Explaining Puzzling Dynamics: Comparing the Use of System Dynamics and Discrete-Event Simulation

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Abstract

Both system dynamics (SD) and discrete-event simulation (DES) are used to help understand and explain puzzling real world dynamics. But what are the similarities and differences between these two approaches and which should be used in a specific circumstance? These are questions few have ventured to answer.

In this research the two approaches are compared by developing an SD and DES model of the same problem situation, a fishery. An SD expert and a DES expert separately develop a model of the fishery through a number of evolutionary steps. At each step differences in the representation and interpretation of the models are identified. Overall it is apparent that while SD illuminates 'deterministic complexity', DES illuminates 'constrained randomness'. Either or both may be important in understanding and explaining puzzling dynamics. SD and DES should therefore be seen not as opposing modelling approaches, but as complementary.

Key Words

System Dynamics, Discrete-Event Simulation, Modelling Philosophy, Fisheries

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Introduction

Everyday situations present many examples of puzzling dynamics - performance over time that defies intuition and commonsense. You drive for miles at a fast and steady speed on a busy motorway yet sometimes encounter unexpected tailbacks with no apparent cause. You occasionally visit your hairdresser. These visits are always on the same day of the week at the same time but you never know in advance whether you will wait one minute or half an hour for a haircut. The price of your house has doubled in recent years, but you and your neighbours have not doubled your income, the street still looks the same, and domestic population is reported to be falling. British consumers have been eating fish and chips for generations and now you read that the Prince of Wales is calling for a halt to this national tradition to prevent a collapse in North Sea cod-fish stocks[i].

One way to investigate such puzzling dynamics is to build a computer simulation model that represents the various interrelated factors and pressures at work in the situation, and then run the model to see whether or not it is capable of generating similar puzzling performance. If a model can, in some meaningful way, mimic observed performance then modellers claim they have an explanation for the phenomenon. In developing a simulation model to investigate puzzling dynamics, the analyst can select one of two distinct types of simulation approach: system dynamics (SD) (Sterman 2000, Coyle 1996, Richardson and Pugh 1981, Forrester 1961) and discrete-event simulation (DES) (Law and Kelton 2000, Banks et al 2001, Robinson 2004, Pidd 2004). Both are widely used to examine the performance over time of interconnected systems. The analyst is left to select the appropriate method. It is apparent that most analysts opt for the method with which they are most familiar (Meadows 1980). Perhaps this is unsurprising given that there appear to be very few studies that compare SD and DES, let alone give guidance on which approach might be most appropriate in different circumstances. Our intention in this paper is to address the question of which method to use and why by exploring how SD and DES models help us make sense of puzzling dynamics.

Existing Comparisons of SD and DES

We begin with a brief review of the few existing comparisons of SD and DES in the literature. Collectively they highlight several important technical and conceptual differences between the approaches.

Coyle (1985) discusses how discrete events might be modelled in a system dynamics simulator. In doing so he notes two key differences between the SD and DES approach. First there is the tendency for DES models to include randomness. He argues that in SD models stochastic noise can be subsumed into an appropriate delay. The second difference he identifies is that in DES modelling an open-process structure is adopted, while in SD a closed-loop structure is used in which feedback is explicitly identified.

Writing from the perspective of healthcare modellers Brailsford and Hilton (2000) briefly describe health-related DES and SD studies including a system dynamics model of NHS waiting lists for cardiac surgery and a discrete event model of AIDS transmission in a localised population. Table 1 summarises the main technical distinctions the authors identify from their experience of modelling in general and from these studies in particular.

Discrete Event Simulation	System Dynamics
Systems (such as healthcare) can be viewed as networks of queues and activities	Systems (such as healthcare) can be viewed as a series of stocks and flows
Objects in a system are distinct individuals (such as patients in a hospital), each possessing characteristics that determine what happens to that individual	Entities (such as patients) are treated as a continuous quantity, rather like a fluid, flowing through reservoirs or tanks connected by pipes
Activity durations are sampled for each individual from probability distributions and the modeller has almost unlimited flexibility in the choice of these functions and can easily specify non-exponential dwelling times	The time spent in each reservoir is modelled as a delay with limited flexibility to specify a dwelling time other than exponential
State changes occur at discrete points of time	State changes are continuous
Models are by definition stochastic in nature	Models are deterministic
Models are simulated in unequal timesteps, when "something happens"	Models are simulated in finely-sliced time steps of equal duration

Table 1: Technical Differences Between DES and SD Identified by Brailsford and Hilton (2000)

Writing from the perspective of an experienced system dynamics modeller Lane (2000) identifies conceptual differences between DES and SD in terms of the categories shown in table 2. Consider just a few of these categories. There is the modeller's perspective on complexity and the distinction between detail complexity in DES (the network of activities and queues conceived at a functional operating level) and dynamic complexity in SD (closed feedback loops linking stocks and flows conceived at a cross-functional strategic level). Related to the perspective on complexity there is the degree of resolution of models: a close-up resolution in DES that picks out individual entities, attributes, decisions and events versus a distant resolution in SD that captures homogenised entities and continuous policy pressures. There is the type of problem studied, usually operational for DES and more strategic for SD. There is the portrayal of human agents viewed as decision makers in DES (choosing between well-defined options) and as boundedly rational policy implementers in SD (responding to organisational pressures for change). There are model outputs that in DES take the form of point predictions and detailed performance measures and in SD take the form of simulations that enhance understanding of the structural source of behaviour modes in SD. It should be noted that Robinson (2001) does not agree with this last point in regard to DES, where he argues that DES can be used for developing an understanding of a system's behaviour and does not necessarily have to focus on point prediction.

	Discrete Event Simulation	**System Dynamics**
Perspective	Analytic; emphasis on detail complexity	Holistic; emphasis on dynamic complexity
Resolution of models	Individual entities, attributes, decision and events	Homogenised entities, continuous policy pressures and emergent behaviour
Data sources	Primarily numerical with some judgemental elements	Broadly drawn
Problems studied	Operational	Strategic
Model elements	Physical, tangible and some informational	Physical, tangible, judgemental and information links
Human agents represented in models as	Decision makers	Boundedly rational policy implementers
Clients find the model	Opaque/dark grey box, nevertheless convincing	Transparent/fuzzy glass box, nevertheless compelling
Model outputs	Point predictions and detailed performance measures across a range of parameters, decision rules and scenarios	Understanding of structural source of behaviour modes, location of key performance indicators and effective policy levers

Table 2. Conceptual Differences Between DES and SD Identified by Lane (2000)

Further comparisons are found in DES textbooks (though interestingly not in SD textbooks). For example Pidd (2004) comments on the relative level of detail in DES and SD models noting that while discrete event models concentrate on the state changes and interactions of individual entities it is normal in system dynamics to operate at a much more aggregate level by concentrating on the rates of change of populations of entities. Moreover he succinctly observes that "In order to model feedback systems for simulation it is important to concentrate on their structure rather than their content. The structure defines how the variables interact, the content is the meaning of those variables for the organisation". Robinson (2004) observes that DES is generally more appropriate when the details of a system need to be modelled, especially when individual items need to be tracked.

Finally, in her doctoral thesis, Mak (1992) investigates how activity cycle diagrams for DES models can be converted into stock and flow representations, developing guidelines and software to automate the process. In doing so she identifies a number of differences between the DES and SD approach. Many of the differences are similar to those already described above. In addition, she notes that SD models explicitly show information feedback while DES models do not, albeit that this information is normally held within the logic of DES models. It is also noted that SD models tend to study the interaction of control policies, exogenous events and feedback structure. DES models tend to be used for 'what-if' experimentation, in which the effect of various options are investigated.

A shortcoming of all of these comparisons is that they are written from the perspective of either a specialist in SD or a DES specialist. A comparison of the two approaches that brings together the world views of SD and DES modellers does not appear to exist. Such a comparison based on a literature search is confounded by the lack of literature on the underlying philosophy of DES modelling. Whereas SD modellers have a well-formed modelling philosophy (Forrester 1968, Lane 1999, Morecroft 2004, Richardson 1991, Sterman 1989), such writings seem to be almost non-existent within the DES community.

Research Focus

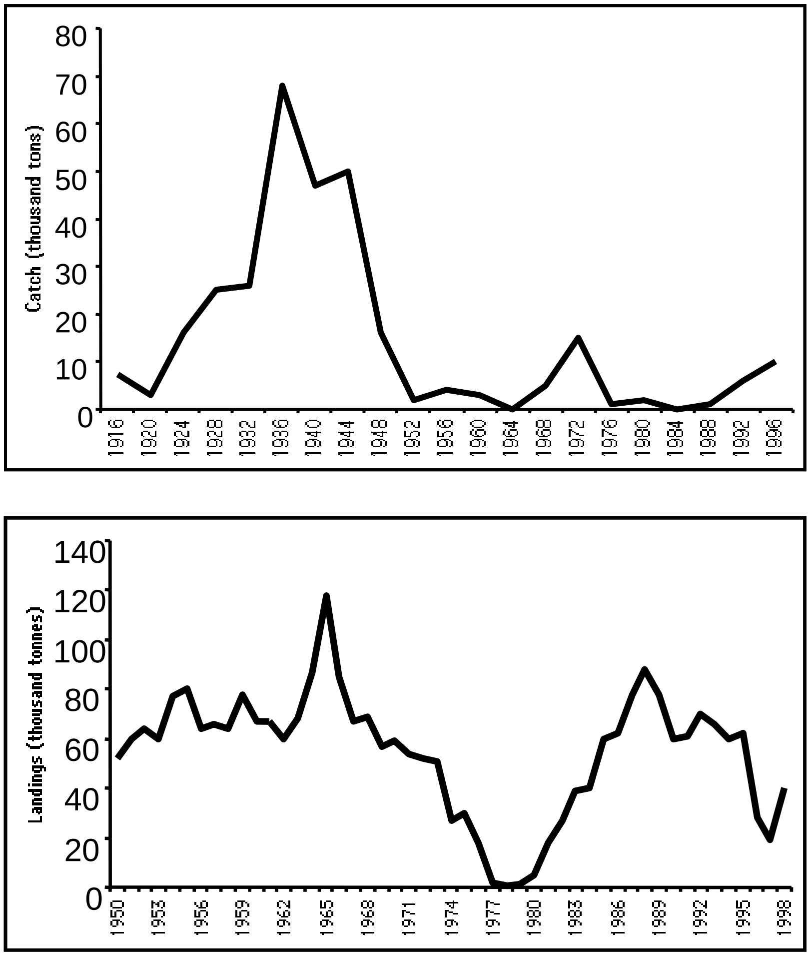
Rather than focus on technical and conceptual differences, we compare the nature of *explanations and insights* these two approaches have to offer about puzzling dynamics. Our premise is that the modelling style you choose affects the way you represent and interpret phenomena from the real world. Broadly speaking SD primarily investigates the performance over time of an interconnected system arising from its internal feedback structure. DES primarily investigates the performance over time of an interconnected system subject to internal (e.g. process failure) and external (e.g. environmental conditions) random variability. Either approach can portray realistic situations such as those mentioned above: the movement of traffic on a motorway, the build-up of queues in retail outlets or the rise and fall of fish stocks But what do they tell us? What, if anything, is different about the understanding, explanation and communication of dynamics that arises from such alternative styles of modelling?

These questions stem from our complementary professional backgrounds. Both of us are experienced modellers, one specialising in SD (Morecroft) and the other in DES (Robinson). We share an interest in how people learn from models and simulation, and the relationship between hard and soft OR (Morecroft 2004, Robinson 2001, Morecroft and Sterman 1994). In this respect, this work addresses the shortcoming of previous comparisons, by drawing together expertise from the quite separate SD and DES worlds.

Erratic Fisheries – Chance, Destiny and Limited Foresight

For our comparison we developed two models of similar size and detail to represent the dynamics of fisheries. There are several reasons for choosing fisheries. The application is novel (at least among SD-DES comparisons), yet appropriate and important. The problems of overexploitation facing international fisheries are well known, widely reported in the press and a subject of government policy in many nations. The performance of international fisheries is indeed puzzling. Fish naturally regenerate. They are a renewable resource, in apparently endless supply, providing valuable and healthy food for billions of consumers and a livelihood for millions of fishing communities worldwide. The fishing industry has been in existence since the dawn of civilisation and should last forever. Yet fish stocks around the world are volatile and some are even collapsing. Once rich fishing grounds such as Canada's Grand Banks now yield no catch at all. Stocks in other areas, such as the English Channel, the North Sea and the Baltic, are in terminal decline. Figure 1 shows typical volatile time series data from real fisheries. The top chart shows the Pacific sardine catch in thousands of tons over the period 1916 to 1996. The annual catch grew remarkably between 1920 and 1940, starting around 50 thousand tonnes and peaking at 700 thousand tonnes – a fourteen fold increase. Over the next four years to 1944 the catch fell to 500 thousand tonnes, stabilised for a few years and then collapsed dramatically to almost zero in 1952. Since then it has never properly recovered. The bottom chart shows a similar story for the North Sea Herring Catch in the period 1950 to 1998. However, in this case following a collapse between 1974 and 1979, the fishery did recover in the 1980s and early

1990s with an average annual catch around 600 tonnes, similar to the catch in the 1950s and 1960s.



Source: Nichols, John. "Saving North Sea Herring." Fishing News February 1999.

Figure 1: Pacific Sardine Catch (top) and North Sea Herring Catch (bottom) from Fishbanks Debriefing Materials (Meadows et al 2001)

This visible and contemporary problem is amenable to small and transparent models that (despite being small) nevertheless portray dynamic complexity typical of SD and DES. Since neither of us are experts on fisheries we have based our models loosely on a popular fisheries gaming simulator called Fishbanks Ltd (Meadows et al 2001) used to teach principles of sustainable development to a wide variety of audiences ranging from politicians, business leaders and government policy advisers to fishing communities and high school students.

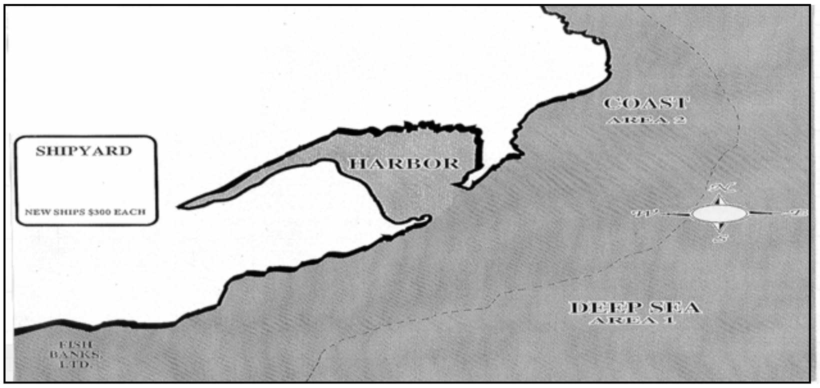


Figure 2: An Imaginary Fishery – the Game Board
of Fishbanks Ltd

Figure 2 shows the Fishbanks gameboard and its imaginary fishery. There is a finite offshore region of ocean containing a single species of fish. Fish regenerate as a function of the existing population. The local fishing community buys ships from the shipyard and takes them to sea to harvest fish. The total catch depends on the number of ships, the fish population and other factors such as the weather. In the game, as in real life, the fish population is not known accurately, although it can be estimated. Also, in the game, as in real life, the process of fish regeneration is not fully understood by those in the system (players or fishermen). Regeneration is related to the (unknown) fish population, but the relationship is complex and may involve other external factors.

We have taken this situation as a common starting point and then separately developed SD and DES models using the conceptualisation, visualisation, formulation and interpretation guidelines of our respective modelling disciplines. From the very outset we were aware of philosophical differences in the way we approached the problem. A system dynamicist takes the view that puzzling dynamics arise from endogenous, deterministic and structural properties of the system – the natural laws governing fish regeneration, the policies guiding investment in ships, the productivity of ships for harvesting and processes of stock accumulation that accurately account for and conserve the number of ships and fish introduced or removed from the system. All these relationships form the feedback structure of the fishery that can be visualised as a network of interlocking feedback loops. The destiny of the fishery (whether it is sustainable and whether future harvest rates will grow, remain stable or collapse) is assumed to be predetermined by the feedback structure, although this future is not known with certainty by fishermen. They, like any other stakeholders in business and society, have limited foresight relative to the dynamically complex system they operate. It only takes two or three non-linear feedback loops (in a system comprising as few as two stock accumulations) to generate puzzling, counterintuitive dynamics. A simple SD fisheries model comfortably meets this complexity criterion.

In contrast a discrete-event modeller takes the view that puzzling dynamics arise from the interaction of random processes coupled together by endogenous structure (Robinson 2004). So again, the natural laws governing fish regeneration and the rules for investment in ships and harvesting are important, but are now assumed to be overlaid by random processes. For example, fish regeneration, though related endogenously to the size of the fish stock, is also affected by a variety of external factors (e.g. the climate and environmental changes), beyond the control of stakeholders, factors that manifest themselves as random variation. Similarly the harvest rate or fish catch is influenced endogenously by the size of the fishing fleet (with more ships you can expect a bigger total catch, other things being equal), but is also affected by random operational factors such as the position of ships at sea, the mood of the crew and the weather. The destiny of the fishery is assumed to be partly and significantly a matter of chance. This future is not known with certainty because it involves random variation. Moreover, the effect of randomness is counterintuitive to fishermen, (as it would be to other stakeholders with limited but normal human foresight), because it involves another kind of dynamic complexity, this time arising from multiple interacting random processes. It takes only two or three interacting random processes, even in a linear system, to generate puzzling dynamics. A simple DES fisheries model comfortably meets this complexity criterion.

It is an empirical matter whether a source of variability in a model is shaped by factors other than those endogenously specified. For example the fish regeneration rate in a SD fisheries model is expressed as a non-linear function of the fish population – an endogenous feedback relationship linking the accumulated stock of fish to its rate of increase. A DES model will include a similar relationship, because it fits the facts, though the non-linearity would not normally receive great attention. Instead attention shifts to the random process that is presumed to overlay population-dependent regeneration. These differences in formulation will be explored more carefully later. But for now consider the philosophical difference. There is scientific evidence for an endogenous formulation controlling regeneration (see for example Townsend, Begon and Harper 2003, an introductory ecology textbook), which can be described as a "humped relationship between the net recruitment into a population (births minus deaths) and the size of that population resulting from the effects of intraspecific competition". There is also evidence of profound external environmental fluctuations for example an El-Nino event "when warm tropical water from the north reduces the upwelling, and hence the productivity, of the nutrient-rich cold Peruvian current coming from the South". Either or both deterministic-endogenous and random-external formulations may be appropriate. In a practical fisheries modelling project the facts would obviously be pertinent and modellers, SD or DES, could (with varying degrees of ease) adapt their model and formulations accordingly. However, our point here is to observe that the type of representation and explanation for puzzling dynamics that a modeller seeks depends on the approach adopted. It is natural for a SD modeller to look for an endogenous structural representation that fits the available facts. It is natural for a discrete-event modeller to look for a structural and random process representation that also fits the facts. These unavoidable methodological biases affect what modellers choose to include and how they go about constructing and communicating a model-based argument (see also Meadows (1980) for a discussion of the unavoidable a priori in SD and econometrics). Does this matter? Our in-depth comparison of models and simulations in the next and later sections sheds more light on this question.

Structure and Behaviour in Fisheries: A Comparison of SD and DES Models

The title of this section is instantly recognisable to a system dynamicist. The reason is that in SD an explanation of puzzling dynamics is deemed to exist when one can show, justify and interpret the interlocking feedback loops (structure) that *cause* the dynamic phenomenon (or behaviour over time) of interest. Growth is caused by reinforcing (positive) feedback.

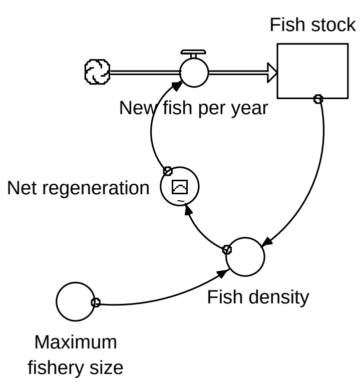
Fluctuations stem from goal-seeking or balancing (negative) feedback involving delayed adjustment. Growth and collapse arise from non-linear reinforcing and balancing feedback combined. Although discrete-event modellers do not normally think in terms of feedback structure (they rarely if ever visualise feedback loops, even when such loops exist) they are nevertheless aware that a combination of structural relationships and random processes lies behind simulated dynamics. To illustrate this difference in approach to meaning and use of model structure we now present and compare, step-by-step, our fisheries models, the corresponding equation formulations, and the simulated behaviour (dynamics) that the structures produce.

Our stepwise analysis begins with a natural fishery in which there are no fishermen, no ships and no harvesting – just a self-regulating fish population governed by biological laws and natural limits to growth. Simulations of both SD and DES models show population growth and saturation, with superimposed random variation in the DES model. We then present a harvested fishery in a series of equilibria, with a fixed number of ships and without randomness or bias in any process. Simulations show the SD and DES models can achieve identical equilibria in terms of fish population and fleet size. We then relax the equilibrium assumptions of our ideal harvested fishery to arrive at more realistic disequilibrium models with potentially volatile population dynamics.   But the assumptions we relax are different and conditioned by our contrasting approaches. In the SD model we incorporate pressure for growth in fleet size, (a bias of human nature – 'more is better') presumed to exist in many investment policies. In the DES model we introduce random variation in fish regeneration and the catch. Again we compare simulations. This time the simulations are quite different, although in both cases the fish population is volatile and departs a long way from the ideal equilibrium. Moreover, the style of explanation for these outcomes (how the structure, processes and behaviour are interpreted and presented, and the use made of diagrams, equations and simulations) is distinctive and unique to each approach.

Alternative Models of a Natural Fishery

SD Model

Recall our imaginary fishery. It is a finite offshore region of ocean containing a single species of fish. How are the dynamics of fish population represented? Figure 3 shows the diagram and equations for a SD model of a natural fishery in the format of the popular ithink language (Richmond et al 2004). This format is pretty much a standard format used for all SD models.



Fish_stock(t) = Fish_stock(t - dt) +
(New_fish_per_year) * dt
INIT Fish_stock = 200
New_fish_per_year = Net_regeneration
Net_regeneration = GRAPH(Fish_density)
(0, 0), (0.1, 50), (0.2, 100), (0.3, 200), (0.4, 320),
(0.5, 500), (0.6, 550), (0.7, 480), (0.8, 300),
(0.9, 180), (1, 0)
Fish_density = Fish_stock/Maximum_fishery_size
Maximum_fishery_size = 4000

Figure 3: Diagram and Equations for SD Model of a Natural Fishery

The fish stock is represented as a level that accumulates the inflow of new fish per year (here the inflow is defined as a net flow of births minus deaths). Initially there are 200 fish in the sea and the maximum fishery size is assumed to be 4000 fish. Incidentally, the initial value and maximum size can be re-scaled to be more realistic without changing the resulting dynamics. For example a fishery starting with a biomass of 20 thousand tons of a given species and an assumed maximum fishery size of 400 thousand tons would generate equivalent results.

The structurally important relationships are those that define the endogenous feedback effect of fish stock on net regeneration (which in this model is identically equal to new fish per year). Net regeneration is a non-linear function of fish density as shown in figure 4. When the fish density is small there are few fish in the sea relative to the maximum fishery size and net regeneration is low, at a value of less than 50 fish per year. In the extreme case where there are no fish in the sea, the net regeneration is zero. As fish density rises the net regeneration rises too, on the grounds that a bigger fish population will reproduce more successfully, providing the population is far below the presumed theoretical carrying capacity of the ocean region.

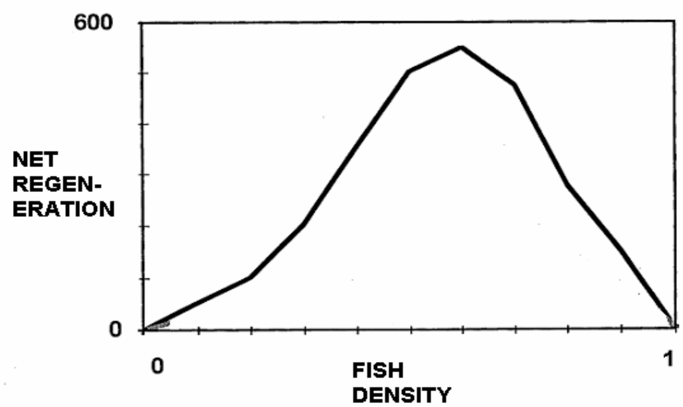


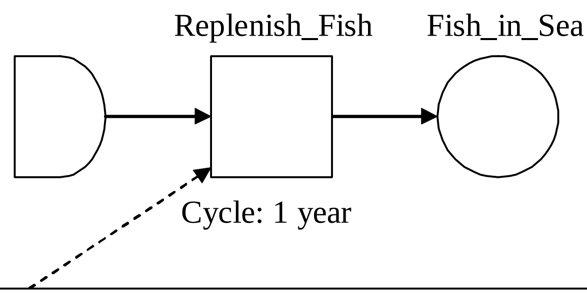
Figure 4: Net Regeneration as a Non-Linear Function of Fish Density

As the fish density continues to rise there comes a point at which net regeneration reaches a peak (in this case almost 600 fish per year) and then begins to fall because food become scarcer. Ecologists say there is increasing intraspecific competition among the burgeoning number of fish for the limited available nutrient. So when, in this example, the fish population reaches 4000 the fish density is equal to 1 and net regeneration falls to zero. The population is at its maximum natural sustainable value. The structural result of this non-linear relationship is a closed feedback loop. Technically speaking it is a reinforcing (positive) loop of variable gain (or strength). As we will see later this loop, and the equations that underlie it, generate growth and saturation.

DES Model

Figure 5 shows the diagram and equations for a DES model of the same fishery. Unlike SD, there is no agreed standard diagramming method for representing DES models. Various approaches are available including activity cycle diagrams (Hills, 1971), process mapping/process flow diagrams (Davis, 2001), Petri nets (Torn, 1981), event graphs (Som and

Sargent, 1989) and the ‘unified modeling language’ (UML) (Richter and März, 2000). Pooley (1991) gives a useful summary of diagramming techniques for DES. For the purposes of this work, process flow diagrams have been used.



New_Fish = Fish_in_Sea x Normal (0.2, 0.02)

If Fish_in_Sea > 4,000

Fish_in_Sea = 4,000

Endif

<u>Initial Values</u>
Fish_in_Sea = 200

Figure 5: Diagram and Equations for DES Model of a Natural fishery

In figure 5 the fish stock is represented as a queue that is fed by the annual process (cycle of 1 year) of fish replenishment. New fish are sourced from outside the model by the ‘source’ on the left of the diagram. As for the SD model, there are assumed to be initially 200 fish in the sea and a maximum of 4,000 fish can be sustained.

Fish regeneration is seen as a linear, but random, relation to the number of fish in the sea. Fish grow at an average rate of 20% per year, varying according to a normal distribution with a standard deviation of 2%. The limit to growth of 4,000 is represented as a discrete cut-off which does not allow the Fish_in_Sea to exceed this limit.

Comparison of SD and DES Representations

There are some clear differences in the representations presented by the DES and SD model. The SD model uses a stock-flow structure, while the DES model uses queues and processes. There is a clear equivalence between the concepts of stocks and queues, and between flows and processes. The feedback structure is explicit within the SD model, but hidden in the equations of the DES representation. As expected, the DES model includes the randomness, which is not present in the SD version. Meanwhile, the relationship between fish stocks and fish regeneration in the SD model is non-linear, but linear in the DES model.

Simulated Dynamics of a Natural Fishery

Our first simulations show the dynamics of a 'natural' fishery starting with an initial population of 200 fish. There are no ships and no investment. Fishermen are not yet part of the system. The SD model (figure 6) shows smooth S-shaped growth due to its non-linear, deterministic formulations for fish regeneration. Until year 18 the fish stock follows a typical pattern of compounding growth associated with a reinforcing feedback loop. The population grows from 200 to 2500 fish. Fish regeneration (new fish per year) also increases until year 18 as rising fish density enables fish to reproduce more successfully. Thereafter crowding becomes a significant factor according to the non-linear net regeneration curve in figure 4. The number of new fish per year falls as the population density rises, eventually bringing population growth to a halt as the fish stock approaches its maximum sustainable value of 4000 fish.

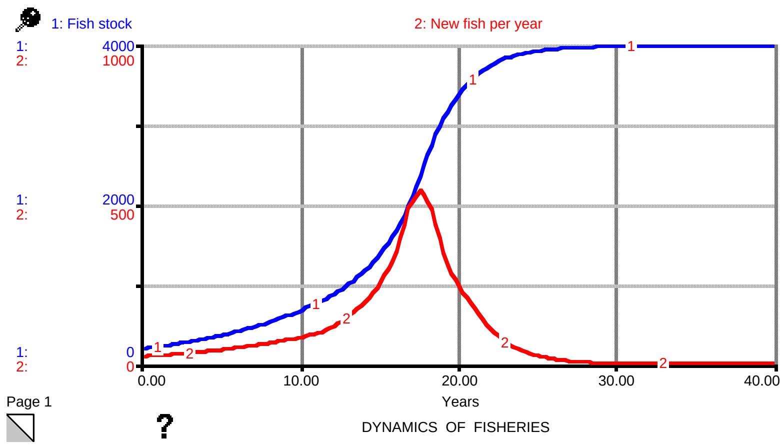
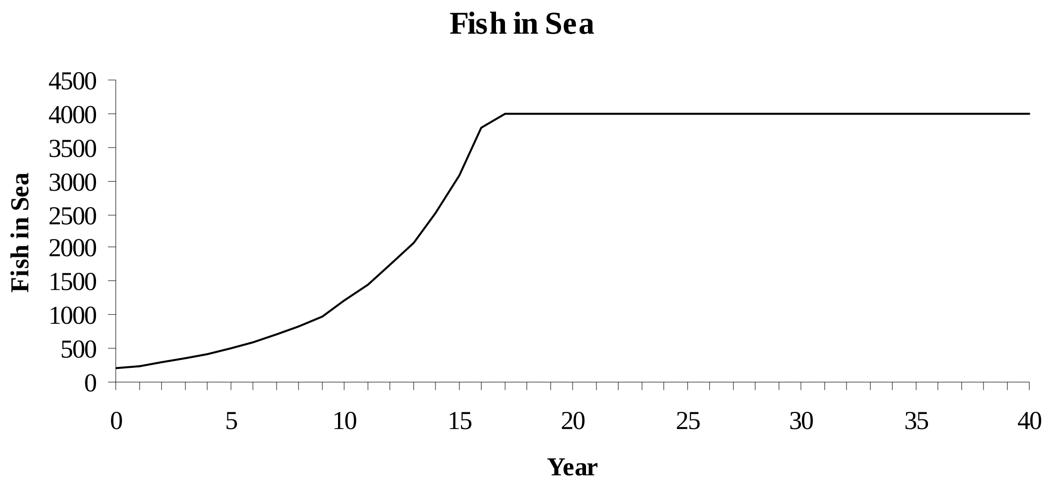


Figure 6: Simulation of SD Model of a Natural Fishery with an Initial Population of 200 Fish and Maximum Fishery Size of 4000

The results from the DES model are shown in figure 7. This is the output from a single replication (a run driven with a specific stream of random numbers). If the random number seeds were changed to perform further replications, the exact pattern of growth and fish regeneration would alter. Figure 7 also shows S-shaped growth, but with two distinct differences. First, the growth is not as smooth due to the randomness within the regeneration process. This is clearly evidenced by the graph showing new fish. Second, the SD representation shows an asymptotic growth towards the limit of 4,000, while the DES model reaches the limit in a discrete step. Both of these differences are a result of the model formulations.



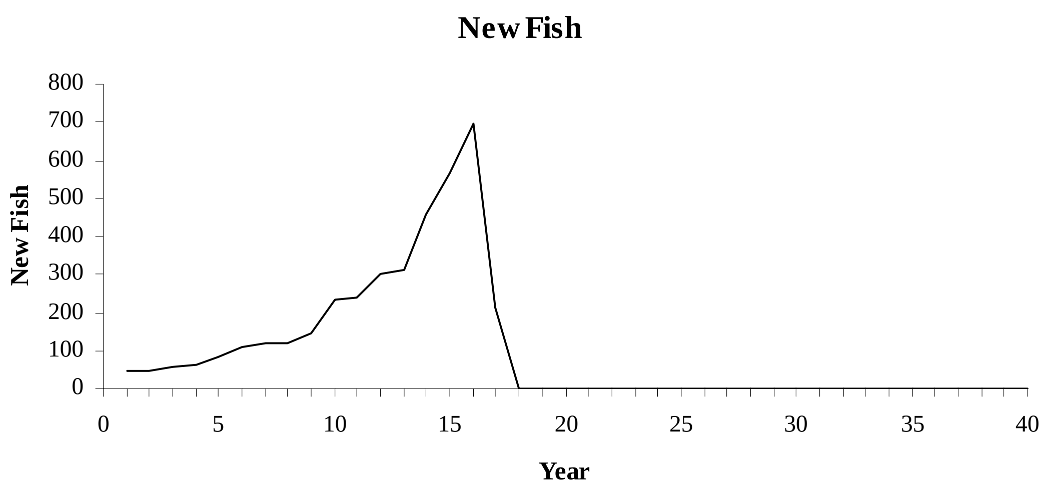


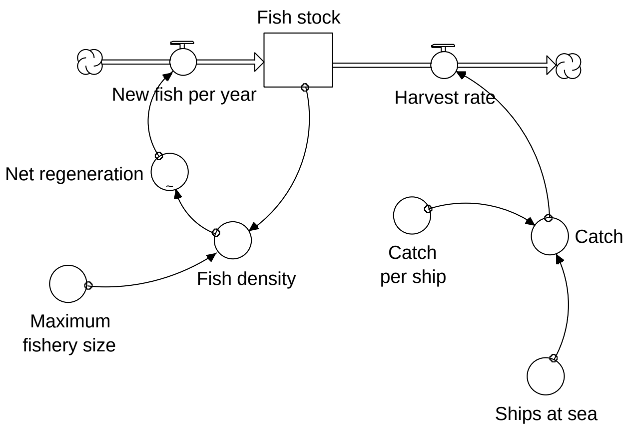
Figure 7: Simulation of DES Model of a Natural Fishery with Initial Population of 200 Fish and Maximum Fishery Size of 4000

Alternative Models of a Simple Harvested Fishery

Imagine that a fleet of ships arrives in the region and sets about harvesting fish. The total catch depends both on the number of ships and their productivity (how many fish each ship catches in a typical year). If we assume there are plenty of consumers that like to eat fish then the fundamental dynamical problem for fisheries is to build a fleet that brings in a large and sustainable harvest. Common sense suggests that if you add a few more ships to a small fleet then the catch will increase. Equally there must come a time when there are too many ships competing for a limited number of fish. System dynamics and discrete event simulation both shed light on the problem of balancing the size of a fishing fleet (and the catch) with a regenerating fish population. What we know from real fisheries is that this balancing act is difficult to achieve. But why?

SD Model

In system dynamics we can make a start on this question by investigating the relationship between catch and fish population under a scenario of varying fleet size. A simple harvested fishery is shown in figure 8. All the original relationships of the natural fishery (figure 3) remain in tact but now the fish stock is depleted by a harvest rate, equal to the catch and proportional to the number of ships at sea.



Fish Stock and New Equations for Harvesting (see figure 3 for remaining equations of a natural fishery)

Fish_stock(t) = Fish_stock(t - dt) + (New_fish_per_year - Harvest_rate) * dt
INIT Fish_stock = 2690 {fish}

INFLOWS:
New_fish_per_year = Net_regeneration {fish/year}

OUTFLOWS:
Harvest_rate = Catch {fish/year}
Catch = Ships_at_sea*Catch__per_ship {fish/year}

Figure 8: Diagram and New Equations for SD Model of Simple Harvested Fishery

DES Model

Figure 9 shows a DES representation for a harvested fishery. The first part of the process flow diagram is the same as for the natural fishery (figure 5). A second process 'Catch_Fish' is now added, which represents the catching of fish which are then sent to the sink on the right side of the diagram. The formula for the number of fish caught consists of two parts. The first sees the catch as an increasing proportion of the fish in the sea, a proportion that increases with the number of ships. The formula is non-linear, giving a reduced catch per ship with increasing numbers of ships. It is envisaged that as more ships are fishing in the same area their productivity will fall.

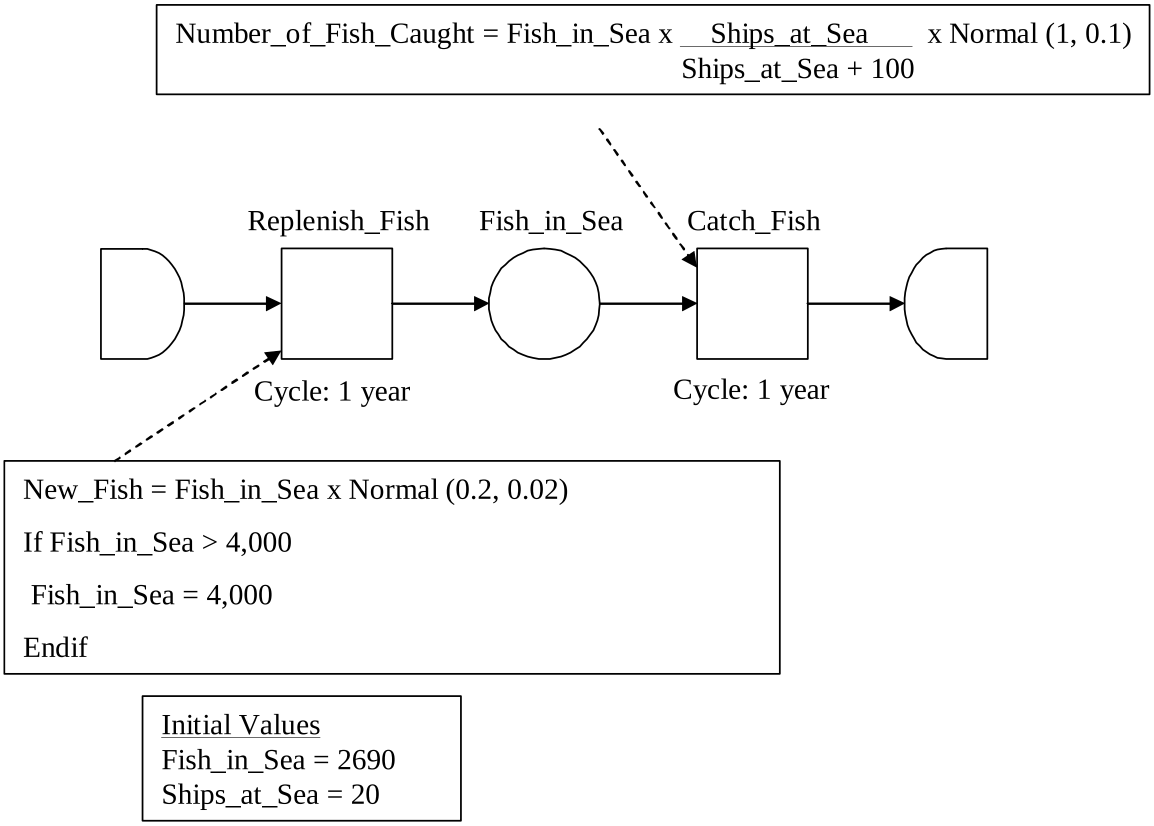


Figure 9: Diagram and Equations for DES Model of a Simple Harvested Fishery

The second part of the formula adds a random element to the catch. Many factors, such as climate and environmental factors, may affect the catch on any given day and in any year. The variation in annual catch is represented by a normal distribution with a standard deviation of 10% of the mean.

Comparison of SD and DES Representations

The differences between the SD and DES models identified for the natural fishery apply equally to this case: the method of representation, the explicitness of the feedback structure and the inclusion of randomness. Interestingly, the DES model represents the catch per ship as a non-linear function of the number of ships, while the SD model represents this as a linear relation. Further, there is an implied feedback structure in the DES model where the catch is related to the number of fish. This non-linear feedback is added to the SD model later on in the step-by-step analysis, when ship purchasing is endogenous.

Simulated Dynamics of a Simple Harvested Fishery: Equilibrium Models

Figure 10 is a simulation of the SD model of a simple harvested fishery in equilibrium at the maximum sustainable yield, with a catch of 500 fish per year by 20 ships from a population of 2690 fish.

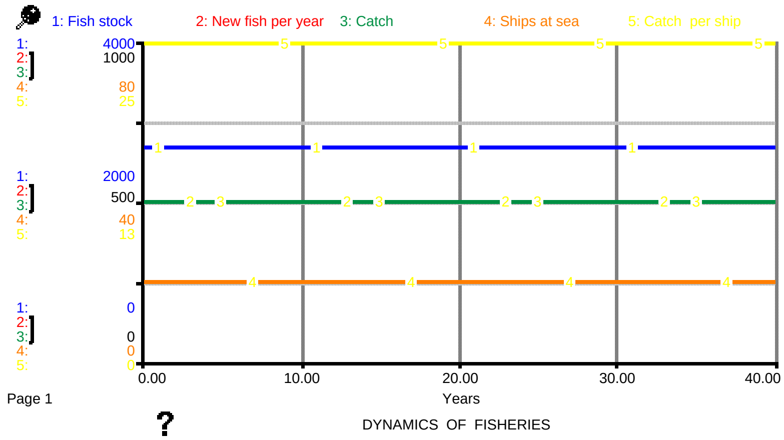


Figure 10: Simulation of SD Model of a Natural Fishery in Equilibrium at Maximum Sustainable Yield with a Population of 2690 Fish and 20 Ships

Figure 11 shows the results of the DES model of the simple harvested fishery. In this simulation the randomness in fish regeneration and catch is removed. As with the SD model, because the catch rate with 20 ships is the same as the regeneration rate, the model is in perfect equilibrium.

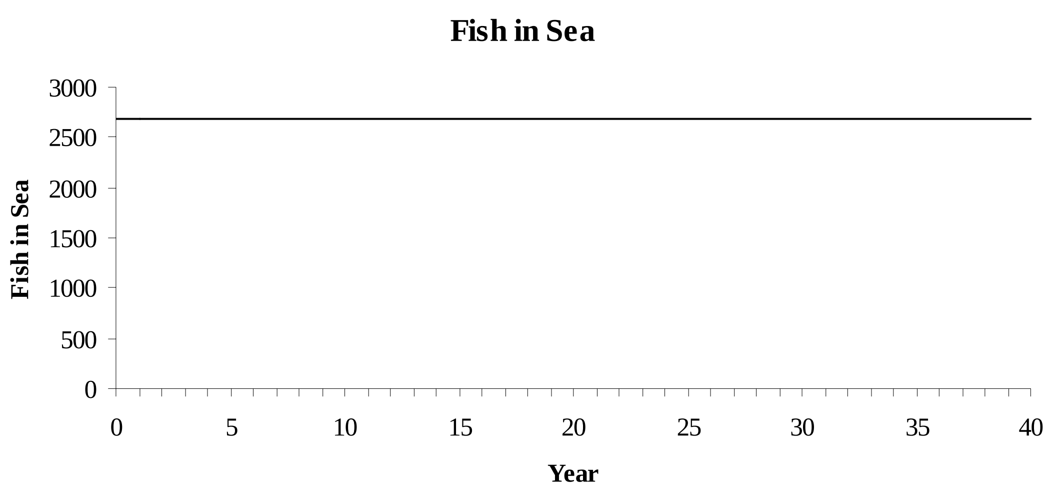


Figure 11: Simulation of DES Model of a Simple Harvested Fishery: Equilibrium Model

Simulated Dynamics of a Simple Harvested Fishery: Non-Equilibrium Models

To move from an equilibrium to a non-equilibrium model, two different approaches are taken in the SD model and the DES model. In the SD model, non-equilibrium conditions are created by changing the size of the fishing fleet. In the DES model, randomness is added to the model to create a non-equilibrium state. These reflect typical analyses that might be carried out with SD model and DES models. The former explores the effects of non-linearities (by changing the number of ships) and the latter explores the effects of randomness.

Consider a scenario in which the fleet size grows in steps of ten from zero to thirty ships. The productivity of these ships is identical. They can each catch 25 fish per year. (Don’t dwell on the numerical value - remember this is an imaginary but scaleable world). In typical SD fashion we assume there is no stochastic variation in productivity. Figure 12 is a simulation of this stepwise scenario. At the start the fishery is full of fish. There are four thousand of them. The population is in equilibrium, a non-stochastic equilibrium, where births exactly equal deaths. Ten ships arrive in year 4 and for the next 12 years they harvest the fishery. The catch rises to 250 fish per year (10*25). As a result the fish stock begins to fall. Then something dynamically interesting happens. Because the fishery is less heavily populated, fish regenerate faster. The lower the fish stock, the lower the fish density and the higher the number of new fish per year, as determined by the values on the right of the non-linear net regeneration function described earlier. As the years pass the number of new fish added to the population each year approaches ever closer to the harvest rate (and the catch) and so, by the end of year 15, the fish population settles into a sustainable equilibrium.

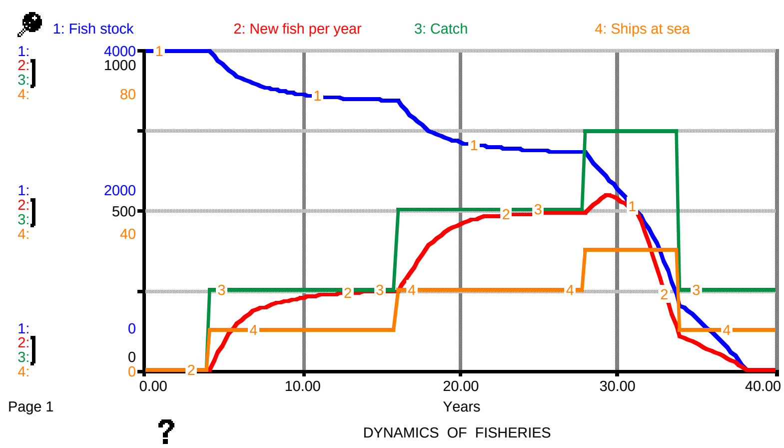


Figure 12: Simulation of SD Model of a Harvested Fishery with Stepwise Changes in Fleet Size and an Initial Population of 4000 Fish

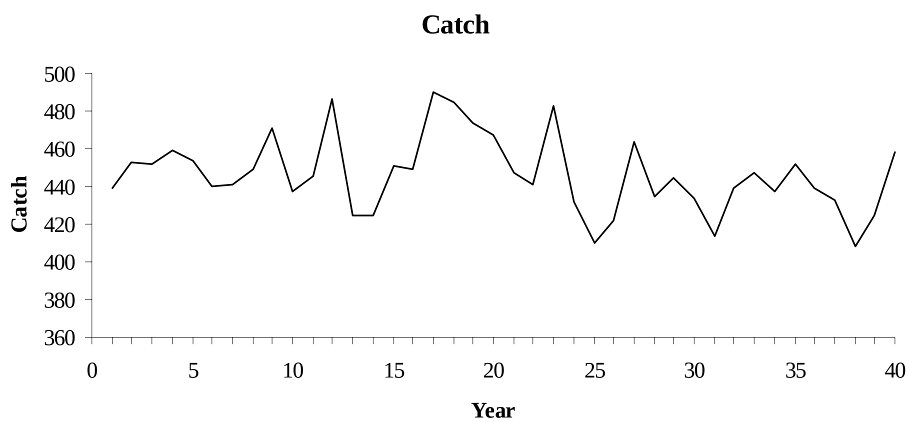
Then in year 16 another ten ships arrive, bringing the fleet size to twenty and they fish for a further twelve years. A similar process unfolds. A doubling of the fleet leads to a doubling of the harvest rate, a fall in the fish population and eventually a compensating rise in the net regeneration of fish. By the end of year 27 the fishery has settled into a new sustainable equilibrium, with a lower fish population and a higher harvest rate. The fishery is robust in the face of rising fleet size because, according to the regeneration curve, lower fish density still leads to a compensating increase in new fish per year.

In year 28 yet another ten ships arrive, bringing the total to thirty. For almost two years it looks as though the fishery will continue its bountiful supply. The catch rises to 750 fish per year (30*25). The population falls below its previous equilibrium (of about 2700 fish) and the number of new fish per year begins to rise. However, by year 30 it is clear something new is happening. While the catch remains at 750, the number of new fish per year begins to fall (for the first time in the entire simulation). As a result the rate of decline of the fish stock begins to accelerate (rather than to moderate). The fishery has passed the peak of the net regeneration curve. It is now operating on the left-hand side of the curve, beyond a critical ‘tipping point’. The fish density is now so low that any further reductions cause the regeneration rate to decline rather than rise. There are simply too few fish in the sea to breed at the rate previously achieved.

The fish population continues to fall precipitously and is now being over-harvested. At the end of year 33 the population is down to 1000 and still falling.

The model provides one further insight into the dynamics of fish stocks. Imagine, at the start of year 34, the fleet is reduced to only 10 ships, the size it was between years 4 and 16. Back then the fishery had achieved a sustainable equilibrium. Now it is unable to do so. Not surprisingly the catch falls dramatically back to 250 fish per year (10*25) as ships are removed or idled. But net new fish per year is even lower at around 100 fish per year. The fish population and fish density therefore decline. Before, when the fishery was teeming with fish, a fall in fish density boosted regeneration, but no longer. The fishery finds itself in terminal decline. By year 38 the population has collapsed to zero. The message from this compact system dynamics model is that a harvested fishery is dynamically complex, even without randomness, due to stock accumulation, feedback and non-linearity.

Figure 13 shows the results from a simulation of the harvested fishery with the DES model, now with randomness included for the catch and regeneration of fish. Because there is randomness in the model the simulation has been replicated 10 times, using different random number streams, the results showing the mean of the replications. The use of multiple replications is standard practice in DES modelling for determining the range of outcomes and the mean performance of a system (Law and Kelton 2000, Robinson 2004). The results show the catch and the number of fish in the sea over a 40 year period.



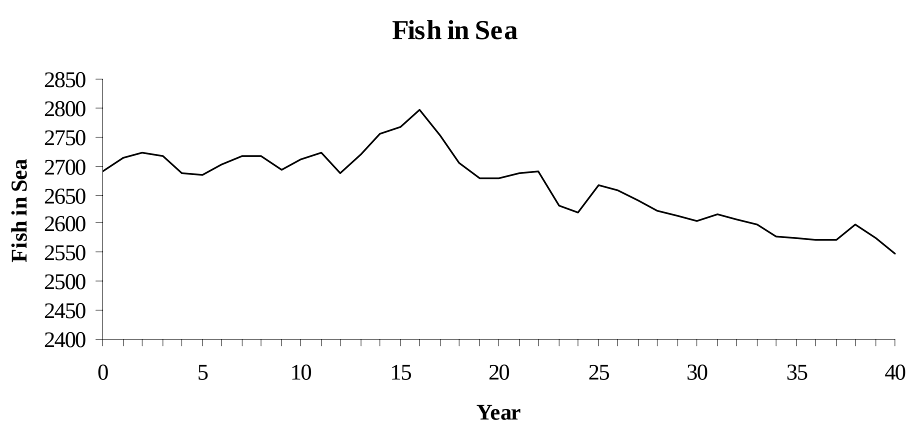


Figure 13: Simulation of DES Model of a Simple Harvested Fishery: Non-Equilibrium Model

The graphs show the variation in the annual catch with the mean shifting between just above 400 to just below 500. Similarly there is some variation in the fish stock, peaking at about 2,800 and falling to about 2,600. Such variation is not surprising given the randomness in the model. It would be difficult to predict the interconnected effect of variations in fish regeneration and fish catch without a simulation.

Inspecting the graph for the fish in the sea there appears to be a downward trend. This is surprising as the system is in perfect equilibrium (the catch and regeneration rates are the same) as demonstrated by the results from the equilibrium model. As such, it would be assumed that the steady-state mean of the model including randomness would remain constant, albeit that there are annual variations. A longer run of the simulation, however, confirms that there is a downward trend in the fish stock (figure 14). Here the fish stock falls from 2,690 to 300 over 10,000 years. Indeed, after 20,000 years the fish stock has disappeared altogether. Experiments showed that the greater the randomness in the system, as defined by the standard deviation, the faster the collapse in fish stocks.

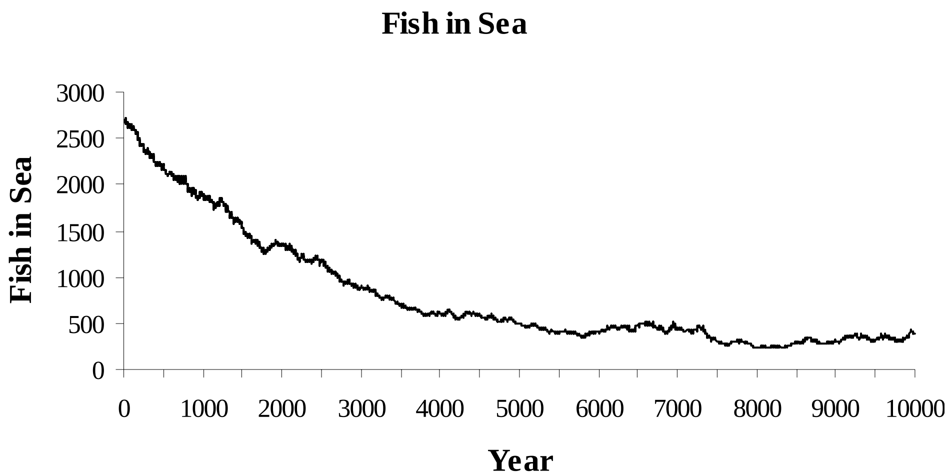


Figure 14: Simulation of DES Model of a Simple Harvested Fishery: Long Run with the Non-Equilibrium Model

How can these puzzling dynamics occur in a system that is apparently in equilibrium? The reason is most simply explained with reference to an example. Starting with, say, a fish stock of 1,000 in any particular year, the probability of there being 10% more or 10% less fish in the next year is the same. This can be concluded because the distributions used in the simulation are symmetrical. However, the probability of returning to the equilibrium of 1,000 fish from 1,100 or 900 fish is not the same. To decrease from 1,100 to 1,000 fish requires only a 9.1% fall in the fish population. To increase from 900 to 1,000 fish requires an 11.1% increase. Because the distributions are symmetrical, the probability of increasing the fish population of 900 back to the equilibrium is lower than probability of reducing it from 1,100 to 1,000. As a result, there is a constant downward pressure on the fish population, with ‘bad’ years in which the fish population falls being hard to recover from. Ultimately this leads to the complete collapse of the fish population.

The SD and DES non-equilibrium models are based on quite different assumptions. The SD model investigates the effect of changing the number of ships over time, while the DES model represents the effect of random variation in the regeneration of fish and the catch. The results of the two models are, however, the same. Both lead to a collapse in the fish stock, albeit over quite different timescales. Both demonstrate a dynamic that could not easily have been predicted without the simulation.

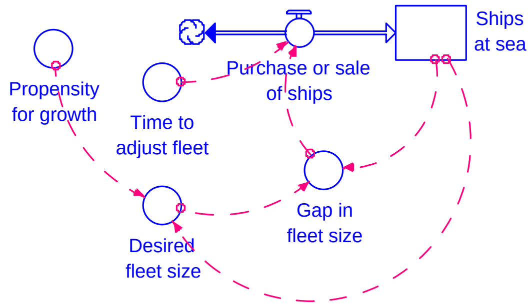
Alternative Models of a Harvested Fishery with Endogenous Ship Purchasing

Both the SD and DES models show that a fishery can operate for long periods in equilibrium providing there are an appropriate number of ships at sea – not too few and not too many. Here a long period may be hundreds of years, spanning the lifetime of a stable fishing community. The remaining piece of the dynamical puzzle is the investment process through which fishermen adjust the fleet size. Why would they purchase too many ships if, as we have seen, a large fleet can lead to overfishing? If there were too many ships at sea why wouldn't fishermen reduce the fleet size, sell ships, halt investment and so re-establish a sustainable equilibrium? A comparison of the investment process in SD and DES provides distinctive answers to these questions.

SD Model

A system dynamics modeller thinks of investment as a collective decision making process (or policy) representing, in aggregate, the judgements of those people most closely involved (fishermen in this case) and the information sources on which their decisions are based. Such decision making processes are behavioural in the sense that they capture the broad intention of investment without necessarily assuming decision makers have perfect information or perfect foresight. A typical investment policy has three main parts. There is a goal, a specific condition to be achieved, in this case the desired number of ships in the fleet. There is monitoring of the current state of the system, how many ships are currently in operation. And finally there is corrective action, the purchase or sale of ships, to bring the current state of the system in line with the goal. This overall three-part process is known as 'asset stock adjustment' and is absolutely central to an information feedback representation of business and social systems (Sterman 2000). It is a process generalisable across a wide range of investment situations covering inventories, tangible capital goods, human resources, and intangible assets. At the heart of the decision making is subtle, purposive (and often judgmental) information processing in which people with responsibility for investment form a view of the appropriate incremental adjustment of important assets.

Figure 15 shows asset stock adjustment in the fisheries model. Notice that connections between variables are depicted as dotted lines denoting flows of information. The connections are not 'hardwired' as they were for the natural fishery. They are discretionary and reflect the information available and deemed most relevant to investment. The desired fleet size (the goal) depends on the number of ships at sea and the propensity for growth. Specifically the desired fleet size is equal to ships at sea multiplied by a factor (1+ propensity for growth). Here is an important behavioural assumption. Since fishermen don't have the information to decide an optimal fleet size they form their goal more simply with reference to the existing fleet size. We assume that the normal propensity for growth is 0.1, so the desired fleet size is 10 percent larger than the current fleet size. In other words fishermen normally and collectively want a bigger fleet than they now have, an attribute of human nature - bigger is better, growth is inherently attractive. As we will see later the propensity for growth also depends on conditions in the fishery, a poor catch will dampen enthusiasm for a larger fleet, despite an underlying bias toward growth.



Ships_at_sea(t) = Ships_at_sea(t - dt) + (Purchase_or_sale__of_ships) * dt
INIT Ships_at_sea = 4 {ships}

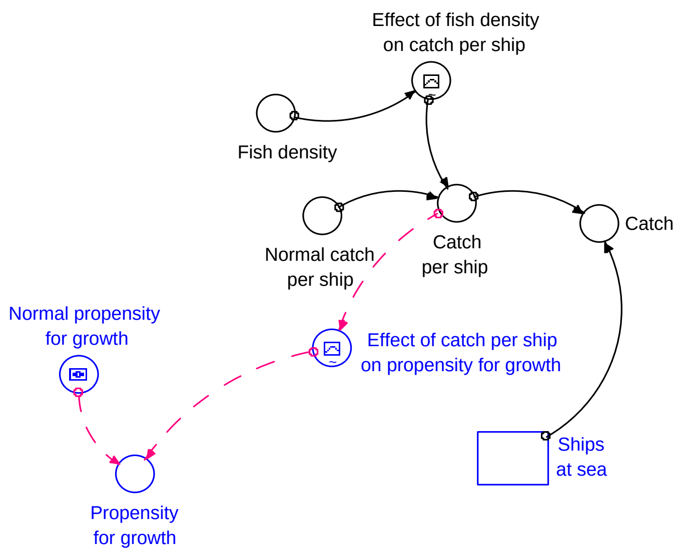
Purchase_or_sale__of_ships = Gap_in_fleet_size/Time_to_adjust_fleet {ships/year}
Gap_in_fleet_size = Desired_fleet_size - Ships_at_sea {ships}
Desired_fleet_size = Ships_at_sea * (1 + Propensity_for_growth) {ships}
Propensity_for_growth = …. See later for this important formulation, for now just assume that normally the propensity for growth is positive and non-zero
Time_to_adjust_fleet = 1 {year}

Figure 15: Asset Stock Adjustment – The Decisionmaking Process for the Purchase or Sale of Ships in the Fishery

Once the desired fleet size is established then the rest of the asset stock adjustment formulation is easy to understand. The gap in fleet size is the difference between the desired fleet size and ships at sea. If there is a large positive gap then conditions for investment are favourable. The purchase or sale of ships closes the gap over an assumed time span of one year which is the time taken to adjust the fleet (including ordering, construction and delivery).

Perhaps the most crucial formulation in the SD model is the propensity for growth and the factors that determine it. As mentioned above fishermen do not know the optimal fleet size and so they prefer, more simply and pragmatically, to grow the fleet until there is compelling evidence to stop. The question is what evidence is persuasive enough to curb investment and will this result in a sustainable balance between the fish population and ships at sea? In system dynamics evidence takes the form of information. Persuasive information is both credible and readily available to decision makers. In a real fishery, fishermen know the catch per ship – they themselves bring in the catch and it is vitally important to their livelihood. They may also know, at least roughly, the total catch of all ships in the fishery. Significantly they don't know the fish population or the fish regeneration rate. That's all happening under water. Moreover they don't believe scientific estimates of low fish stocks unless confirmed by the catch. Such practical considerations suggest that propensity for growth is curbed by low catch rather than by objective evidence of fish stocks. As a result investment is boundedly rational, sensing only indirectly the true balance of the fish population on which the long-term sustainability of the fishery depends.

Figure 16 shows one possible SD formulation that captures the essential limited information characteristic of fishermen's boundedly rational decision making. Propensity for growth depends on the normal propensity for growth (set at 0.1 or 10 percent, to reflect a prevalent view that growth is a good thing) multiplied by the
curbing effect of catch per ship. This curbing effect is non-linear and captures another typical human tendency to ignore bad news until it is really bad. If catch per ship falls from 25 fish per year to15 per year (a 40 percent decline) propensity for growth falls from .1 to .09 (a decline of only 10 percent). Thereafter the effect becomes much stronger. If catch per ship falls to 10 fish per year then propensity for growth falls to zero and fishermen stop purchasing ships. If the catch falls still further then the propensity for growth becomes negative and fishermen sell ships because collectively they sense it is futile to retain a large and unproductive fleet.



Catch = Ships_at_sea*Catch__per_ship {fish/year}
Catch__per_ship =
Effect_of_fish_density_on_catch_per_ship*Normal_catch__per_ship {fish per ship/year}
Normal_propensity_for_growth = .1 {fraction}
Propensity_for_growth =
Normal_propensity_for_growth*Effect_of_catch_per_ship_on_propensity_for_growth {dimensionless}
Effect_of_catch_per_ship_on_propensity_for_growth =
GRAPH(Catch__per_ship)
(0.00, -0.48), (2.50, -0.45), (5.00, -0.37), (7.50, -0.27), (10.0, 0.00), (12.5, 0.64), (15.0, 0.9), (17.5, 0.995), (20.0, 0.995), (22.5, 1.00), (25.0, 1.00)
Effect_of_fish_density_on_catch_per_ship = GRAPH(Fish_density {dimensionless})
(0.00, 0.00), (0.1, 0.4), (0.2, 0.68), (0.3, 0.8), (0.4, 0.88), (0.5, 0.96), (0.6, 1.00), (0.7, 1.00), (0.8, 1.00), (0.9, 1.00), (1, 1.00)

Figure 16: Propensity for Growth and Catch per Ship

Catch per ship is essentially a measure of ships' productivity. Not surprisingly in real fisheries productivity varies over time and between ships. Catch per ship is modelled here as a deterministic function of fish density. The scarcer are the fish the lower the productivity. But the relationship is non-linear. For moderate to high fish density (between .5 and 1) catch per ship remains close to normal. The assumption is that fishermen don't really notice a difference in the catch if the sea is teeming with fish or only half-teeming with fish, because fish tend to school or cluster. Catch per ship is still 68 percent of normal when the fish density is only .2, or in other words when the fish population is 20 percent of the maximum sustainable. But thereafter catch per ship falls quickly to zero as schools of fish become increasingly difficult to find and are hotly contested by rival ships.

DES Model

In DES modelling there is no equivalent to the 'asset stock adjustment' process in SD modelling. Policies for purchasing and releasing ships would be determined by discussion with relevant stakeholders, as in SD, but without the guiding framework of stock adjustment. In this case a simple policy for adjusting the number of ships is added to the model, using the formula:

Ships_at_Sea = Caught/22

In other words, for every 22 fish caught in any year, one ship will be allowed to fish in the following year. This represents an information feedback process between the catch and the number of ships, which can be thought of as a reinforcing loop. This facet, however, is not made explicit in the DES model formulation.

Comparison of SD and DES Representations

In addition to the differences identified for earlier versions of the models, there is now the way that decision making processes are perceived. It is apparent that in SD the modeller is guided by principles for modelling decision making that help specify typical decision rules of actors in the system. These principles include five formulation fundamentals, described in Sterman (2000, chapter 13), based on ideas from information feedback theory and behavioural decision making for portraying purposive behaviour, subject to bounded rationality. In DES such principles do not appear to be in common use. Instead, decision making processes are derived from direct discussion with and observation of decision makers (Robinson et al 2005). Uncertainties in making decisions are primarily derived from future unknown stochastic events, which in themselves engender a particular and different form of bounded rationality.

Simulated Dynamics of a Harvested Fishery with Endogenous Investment

The simulations in this section start with both SD and DES models in a sustainable equilibrium. The SD model starts with 10 ships and 3370 fish, resulting in a catch of 250 fish per year, (below the maximum sustainable yield to allow room for growth and to investigate boundedly rational misinvestment). The DES model starts with 20 ships and 2690 fish, resulting in an average catch equal to the regeneration of fish (at a theoretical equilibrium of 500 fish per year), to investigate stochastic misinvestment (described later). The equilibrium is then disturbed in contrasting ways typical of each approach.

In the SD model the normal propensity for growth is artificially held at 0 at the start of the simulation. A small-is-beautiful mindset has temporarily taken hold. Then in year 10 growth-is-beautiful resumes as the normal propensity for growth returns to a value of 0.1, or 10 percent of the current fleet size. Figure 17 shows the results. Equilibrium prevails until year 10. Then the number of ships at sea increases steadily under the influence of an investment policy biased toward growth. For more than ten years the catch rises. Meanwhile the catch per ship remains steady, suggesting that continued investment is both feasible and desirable. Below the waves conditions are changing, but remember these conditions cannot be directly observed by fishermen. The regeneration rate of fish (new fish per year) rises healthily as one would expect in a well-harvested fishery. The fish population falls, but that too is expected in a harvested fishery.

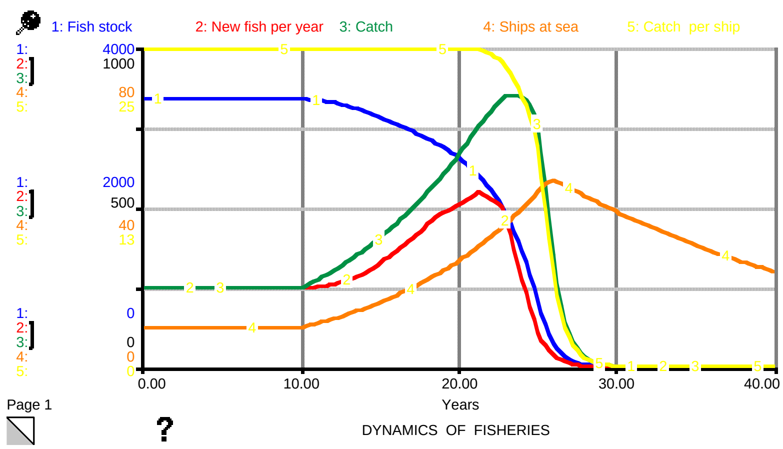


Figure 17: Simulation of SD Model of a Fishery that Starts in Equilibrium, Grows with Investment and then Unexpectedly Collapses

Signs of trouble appear underwater in year 21 when, for the first time, regeneration (new fish per year) falls. This reversal of replenishment is a signal that the fishery has passed the tipping point of the non-linear regeneration curve. The decline in the fish stock begins to accelerate. But interestingly the catch continues to rise for fully three more years, until year 24, and the catch per ship remains close to normal. From the viewpoint of growth-oriented fishermen floating on the surface of the sea it is business as normal. The fleet continues to grow until year 26 when it reaches a size of 46 ships. By then the catch per ship has fallen to less than one third of normal (only 8 fish per ship per year instead of 25), sufficient to curb further investment.

By now the hidden fish stock has fallen to a precariously low level of only 300, less than one tenth of its initial value. With so few fish in the sea the regeneration rate is very low at only 30 new fish per year, well below the catch of around 300 fish per year. Fishermen are now well aware of the underwater crisis and respond accordingly by selling ships. The fleet size falls from a peak of 47 ships in year 26 to 39 ships in year 30. But it is too little action too late. The boundedly rational investment policy is unable to reduce the fleet quickly enough to halt the decline of the fish stock. By year 30 there are only four fish left in the sea and regeneration has fallen to zero. The fishery has collapsed with a huge excess of relatively new ships owned by fishermen reluctant to sell and still dependent on the fishery for their livelihood. The dismal dynamics of the Pacific Sardine Catch in figure 1 have been played out in a purely deterministic non-linear simulation model.

Figure 18 shows the output from the DES model with investment in ships. As before, the results shown are the mean of 10 replications. Over the 40 year period it is apparent that the output is moving into an oscillation that is characteristic of a delayed negative feedback loop. This is confirmed by a longer simulation run (figure 19). The amplitude and frequency of the oscillation is varying due to the random nature of the fish catch and fish regeneration.

The oscillation represents a puzzling dynamic. The system is theoretically in equilibrium with the fish catch and regeneration rates set as equal. So what is the cause of the oscillation? Figures 18 and 19 show, unsurprisingly, that the catch oscillates in line with the number of ships at sea. There is a lag, however, between an increase or decrease in the fish stock and a corresponding increase or decrease in the number of ships. This is to be expected as the purchase and sale of ships is dependent on the previous year's catch.

At the beginning of the simulation the number of ships, the catch and the fish in the sea remain relatively stable, as would be expected in an equilibrium state. In year 17 there is an increase in the number of fish caught. This is presumed to be a combination of two random events, a good year for fishing and a previous good year for regeneration, as evidenced by the catch and fish stock graphs. As a result of an increased catch more ships are purchased. As more ships are purchased the catch initially grows, but eventually this affects fish stocks and the catch then falls leading to disinvestment in ships. Once started, the oscillation perpetuates as in any typical delayed negative feedback loop. The oscillation is a result of an initial random variation, to which the ship investment policy reacts, causing the fishery to move into a permanent oscillation of fish stocks, catch and ships. Had there been no random variations, then the oscillation would not have started. Note that from a SD perspective a one-time step change in either the catch or ships at sea would trigger a similar cyclical behaviour.

What the model demonstrates is a ship investment policy that is too sensitive to random variations (stochastic misinvestment). The decision to grow the shipping fleet is based on the only measurable data concerning likely fish stocks, that is, the catch. However, due to random variations in the catch an increased catch does not necessarily indicate a growth in fish stocks. Indeed, it is possible for fish stocks to fall and the catch to rise. In this example there should not have been any investment in ships, as there was no underlying trend suggesting an increase in fish stocks. The fishermen have simply reacted to a random variation in the catch.

Here it is useful to think of the problem in terms of the two types of variation identified in statistical process control theory (Montgomery and Runger, 1994). 'Common' causes of variation are simply random variations that do not indicate any underlying change in the system. 'Special' causes of variation are shifts that do indicate an underlying change, or trend. In quality control the aim is to devise policies that only react to special causes of variation. In the fisheries example we see a typical case of an over sensitive policy in which a change is made as a result of common causes of variation. Such a reaction can lead to an unexpected outcome, in this case the result is the oscillation evidenced in figures 18 and 19.

The SD and DES models represent different policies for investment in the fishing fleet. Both policies are shown to be defective. In the SD model the policy leads to a complete collapse in fish stocks whose deterministic regeneration rate is highly non-linear. In the DES model the investment policy combined with random variations leads to a boom and bust business cycle in fish stocks whose stochastic regeneration rate is essentially linear, but capped. Interestingly these behaviours closely represent the behaviours of the real fisheries shown in figure 1. The Pacific sardine data showed a collapse in the sardine catch and presumably the sardine stock.

This is similar to the output of the SD model. Meanwhile, the North Sea herring data seems to show the beginnings of an oscillation in the catch similar to that predicted by the DES model.

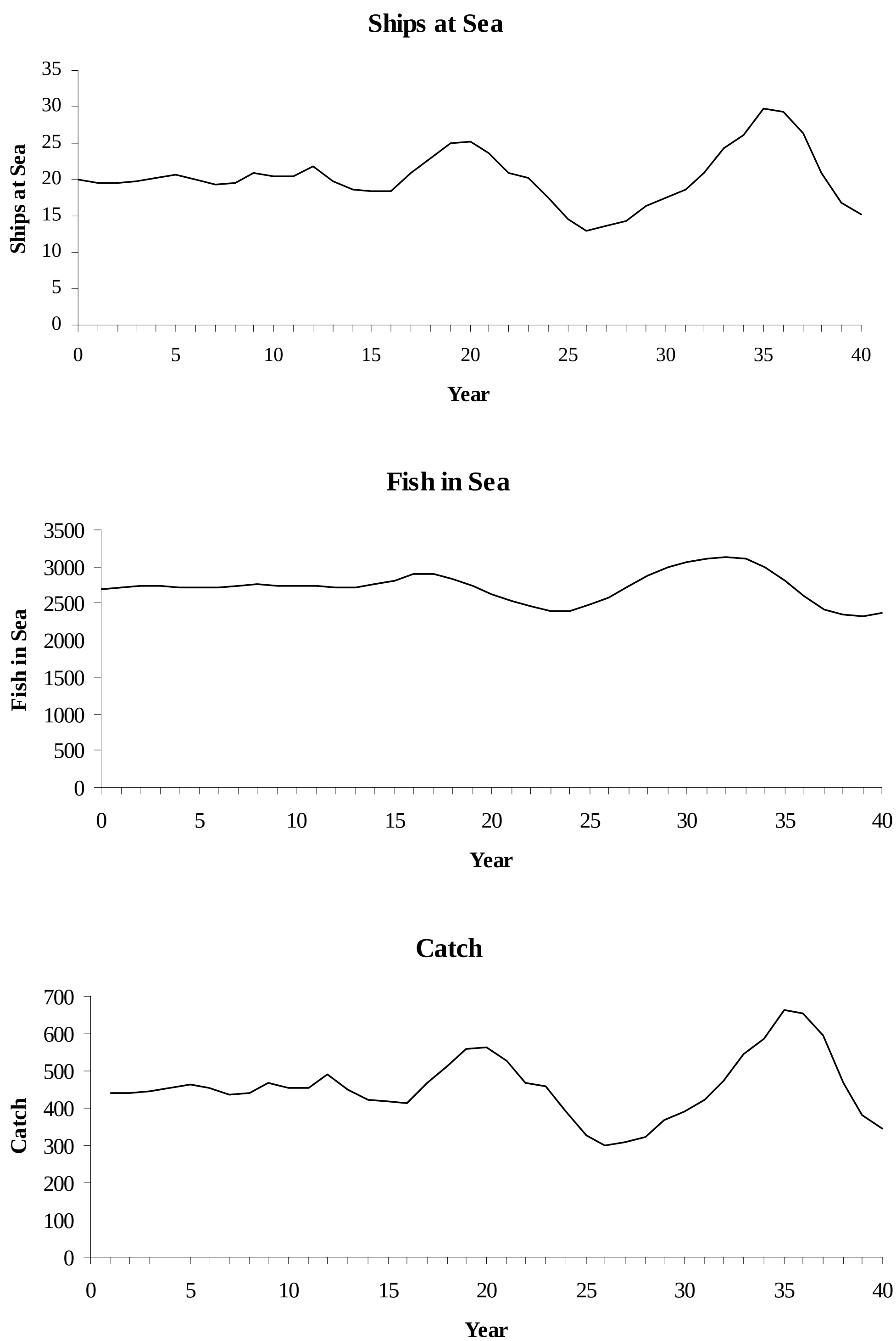


Figure 18: Simulation of DES Model with Investment showing Start of Oscillation

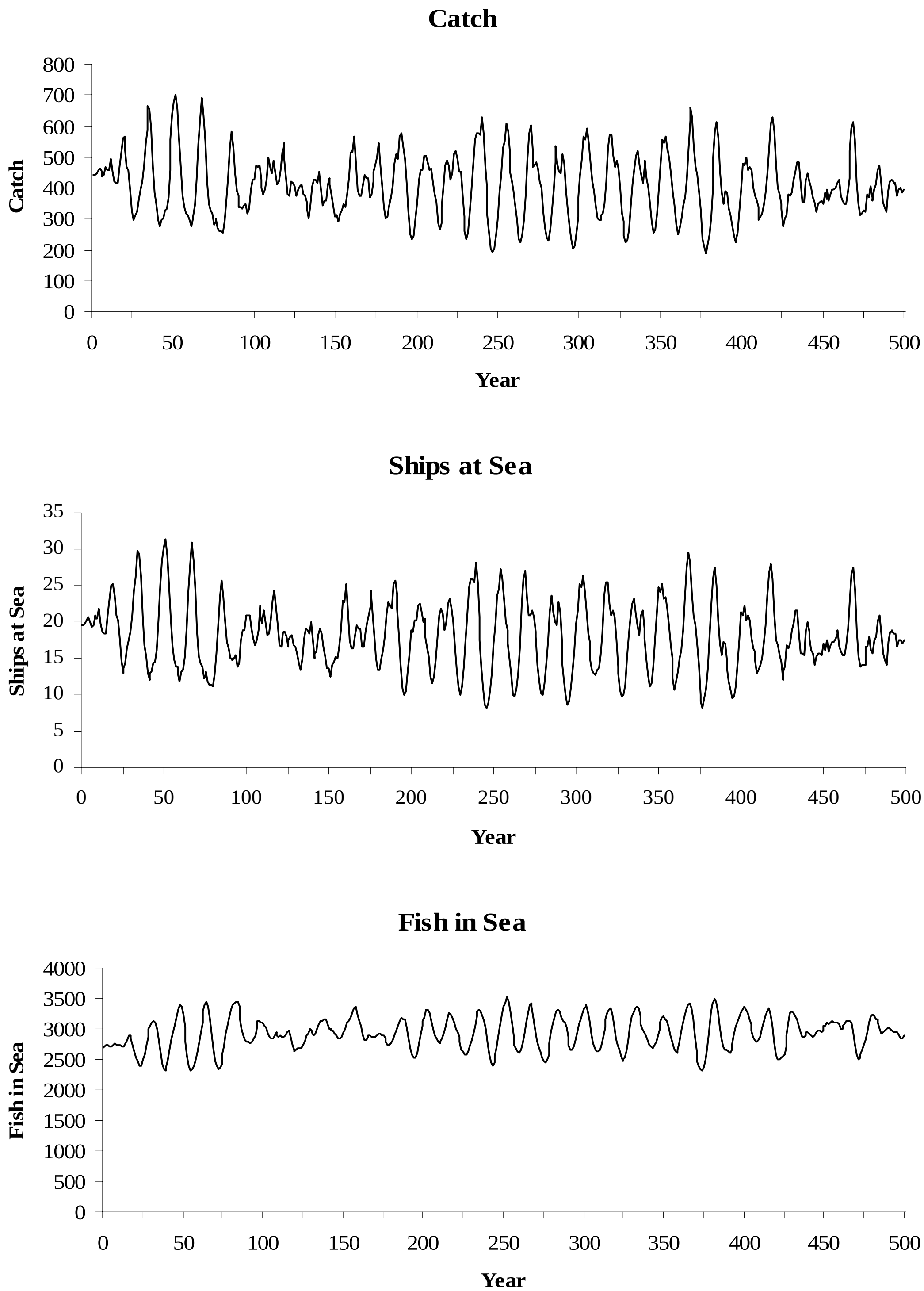


Figure 19: Simulation of DES Model with Investment showing Oscillation over 500 Years

Concluding Discussion

The processes of developing SD and DES models of the same problem situation are described above. The models have been developed separately by an expert in each field with a view to understanding the nature of the modelling process and insights gained from the two types of modelling approach. Our premise was that the use of SD or DES affects the representation and interpretation of phenomena from the real world. This premise is borne out in the work described.

Table 3 summarises the key differences in the SD and DES approaches that have emerged as a result of this investigation into the fisheries problem. Albeit the list of differences is not exhaustive and not all differences would apply to every modelling situation, nevertheless it is obvious that many of these differences are similar to those identified in previous studies comparing SD with DES described at the start of this paper.

In general it would seem SD is primarily involved with understanding the performance over time of an interconnected system arising from its internal feedback structure. This feedback structure is made explicit in the representation of an SD model and expressed through a series of equations that are frequently non-linear. Randomness is rarely considered and when included is simplified and sometimes subsumed into an appropriate delay. Growth and decay processes are normally seen to be exponential or s-shaped in form. A number of standard recurring modelling structures exist (often stemming from assumptions about bounded rationality and managerial decisionmaking) that guide model conceptualisation and equation formulation in SD models. The diagramming format for representing SD simulation models (stock and flow diagrams) is seen as a standard, though causal loop diagrams are also widely used to qualitatively depict feedback structure.

SD	DES
Representation	
System represented as stocks and flows	System represented as queues and activities (processes)
Feedback explicit	Feedback implicit
Many relationships are non-linear	Many relationships are linear
No randomness (subsumed into delays)	Randomness explicitly modelled
Growth/decay modelled as exponential or s-shaped	Growth/decay represented as random often with discrete steps e.g. a cut-off point
Standard recurring modelling structures exist e.g. asset stock adjustment process	Standard modelling structures generally do not exist
Standard diagramming format	No agreed standard diagramming format
Interpretation	
Feedback and delays are vital to system performance	Feedback and delay are not emphasised
Randomness is not normally important to system performance	Randomness is a vital element of system performance
Structure leads to system behaviour	Randomness leads to system behaviour

Table 3. Key Differences between SD and DES Approach Emerging from Fisheries Model

DES primarily focuses on the performance over time of an interconnected system subject to internal and external random variation. Feedback structures are included in these models, but they are not made explicit. This use of feedback contradicts Coyle's (1985) view that DES models are always open-process structures. DES modellers tend to adopt relationships that are linear in form, although not exclusively. Meanwhile, randomness is seen as a vital part of system behaviour and it is explicitly modelled. Growth and decay processes are therefore seen as random but limits are often represented as discrete cut-off points. DES modellers do not have standard modelling structures to guide equation formulation, nor is there an agreed diagramming format for representing DES models.

Building on these representational facets, SD modellers see feedback, delays and non-linearities as vital to the performance of a system, while randomness is normally of little or no importance. DES modellers place the emphasis on randomness with little direct concern for the effects of feedback. As a result SD modellers see feedback structure as the prime source of system behaviour, while DES modellers consider randomness to be the main cause.

What is clear is that SD and DES adopt quite different modelling philosophies. The similarities between the two approaches seem to end at the fact that both are simulation methods aimed at modelling the progress of a system through time. Further to this, and based on our experiences with the fisheries model, we might argue that both adopt an evolutionary approach to model development.

Having identified a series of differences between SD and DES modelling, we return to the original question of this paper: which method to use and why? In the case of fisheries both models seem to offer plausible explanations for the behaviours seen in figure 1. This outcome would suggest that neither method is necessarily superior to the other, but that either method may be useful in different circumstances. While each approach represents certain facets of the real world, both approaches also simplify specific facets of the real world. Given that both SD and DES modellers would agree that all useful models are simplifications of reality (Meadows 1980, Pidd 2003) this selective attention of the two approaches is not in itself a shortcoming. It is, however, important that modellers firstly recognise what simplifications a modelling approach entails and secondly that they select a modelling approach based on the facets of the problem situation and the facets of the modelling approach. Table 3 should help in determining what facets each modelling approach includes and what it excludes. Interpreting the important facets of the real world is dependent on the specific problem situation.

Where the facets of the real world and their implications are not clearly understood (which is likely to be the main motivation for modelling) then the advice might be to build both types of models, since both give important and possibly differing insights. Indeed, Renshaw in writing about the modelling of biological populations states:

> The tragedy is that too few researchers realize that *both* deterministic [SD] and stochastic [DES] models have important roles to play in the analysis of any particular system. Slavish obedience to one specific approach can lead to disaster… So pursuing both approaches simultaneously ensures that we do not become trapped either by deterministic fantasy or unnecessary mathematical detail. (Renshaw 1991, p. 2)

Perhaps it is time that more SD and DES modellers crossed the divide and considered applying both approaches, or at least considered more carefully situations in which the application of both approaches might yield complementary insights. This step requires more than simply learning about the modelling techniques and tools involved in either approach. The modeller also needs to adopt, or acknowledge, a completely different modelling philosophy and to temporarily suspend deeply held beliefs about reasons for system performance across time. Our experiences with the simple fisheries models have made us more aware, and more accepting, of alternative plausible interpretations for puzzling dynamics. We have moved forward in what Lane (2000) has described as 'mode 3 discourse' between DES and SD, building on a growing appreciation of differences and similarities between the two approaches. Probably each of us will remain anchored in our core disciplines, but we can now see enough of the 'other' discipline to sense where future collaboration might be beneficial.

A sample of collaborative thoughts and ideas is a fitting end to the paper. We have discovered paradigm differences between DES and SD. One loose yet concise way to communicate these differences is to say that DES illuminates 'constrained randomness' whereas SD illuminates 'deterministic complexity'. The real world contains both. Maybe constrained randomness is most evident in functional/operational problems of the kind most often tackled by DES modellers, whereas deterministic complexity shows up in cross-functional/strategic problems most often addressed in SD. But maybe not. Perhaps there is both 'strategic DES' and 'operational SD' and it's just a matter of which components you chose for your simulated enterprise and whether or not you believe randomness plays a significant role in those particular aspects of business and society. To take a practical example, the oil producers' microworld (Langley et al 1999) is an industry level deterministic SD simulator linking rival aggregate producers to world demand in order to understand global oil market dynamics. There are five main sectors or components in the model. There is no reason why these same sectors could not be reconceptualised to emphasise the randomness and turmoil that undoubtedly pervades the oil industry. On the other hand, in the manufacturing heartland of DES exemplified by, for instance, the brick factory model reported by Robinson and Higton (1995), there is surely an SD model of the same factory involving the same departments as the existing DES model. However, instead of investigating the stochastic interaction of individual factory machines and manufacturing processes it would emphasise deterministic non-linear feedback processes in manufacturing control and shed new and complementary light on factory management and brick production. Food for thought ……

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[i] Article in the Sunday Times, 29th February 2004, entitled "Charles call for cod'n'chips curb". In the same edition a letter was published from nine former British secretaries of state for the environment and the current secretary of state. The ten pledged support for the Marine Stewardship Council in its global efforts to make fishing more sustainable and to ensure there will be fish for our children and grandchildren.