfed agriculture produce high water stress. The reason being that in order to meet food demand, substantial water is necessary to produce sufficient food. A different mechanism that is important is related to the dilution factor. This factor specifies how much water needs to be mixed with used water in order to meet a minimum water quality standard. The lower this value, the more concentrated the pollution is, and the more water is needed to dilute it.

Table 2: Box limits identified with PRIM

uncertainty	box 1			box 2			rest box		
	range			range			range		
beta food consumption	3303.14	-	3499.95	3155	-	3499.95	2500.03	-	3499.95
Yield Ratio for rainfed to irrigated agriculture	0.4	-	0.62	0.4	-	0.77	0.4	-	0.8
Domestic Dilution Factor	5	-	8.53	5	-	8.83	5	-	10
alpha crops	2	-	2.39	2	-	2.48	2	-	2.5
gamma crops	1990.88	-	2010	1990.83	-	2010	1990	-	2010
beta crops	0	-	0.48	0	-	0.5	0	-	0.5
Agricultural Polluted Fraction	0.7	-	0.94	0.7	-	0.95	0.7	-	0.95
Fcl	0.5	-	0.6	0.5	-	0.6	0.5	-	0.6
gamma withdrawals	2000	-	2099.99	2000	-	2074.33	2000	-	2099.99
alpha food consumption	1500.04	-	1999.96	1500.04	-	1975.46	1500.04	-	1999.96
Max Groundwater Withdrawal	7	-	10	7	-	9.87	7	-	10
delta irrigated area	15	-	40	16.44	-	40	15	-	40
Domestic Polluted Fraction	90	-	100	90	-	99.52	90	-	100
Fractional Usage of Desalination Capacity	0.3	-	0.7	0.3	-	0.67	0.3	-	0.7
gamma irrigated area	1980	-	2000	1982.11	-	1998.84	1980	-	2000
gamma food consumption	1940	-	1960	1941.06	-	1958.88	1940	-	1960
Industrial Dilution Factor	5	-	10	5	-	9.72	5	-	10
Base Specific Water Intake	9000.17	-	11999.88	9692.04	-	11999.88	9000.17	-	11999.88

In conclusion, the analysis of this model shows that the diversity of behaviors generated by this model is rather poor. The dynamics is roughly the same across the 10,000 experiments. Focusing on the maximum value of the water stress, we see that it is driven on the one hand by food demand and low yield figures from rainfed agriculture, and on the other hand by water pollution. High level policy implications that follow from this analysis include the need to maximize yields from rainfed agriculture, and the need to minimize the pollution due wastewater by increasing waste water treatment or making more effective use of water by matching water use to water quality.

4.2 WorldWater

4.2.1 Uncertainties

In earlier analyses, Simonovic (2002) explored three scenarios: the base scenario from World3, a 'double run' scenario which includes strong technological development over a period of twenty years, and the stable run from Meadows et al (1992). Each of these scenarios involve a set of changes to several parameters, including the turning off or on of a technology, its maturation over time represented by a lookup, etc. Each of these changes has been included as a separate factor, allowing us to explore hybrids between these three scenarios. In addition, Simonovic (2002) list a number of additional major uncertain factors including the costs of various water resources, the rate of sustainable supply, and the ratio between water consumption and water withdrawal. These have been included too.

4.2.2 Open exploration

In order to investigate the consequences of these uncertainties on model behavior, we generated a Latin Hypercube sample of 10,000 experiments and explored the model behavior across these 10,000 computational experiments. As outcome indicators, we focused on water scarcity and the size of the world population. Water scarcity is the unfulfilled water demand, and is a proxy for the severity of water shortage.

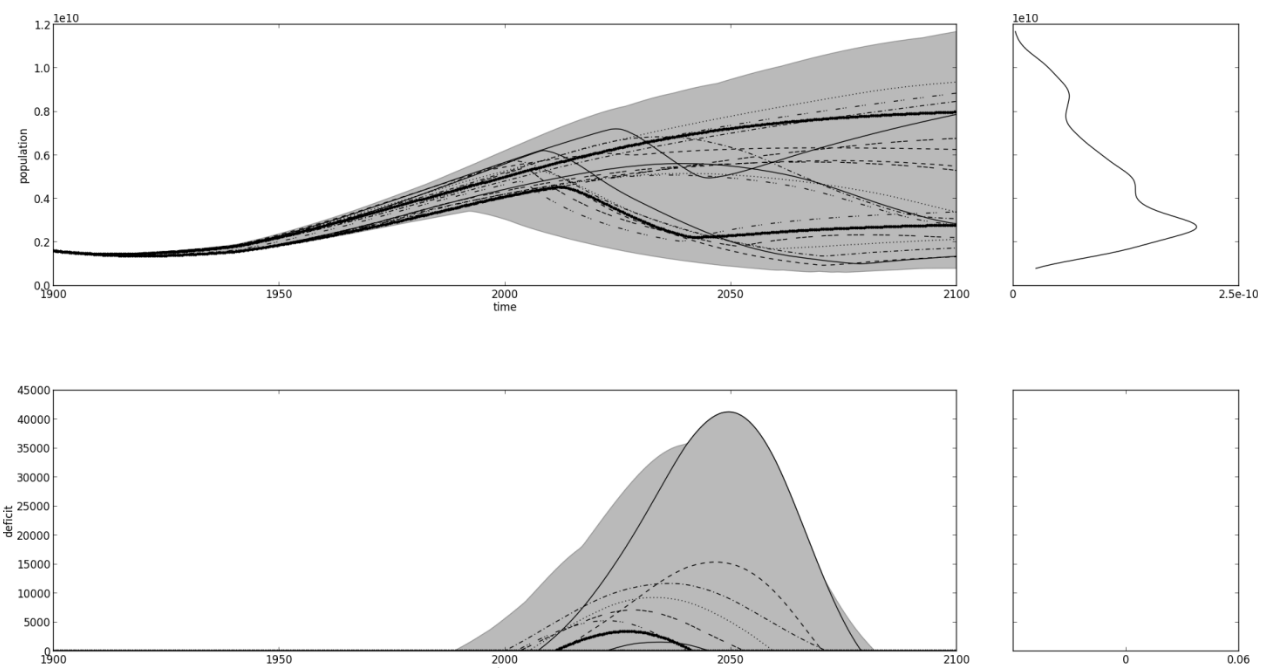

Figure 3: Envelopes and exemplar runs for population and deficit

Figure 3 shows the bandwidth, or envelope, of the results in shaded grey, with a set of example model runs imposed on top. On the right hand side, a Gaussian Kernel Density (KDE), which is like a continuous histogram, is shown. In contrast to ANEMI, WorldWater shows a substantially larger variety of behavioral dynamics. There are runs where population first rises, before it starts to drop at around 2020, after which in some cases it recovers again.

Next, we investigate the deficit. Analogously the water stress in case of ANEMI, we concentrate here on the maximum value of the deficit over the run. Figure 4 shows the resulting histogram. Note that the y-axis is log scaled. As can be seen, there is a substantial number of experiments where no deficit occurs et al. The maximum value for the deficit is around 40,000 km^3.

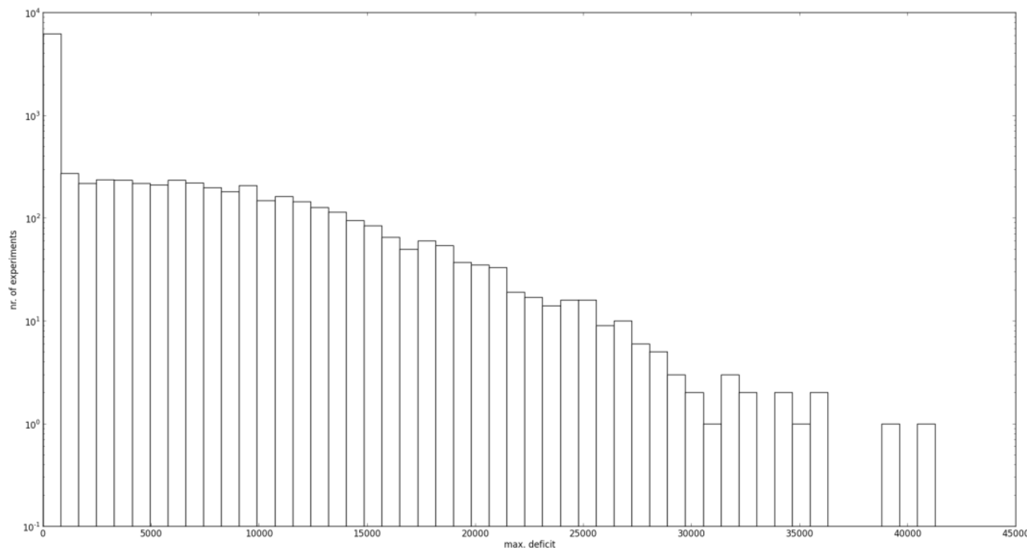

Figure 4: Histogram of the maximum deficit encountered for each experiment

The next step is to investigate what drives the deficit. Given that the majority of runs shows no deficit, we focus the analysis on the presence or absence of a deficit. Again, PRIM is used to identify the subspaces in the uncertainty space that contain a high concentration of deficit experiments. Table 3 shows the resulting box limits that jointly explain 99% of the deficit cases. The deficit is primarily driven by the aow factor, which drives the pollution of waste water, the switch for using pollution reducing technology, and the average lifetime of industrial capital.[2] The basic mechanism in this model that seems to be driving the deficit is the pollution of water and the need to dilute this waste water.

Table 3: Box limits identified with PRIM

uncertainty	box 1	box 2	rest box
	range	range	range
factor aow	212.33 - 300.00	126.62 - 300.00	100.01 - 300.00
switch ppoll tech PTD	True	true	True, False
p avg life ind cap	14.22 - 18.00	14.00 - 18.00	14.00 - 18.00
t policy year	1976 - 1995	1975 - 1995	1975 - 1995

Figure 5 supports the conclusion that the main mechanism that drives the deficit is the need for dilution of waste water. This figure shows the relative usage for each water use type for the experiment with the maximum deficit. As can be seen clearly, over the course of 2000-2050, the need for dilution of water is the primary type of water use. Policy implications are straightforward: reduce waste water and make more effective use of water based on matching water quality with demand.

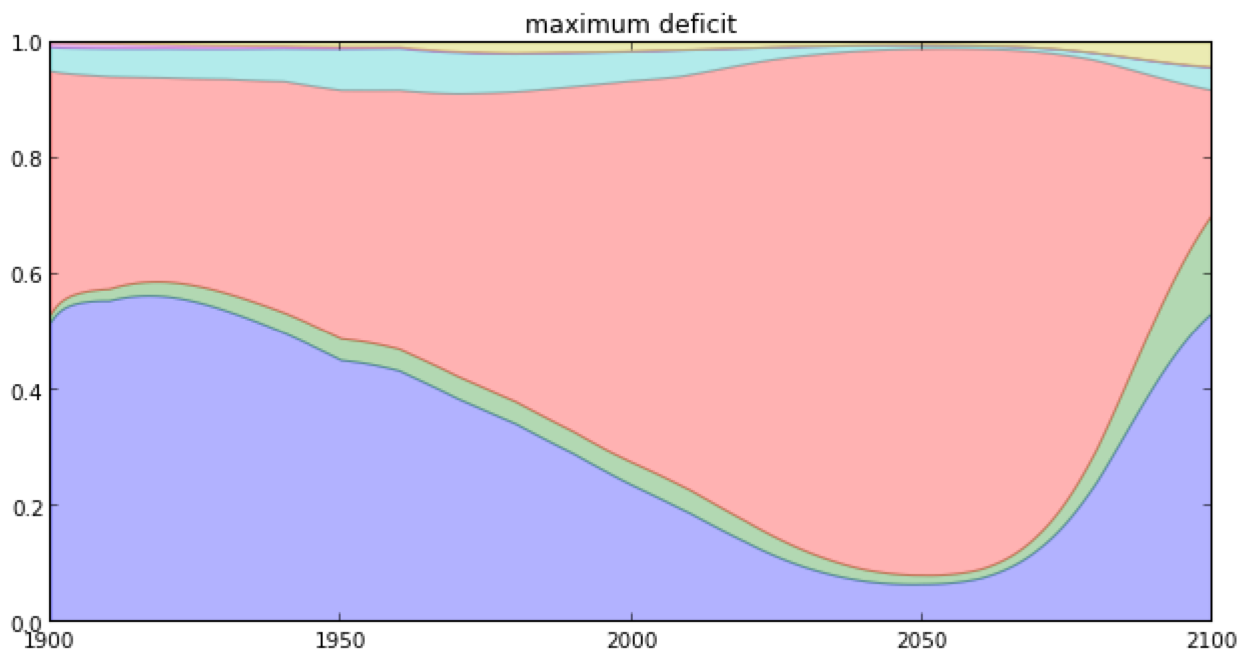

Figure 5: The relative usage of water for the maximum deficit case. Blue is agriculture, green is industry, pink is dilution of waste water, light blue is municipal use, and yellow is reservoir losses.

[2] It is surprising that using pollution reducing technologies increases the deficit. We are investigating whether this is due to an error on our part, or a correct conclusion. The final paper for the conference will be updated in light of this further investigation.

5 Concluding remarks

The starting premise of this paper was that any investigation of global limits needs to address the problems caused by the feedbacks between earth bound systems and processes, and the fact that our understanding of these systems is incomplete and intrinsically uncertain. We have argued that the first problem could be addressed by using integrated system dynamics models. In this way, an integrated endogenous view on global limits is taken. In order to address the uncertainty, we have argued that the exploratory use of models is a way of assessing the implications of the uncertainty. To demonstrate this approach, we analyzed two substantially different models of the global world water cycle, focusing on conditions under which there is sever water shortage.

An issue complicating the analysis of the two models is the fact that the uncertainties explored for the two models are substantially different. As a result, it is only possible to draw conclusions about the models in isolation, rather than also being able to assess how the same uncertainty would play out in the different models. In future work, we intent to work towards identifying as many factors that are present in both models, in order to carry out such analyses. Similarly, there is only a partial overlap with respect to indicators. Both models include population, while the scarcity of water is represented as either water stress (ANEMI) or water shortage (WorldWater). In future work, we intent to develop one or more metrics that can be added to both models, resulting in commensurable models with respect to outcome indicators.

A second issue is that the choice for integrated system dynamics models, while addressing the problem of interactions between earth bound systems and processes, results in a loss of specificity. A crucial issue in the global water cycle is the time and location of water availability. The models used here are not geospatially explicit, and hence little can be said about how and where the severe water shortage will occur. A challenge for future research is to combine the strength of the endogenous view offered by system dynamics models with the geospatial detail over by hydrological world water models.

Reflecting on the methodology, we only utilized one style of exploratory system dynamic, namely an open exploration. Future work could extend the analysis offered here by complementing it with a directed search into extremes that the models are able to introduce. In particular, we are curious to test whether ANEMI can produce other behavioral dynamics than the limited set currently observed. Related to this, including the system dynamics critique on dice in our analysis could in fact help in producing a richer set of behavioral dynamics.

With respect to limits to planetary fresh water use, we conclude that these limits are closely tied to the future demand for food, the yields of rainfed agriculture, and the extent to which waste water needs to be diluted. These conclusions are based on the exploration of ANEMI and WorldWater across uncertainties related to these models in isolation. Future work, or changing the uncertainties taken into consideration could change these conclusions. Still, the fact that in both models dilution of waste water is an important factor suggests that this finding is relatively robust.

References

Alcomo, J., P. Döll, et al. (2003). "Development and Testing of the WaterGAP 2 Global Model of Water Use and Availability." Hydrological Sciences Journal **48**(3): 317-337.

Arnell, N. W. (1999). "A simple water balance model for the simulation of streamflow over a large geographic domain." Journal of Hydrology **217**(3): 314-335.

Bankes, S. C. (1993). "Exploratory Modeling for Policy Analysis." Operations Research **4**(3): 435-449.

Bouwman, A. F., K. W. van der Hoek, et al. (2005). "Exploring Changes in World Ruminant Production Systems." Agricultural Systems **84**(2): 121-153.

Chahine, M. T. (1992). "The hydrological cycle and its influence on climate." Nature **359**(6394): 373-380.

Davies, E. G. R. (2007). Modelling Feedback in the Society-Biosphere-Climate System. Department of Cival and Environmental Engineering. London, Ontario, Canada, The University of Western Ontario. **PhD**.

Davies, E. G. R. and S. P. Simonovic (2008). An Integrated System Dynamics Model for Analyzing Behaviour of the Social-Economic-Climatic System: Model Description and Model Use Guide. London, Ontario, Canada, University of Western Ontario.

Davies, E. G. R. and S. P. Simonovic (2010). "ANEMI: a new model for integrated assessment of global change." Interdisciplinary Environmental Review **11**(2/3): 127-161.

Davies, E. G. R. and S. P. Simonovic (2011). "Global water resources modeling with an integrated model of the social-economic-environmental system." Advances in Water Resources **34**(6): 684-700.

de Fraiture, C. (2007). "Integrated water and food analysis at the global and basin level. An application of WATERSIM." Water Resources Management **21**(1): 185-198.

Fiddaman, T. S. (1997). Feedback Complexity in Integrated Climate-Economy Models. Sloan School of Management. Cambridge, Massachusetts, Massachusetts Institute of Technology. **PhD thesis**.

Ford, A. and H. Flynn (2005). "Statistical screening of system dynamics models." System Dynamics Review **21**(4): 273-303.

Forrester, J. W. (1961). Industrial Dynamics. Cambridge, MIT Press.

Friedman, J. H. and N. I. Fisher (1999). "Bump hunting in high-dimensional data." Statistics and Computing **9**(2): 123-143.

Goudriaan, J. and P. Ketner (1984). "A simulation study for the global carbon cylce, including man's impact on the biosphere." Climatic Change **6**: 167-192.

Hamarat, C., J. H. Kwakkel, et al. (2013). "Adaptive Robust Design under Deep Uncertainty." Technological Forecasting and Social Change **80**(3): 408-418.

Harvey, L. D. and S. H. Schneider (1985). "Transient Climate Response to External Forcing on 10^0-10^4 Year Time Scales Part 1' Experiments With Globally Averaged, Coupled, Atmosphere and Ocean Energy Balance Models." Journal of Geophysical Research **90**(1): 2191-2205.

Hodges, J. S. and J. A. Dewar (1992). Is it You or Your Model Talking? A Framework for Model Validation. Santa Monica, CA, USA, RAND.

Hunger, M. and P. Döll (2008). "Value of river discharge data for global-scale hydrological modeling." Hydrology and Earth System Sciences **12**: 841-861.

Kwakkel, J. H., W. Auping, et al. (2013). "Dynamic scenario discovery under deep uncertainty: the future of copper." Technological Forecasting and Social Change **80**(4): 789-800.

Kwakkel, J. H. and E. Pruyt (2013). "Exploratory Modeling and Analysis, an approach for model-based foresight under deep uncertainty." Technological Forecasting and Social Change **80**(3): 419-431.

Lane, D. C. (2000). "Diagramming conventions in System Dynamics." The journal of the Operational Research Society **51**(2): 241-245.

Lane, D. C. (2000). "Should System Dynamics be described as a 'hard' or 'deterministic' systems approach?" Systems Research and Behavioral Science **17**: 3-22.

Lane, D. C. (2010). "Participative modelling and big issues: defining features of system dynamics." Systems Research and Behavioral Science **27**: 461-465.

Lempert, R. J., B. P. Bryant, et al. (2008). Comparing Algorithms for Scenario Discovery. Santa Monica, CA, USA, RAND.

Meadows, D. H., D. L. Meadows, et al. (1992). Beyond the limits, Chelsea Green.

Meadows, D. H., D. L. Meadows, et al. (1972). The limits to growth, Universe Books.

Meadows, D. H. and J. Robinson (1985). The Electronic Oracle. Computer Models and Social Decisions, Joh Wiley & Sons.

Meadows, D. L., W. W. Behrens III, et al. (1974). Dynamics of growth in a a finite world, Productivity Press Inc.

Miller, J. H. (1998). "Active Nonlinear Tests (ANTs) of Complex Simulation Models." Management Science **44**(6): 820-830.

Molden (2009). "The devil is in the details." Nature **3**(october 2009).

Moxnes, E. (2005). "Policy sensitivity analysis: simple versus complex fishery models." System Dynamics Review **21**(2): 123-145.

Nijssen, B., G. M. O'Donnell, et al. (2001). "Hydrologic sensitivity of global rivers to climate change." Climatic Change **50**(1): 143-175.

Nordhaus, W. D. (2008). A Question of Balance: Weighing the Options on Global Warming Policies. New Haven, CT, Yale University Press.

Nordhaus, W. D. and J. Boyer (2000). Warming the World: Economic Models of Global Warming. Cambridge, Massachusetts, The MIT Press.

Oki, T. and S. Kanae (2006). "Global Hydrological Cycles and World Water Resources." Science **313**: 10681072.

Pruyt, E. (2007). Dealing with Uncertainties? Combining System Dynamics with Multiple Criteria Decision Analysis or with Exploratory Modelling. . 25th International Conference of the System Dynamics Society. Boston, USA.

Pruyt, E. (2010). Scarcity of Minerals and Metals: A Generic Exploratory System Danamics Model. The 28th International Conference of the System Dynamics Society. T. H. Moon. Seoul, Korea.

Pruyt, E. (2010). Using Small Models for Big Issues: Exploratory System Dynamics Modelling and Analysis for Insightful Crisis Management. 18th International Conference of the System Dynamics Society. Seoul, Korea.

Pruyt, E. and C. Hamarat (2010). The Influenza A(H1N1)v Pandemic: An Exploratory System Dynamics Approach. The 28th International Conference of The System Dynamics Society. M. H. Lee. Seoul, Korea.

Pruyt, E. and J. Kwakkel (2012). A Bright Future for System Dynamics: From Art to Computational Science and More. The 30th International Conference of the System Dynamics Society. St Gallen, Switzerland.

Pruyt, E., J. H. Kwakkel, et al. (2011). Energy Transitions towards Sustainability: A Staged Exploration of Complexity and Deep Uncertainty. The 29th International Conference of the System Dynamics Society, Washington DC, USA.

Richardson, G. P. (2011). "Reflections on the foundations of system dynamics." System Dynamics Review **27**(3): 219-243.

Rockström, J., W. Steffen, et al. (2009). "A safe operating space for humanity." Nature **461**(7263): 472-475.

Shiklomanov, I. A. (2000). "Appraisal and Assessment of World Water Resources." Water International **25**(1): 11-32.

Siebert, S. and P. Döll (2010). "Quantifying blue and green virtual water contents in global crop production as well as potential production losses without irrigation." Journal of Hydrology **384**(3-4): 198-217.

Simonovic, S. P. (2002). "World Water Dynamics: Global Modeling of Water Resources." Journal of Environmental Management **66**(3): 349-367.

Sterman, J. D. (2000). Business Dynamics: Systems Thinking and Modeling for a Complex World, McGraw-Hill.

Vörösmarty, C. J., P. Green, et al. (2000). "Global water resources: vulnerability from climate change and population growth." science **289**(5477): 284.

Weaver, C. P., R. J. Lempert, et al. (2013). "Improving the contribution of climate model information to decision making: the value and demands of robust decision making frameworks." WIREs Climate Change **4**: 39-60.

Weiland, F. S., L. van Beek, et al. (2010). "The ability of a GCM-forced hydrological model to reproduce global discharge variability." Hydrology and Earth System Sciences **14**: 1595-1621.