5 Scenario implementation and analysis

5.1 Introduction

The previous chapters have introduced the context of this research, issues to consider and phenomena to capture that lead to the choice of the tools used, and the presentation of the thinking behind scenarios, as well as the explanations of the parameters that differentiate one scenario from another.

This chapter provides the parameters used in the simulations and reference runs for every scenario. An analysis of the extent to which the results are sensitive to certain parametric or structural changes, followed by two specific studies complete the chapter.

Many simulations have been undertaken during the course of this research. Their purpose varied: verifying the model, debugging the code, implementing the various scenarios, investigating the phenomenon observed, and studying the influence of specific aspects or values.

The simulation results presented in this document are a small portion of all those run. And while the structure of the document may suggest a sequence for the modelling and the simulations, it is not chronologically accurate. Important questions needed to be investigated before (or in the process of) implementing the scenarios themselves, and some aspects of the model.

That is why the actual first simulation runs are presented in section 5.5 (detailed study of a particular set of runs). It was followed by the assessment of the structural impact (presented in section 5.3.1), the analysis of visibility (in section 5.3.3), the study of innovation diffusion (in section 5.4), of the density of agents (in section 5.3.2), of the impact of the memory implementation (in section 5.3.4), and finally of the creation of all four scenarios (in section 5.2). Obviously constraints for the modeller are not relevant when it comes to presenting the results, hence the different sequence, which should make this an easier read.

5.2 Scenario Generation

This is the presentation of both common and specific modelling parameters. It sums up the information given above, and expresses the remaining parameters and variables in accordance with the scenarios involved.

Ownership is the probability that a household possesses the appliance. Frequency of use is the daily average frequency owners utilise the appliance. Volume per use is the average amount of water necessary for one event.

Unless explicitly stated otherwise, values used for this analysis are the following.

Appliance	Ownership	Frequency of use	Volume per use
bath	0.98	0.31	80
shower	0.542	0.4	31.25362
power shower	0.309	0.5	61.88837
sprinkler	0.14364	0.023976	2400.247
other_garden_watering	0.459403	0.048858	242.1583
washing_machine	0.954	0.264324	96.7
clothes_hand_washing	0.046	1	13.088
new_washing_machines	0.5	0.28	80
dishwasher	0.395	0.328393	41
hand_dishwashing	0.605	1	16.58634
toilets	1	4.15438	8.831

Table 10: Default values for scenario parameters

Baths have a fixed volume per use, *i.e.* at anytime in the simulation the volume per use is fixed and equal for every user.

Memory decay coefficient is set to 2.5.

Innovation is represented by the possible replacement of the full flush toilets by dual flush ones (effectively a saving water device), from October 1992, and the possible replacement of showers by power showers (effectively a device that tends to increase water use) from April 1990.

Some activities are considered as private, and hence cannot be observed by the neighbours. They are the use of baths, dishwashers and washing machines.

As in everyday life, households have some information about what appliances their neighbours own, not because they have been informed by the neighbour itself, but simply by observing or reflecting upon associated behaviour. These appliances are labelled “semi-public”. Appliances in full view of others, such as for example a sprinkler, are characterised for modelling purposes as “public”.

There are two different cases in which an appliance can be replaced. Either it has reached a “natural” replacement stage, when the household considers the appliance to be old enough for a replacement decision to be reasonable, or it broke. The assumed standard replacement rate is 5 years, *i.e.* on average appliances are changed or replaced every 60 months.

Whether an appliance breaks depends on a probability distribution. The Weibull probability distribution seemed the most appropriate, as it is one commonly used for white goods. The Weibull distribution has a sigmoid pattern, and parameters to adapt the slope and level of the graphical representation. The parameters generally used for white goods in order to approach the actual probability of breaking are 1.2 for the shape, and 35 for the scale.

5.2.1 Creation of scenarios

Generation of scenarios is done according to the method presented in chapter 2. The first step consists of interpreting the conditions described by the Environment Agency.

Parameters used to distinguish specific scenarios in the model are those linked to the appliances, and those linked to the population.

Scenarios have several drivers for household demand, which the Environment Agency classifies as follow:

Water policy drivers, which include metering and water regulations

Technology drivers, which include white goods, and miscellaneous

Behavioural drivers, which include the type and pattern of personal washing

Economic drivers, which include personal affluence

While some of these drivers are included in the current model, some of them have been ignored. There are several reasons for this choice.

Water policy drivers are included in the model as the water regulations are at the origin of the emergence of efficient appliances, and of the removal of high water use appliances from the market. As expressed in section 4.2.4, the limits both in the necessary knowledge to implement metering, and the usefulness of this implementation, due to the structure of the model, have led to the choice of ignoring this component.

Technological drivers are included in the model. They include the emergence of new appliances, or new technologies. Miscellaneous use is not included. The very name of this category expresses the fact that the appliances cannot be designated exactly. Although MAS models allow a very detailed representation of appliances, it is difficult to describe a "miscellaneous" equivalent, due to the lack of definition on what it actually is. Moreover, it would be brave to assume that this "component" would evolve the same way as others, without mentioning what influences it is subject to.

Behavioural drivers are included, and the process involving behavioural changes is clearly one of the main parts of the model.

Economic drivers are included. They are not explicitly in the model, as there are no prices or wealth as such, for reasons explained in chapter 1. They are an indirect parameter, which is present via the behaviour of customers with respect to new products. Additional wealth is assumed when the rate of renewal of appliances is faster in one scenario than in another.

Therefore, keeping in mind these components, different scenarios can be interpreted and translated into assumptions and values of parameters for the associated simulation runs.

As guidelines for differentiating the scenarios, the following table will present endorsements for the influence weighting, as well as the most important point associated to the scenario.

Scenario	Global weight	Local weight	Self weight	Comments
A	10	30	60	Washing machine down to 50l/use Dishwasher down to 30l/use
B	30	10	60	Washing machine down to 80l/use Dishwasher down to 20l/use
C	55	25	20	New technology WC Dishwasher down to 15l/use
D	25	55	20	New technology WC Dishwasher down to 15l/use

Table 11: Main changes between scenarios

Below is a more detailed presentation of all scenarios and the possible evolutions they contain.

Scenario A, called “Provincial enterprise”, is based on individualism and regionalisation. Therefore, the level of self-influence will be the highest of the three. As regionalism is strengthened, the autonomy of local government increases, and the influence of global messages weakens, while the recent focus around smaller communities increases the values and respect of local environment and neighbours.

The weighting selected are:

globalInfluence 10

localInfluence 30

selfInfluence 60

In this scenario, the replacements and disappearance of appliances from the market is as follows:

1985: 9 litres full flush toilet cisterns can be replaced by dual flush (7.5 litres)

1990: showers can be replaced by power-showers

1992: dual flush (7.5 litres) cisterns can be replaced by low volume flush (7 litres)

1993: dual flush (7.5 litres) and full flush (9 litres) cisterns are not available anymore

2001: low volume (7 litres) cisterns can be replaced by low volume (6 litres)

low volume (7 litres) can be replaced by dual flush (4.5 litres)

low volume (7 litres) is not available anymore

2010: dishwashers can be replaced by efficient dishwashers (30 litres)

dual flush (4.5 litres) can be replaced by low volume flush (6 litres)

dual flush (4.5 litres) is not available anymore

washing machines can be replaced by efficient washing machines (60 litres)

Scenario B, called “World Markets”, is associated with a situation of individualism and globalisation. The level of self-influence will remain high, as above. But the government remains very much centralised, and the feeling of belonging to a nation is higher than the feeling of belonging to a local community.

The weighting selected are:

globalInfluence 30

localInfluence 10

selfInfluence 60

In this scenario, the replacements and disappearance of appliance from the market is as follows:

1985: 9 litres full flush toilet cisterns can be replaced by dual flush (7.5 litres)

1990: showers can be replaced by power-showers

1992: dual flush (7.5 litres) cistern can be replaced by low volume flush (7 litres)

1993: dual flush (7.5 litres) and full flush (9 litres) cisterns are not available anymore

2001: low volume (7 litres) cisterns can be replaced by low volume (6 litres)

low volume (7 litres) can be replaced by dual flush (4.5 litres)

low volume (7 litres) is not available anymore

2010: dishwashers can be replaced by efficient dishwashers (30 litres) dual flush (4.5 litres) can be replaced by low volume flush (6 litres)

dual flush (4.5 litres) is not available anymore

washing machines can be replaced by efficient washing machines (60 litres)

Scenario C, or “Global sustainability”, represents the plausible future in which strong communities and globalisation cooccur. The individualistic behaviours tend to disappear, with an increase in community values, while globalisation strengthens the central government system.

The weighting selected are:

globalInfluence 55

localInfluence 25

selfInfluence 20

In this scenario, the replacements and disappearance of appliances from the market is as follows:

1985: 9 litres full flush toilet cisterns can be replaced by dual flush (7.5 litres)

1990: showers can be replaced by power-showers

1992: dual flush (7.5 litres) cistern can be replaced by low volume flush (7 litres)

1993: dual flush (7.5 litres) and full flush (9 litres) cisterns are not available anymore

2001: low volume (7 litres) cisterns can be replaced by low volume (6 litres)

low volume (7 litres) can be replaced by dual flush (4.5 litres)

low volume (7 litres) is not available anymore

2010: washing machines can be replaced by efficient washing machines (40 litres)

dishwashers can be replaced by efficient dishwashers (15 litres)

low volume cisterns (6 litres) can be replaced by dual flush (4.5 litres)

2015: dual flush (4.5 litres) can be replaced by low volume (3.25 litres)

dual flush (4.5 litres) is not available anymore

dual flush (7.5 litres) can be replaced by low volume (4 litres)

full flush (9 litres) can be replaced by low volume (4 litres) low volume (7 litres) can be replaced by low volume (4 litres)

low volume (6 litres) can be replaced by low volume (4 litres)

low volume (6 litres) cisterns are not available anymore

Scenario D, or "Local stewardship", is a situation where strong communities and regionalisation co-occur. Also presenting a relatively low individualism, the society gives importance to local communities, and a decentralised government.

The weighting selected are:

globalInfluence 25

localInfluence 55

selfInfluence 20

In this scenario, the replacements and disappearance of appliances from the market is as follows:

1985: 9 litres full flush toilet cisterns can be replaced by dual flush (7.5 litres)

1990: showers can be replaced by power-showers

1992: dual flush (7.5 litres) cistern can be replaced by low volume flush (7 litres)

1993: dual flush (7.5 litres) and full flush (9 litres) cisterns are not available anymore

2001: low volume (7 litres) cisterns can be replaced by low volume (6 litres)

low volume (7 litres) can be replaced by dual flush (4.5 litres)

low volume (7 litres) is not available anymore

2010: washing machines can be replaced by efficient washing machines (40 litres)

dishwashers can be replaced by efficient dishwashers (15 litres)

low volume cisterns (6 litres) can be replaced by dual flush (4.5 litres)

2015: dual flush (4.5 litres) can be replaced by low volume (3.25 litres)

dual flush (7.5 litres) can be replaced by low volume (3.25 litres)

full flush (9 litres) can be replaced by low volume (3.25 litres)

low volume (7 litres) can be replaced by low volume (3.25 litres) low volume (6 litres) can be replaced by low volume (3.25 litres)

low volume (6 litres) cisterns are not available anymore

dual flush (4.5 litres) is not available anymore

All the following results have been obtained with a wide vision parameter, *i.e.* the households can potentially communicate with other households up to 6 cells away from their own location. As the grid is only a 7-cell square, this comes to considering the vision as complete.

The number of households is set to 20. The household density over the simulations is therefore close to 0.6.

As shown in Moss, Edmonds et al. (2000), the density obviously plays an important role in the result of the simulations. With a density that is not sufficient, the influences amongst agents will come to whether there is any interaction, rather than which agent would be influential in a group of neighbours.

According to the authors, for 100 agents, a grid size of 25x25 has the ability to support a specific phenomenon (in this case word-of-mouth communication), while grid sizes of 30x30 and 50x50 do not. Hence, a density of 16% seems to be sufficient (in his case) to ensure there are enough contacts in the population to allow the existence and / or emergence of the studied phenomenon. Some earlier simulations seemed to suggest some instabilities of water use, with important variation on short timescales. In order to avoid this effect, which will be discussed later, a high density was selected for typical runs.

Other simulations have been run in order to analyse the possible impacts of this parameter, and it will be addressed later.

The next section will present the simulations for the 4 typical sets of inputs associated to the scenarios described above.

5.2.2 Scenario simulations

The comments in this section describe specific simulations, and are therefore only valid with this support. To assist in the analysis, graphs of total water use are included, displaying not only the simulation runs themselves, but also the average of the runs (as the bold line), in order to better visualise the deviation of some of these runs.

The results shown here only refer to the initial simulations, and more detailed comments will accompany the studies of particular properties or phenomena later on, including reruns of the scenarios with slightly different parameters.

5.2.2.1 Scenario A: Provincial Enterprise

A few graphs are provided to help with the representation of the simulation results. When representing scenario outputs, each line represents a different run of the water demand simulation. The time, in months elapsed or in month / year format, is on the X axis and the water demand levels are on the Y axis is. When useful, the monthly average over all runs is also present and is indicated by a thicker line.

The graph shows a generally decreasing trend.

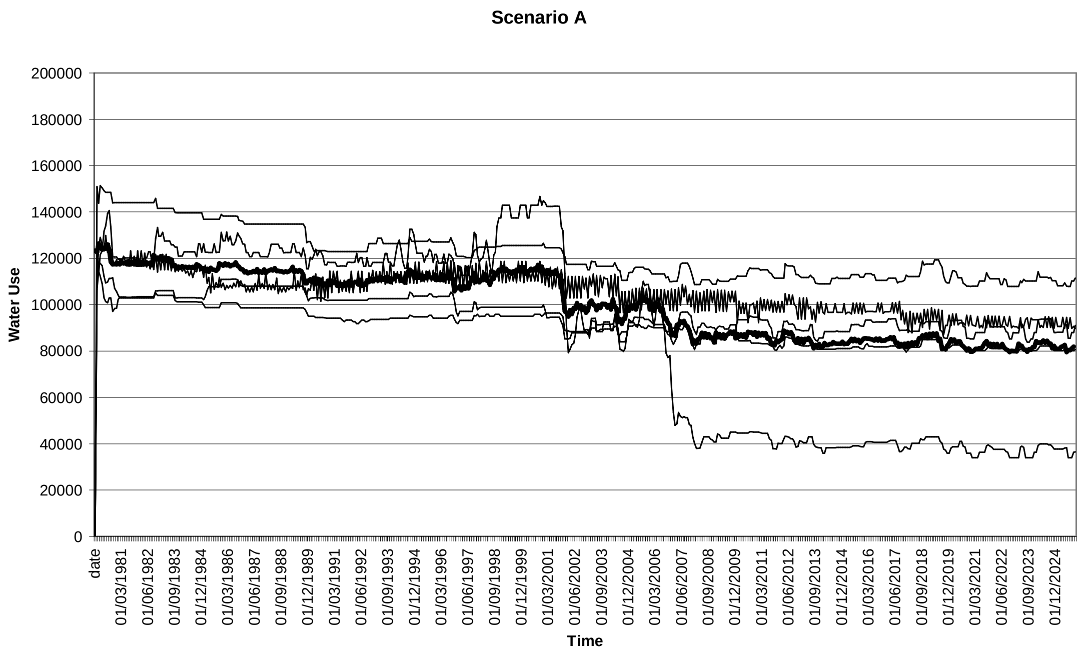

Figure 14: Scenario A

There are two notable series displayed. The first one is the one with extreme behaviours (series1 in the table below). In the same simulation, the variations are such that although it does not start as the highest or lowest water use, increases in 1998 and decreases in 2001 and 2006 have an important effect on the demand levels. Although the first large peak seems to be the obvious consequence of the drought starting in August 2001, the increase starting in 1998 does not seem to have an environmental cause.

The second drop, in 2006, is not justified by the climate either. One can observe that other simulation runs are not affected this way.

The other eye-catching pattern is the frequent micro fluctuations of the data from the second topmost series from 2004. Although the general shape of the water demand is not extreme, it is clear that there is an element of instability that is not present in other runs.

On a statistical aspect, the study of every run provides the following results:

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std.	Variance	Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error
serie0	551	80748,11	114462,00	96121,55	7560,382	5,7E+07	-1,170	,208
serie1	551	33953,98	146715,87	86194,47	40398,38	1,6E+09	-1,762	,208
serie2	551	79552,74	123162,00	90951,40	8004,305	6,4E+07	-,157	,208
serie3	551	87085,42	129830,00	105142,6	9087,055	8,3E+07	-,895	,208
serie4	551	107821,50	151307,00	121604,8	11207,89	1,3E+08	-,615	,208
Valid N (listwise)	551							

Table 12: Descriptive statistics for scenario A

The use of statistical software (SPSS in this case) allows a different analysis, investigating the underlying distribution of these data. As developed earlier in this study, the presence of defined second moments is a critical factor for using statistical techniques upon datasets. It was shown then that this assumption was unsafe. It is now interesting to check whether the generated data also has this property.

In the previous table, a kurtosis value is provided for every data set. The kurtosis value is a measure of the extent to which observations cluster around a central point, a measure of the peakedness of a probability distribution. For a random variable x with mean μ and standard deviation σ, kurtosis is the fourth central moment divided by the squared variance, $E\,(x-\mu)^4 / \sigma^4$. For a normal random variable, kurtosis is 3, but in many cases (including in this research), for clarity, 3 is subtracted away, hence the value becomes 0 for a normal distribution. Positive kurtosis indicates that the observations cluster more and have longer tails than those in the normal distribution (this property is leptokurtosis) and negative kurtosis indicates the observations cluster less and have shorter tails.

To strengthen this conclusion, the table below shows the KS analysis upon the relative changes for every run.

The Kolmogorov-Smirnov Test procedure is non parametric and compares the observed cumulative distribution function for a variable with a specified theoretical distribution, in this case, the normal distribution. The Kolmogorov-Smirnov Z is computed from the largest difference (in absolute value) between the observed and theoretical cumulative distribution functions. This goodness-of-fit test tests whether the observations could reasonably have come from the specified distribution.

The table below hence demonstrates that the probability that any of these differences (labelled as “lag0” to “lag4”, each corresponding to a simulation run) are normally distributed is effectively nil.

One-Sample Kolmogorov-Smirnov Test

		lag0	lag1	lag2	lag3	lag4
N		550	550	550	550	550
Normal Parameters [a,b]	Mean	-28,7096	-156,6409	-77,2439	-42,5606	-72,0661
	Std. Deviation	1445,808	3095,569	840,45950	6124,500	1150,932
Most Extreme Differences	Absolute	,323	,235	,319	,122	,351
	Positive	,323	,235	,319	,122	,351
	Negative	-,283	-,214	-,293	-,115	-,325
Kolmogorov-Smirnov Z		7,577	5,509	7,485	2,855	8,236
Asymp. Sig. (2-tailed)		,000	,000	,000	,000	,000

a. Test distribution is Normal.

b. Calculated from data.

Table 13: Kolmogorov-Smirnov statistics for scenario A

5.2.2.2 Scenario B: World Markets

In the representation of scenario B, there does not seem to be any extreme run. All have slightly decreasing trends, and seem to follow roughly the same pattern.

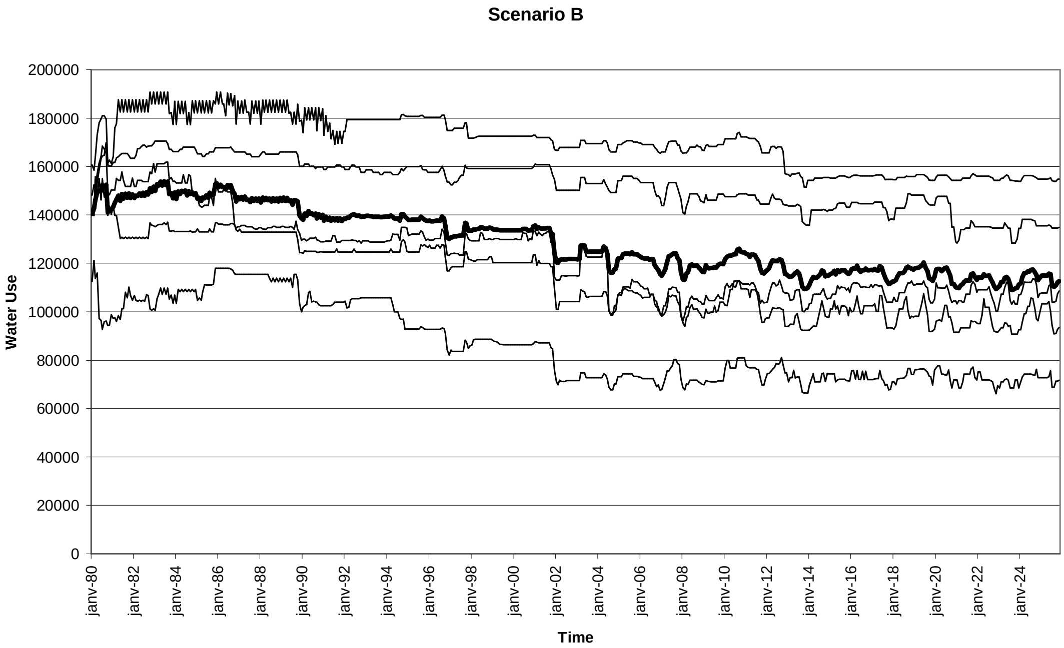

Figure 15: Scenario B

The highest run shows an interesting instability up to 1991. The cycle of households copying each other is broken by the appearance of power showers. The introduction of power showers and their adoption provide new recommendations to households, who discard their showers, and the system is then harmonised. This demonstrates that the high frequency variability observed could be due to a flaw in the processes.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std.	Variance	Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error
serie0	551	140767,00	190807,14	169831,8	11234,02	1,3E+08	-1,107	,208
serie1	551	90751,98	168418,00	119259,4	20231,82	4,1E+08	-1,005	,208
serie2	551	66148,00	121195,00	86511,40	16015,30	2,6E+08	-1,202	,208
serie3	551	128322,92	180953,00	153053,2	10603,98	1,1E+08	-,699	,208
serie4	551	96242,41	155748,00	117397,7	11897,34	1,4E+08	-,708	,208
Valid N (listwise)	551							

Table 14: Descriptive statistics for scenario B

The table above shows a lack of stability amongst various runs of a specific set of simulations. The variance as well as the standard deviation is fairly high, denoting the large differences in values from one series to another. The negative kurtosis expresses a distribution with tails shorter than they would be if it were normally distributed.

As before, the Kolmogorov-Smirnov 2-tailed asymptotic significance confirms the probability of effectively 0 for the assumption of normality to hold for relative changes (still labelled “lags”) in the runs.

One-Sample Kolmogorov-Smirnov Test

		lag0	lag1	lag2	lag3	lag4
N		550	550	550	550	550
Normal Parameters[a,b]	Mean	25,6718	-99,2786	-74,1683	-46,7881	-57,0237
	Std. Deviation	3057,229	2518,925	2078,941	1577,696	2064,745
Most Extreme Differences	Absolute	,244	,205	,209	,318	,229
	Positive	,244	,185	,199	,318	,229
	Negative	-,236	-,205	-,209	-,285	-,220
Kolmogorov-Smirnov Z		5,719	4,818	4,897	7,456	5,375
Asymp. Sig. (2-tailed)		,000	,000	,000	,000	,000

a. Test distribution is Normal.

b. Calculated from data.

Table 15: Kolmogorov-Smirnov statistics for scenario B

5.2.2.3 Scenario C: Global Sustainability

In the runs representing this scenario, there are no micro instabilities as displayed in the previous runs. While one could wonder whether this could be due to the values of endorsements, a look at the results from scenario D (above) would suggest that this is not the case. Further studies of the instability phenomenon are undertaken later, and a possible link with the vision parameter is investigated.

While the patterns of the different runs look similar, there are interesting differences. The water demand does not always seem to change in a (roughly) similar manner. Some reactions to drought are unmistakable, but the 2010 changes in the highest run cannot be explained by climatic conditions. The simultaneous introduction of three new technologies seems to be the reason for such changes.

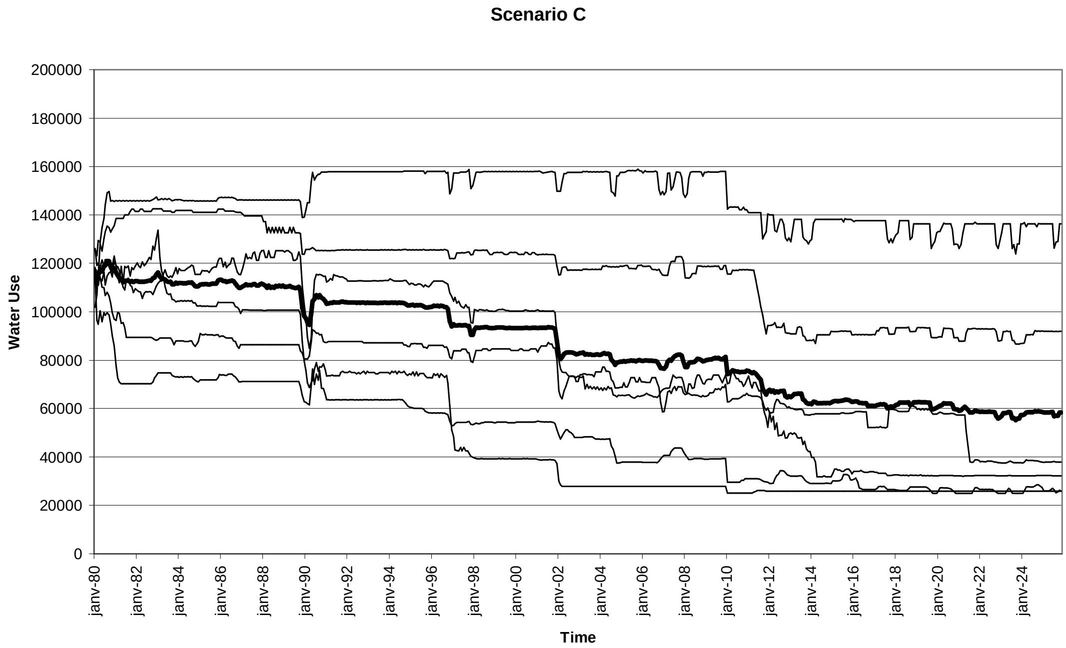

Figure 16: Scenario C

One can notice that from 2014 onwards, there is a grouping of some runs, even more visible after 2022. The 2010 drought does not seem to have a significant impact upon the second topmost series, while the 2011 drop in consumption of this series is the biggest and fastest of all.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std.	Variance	Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error
serie0	551	31783,43	118401,70	68079,39	23410,65	5,5E+08	-1,179	,208
serie1	551	123103,90	158948,99	147009,7	10003,60	1,0E+08	-1,191	,208
serie2	551	37508,86	126069,60	83933,97	28515,66	8,1E+08	-1,509	,208
serie3	551	86609,26	142442,99	115852,9	18021,78	3,2E+08	-1,247	,208
serie4	551	24988,80	114684,80	48777,34	18838,64	3,5E+08	-,818	,208
serie5	551	25129,30	133619,18	52787,83	33347,58	1,1E+09	-,956	,208
Valid N (listwise)	551							

Table 16: Descriptive statistics for scenario C

The descriptive statistics show the same negative kurtosis as for the previous scenarios, with shorter tails, also allowing the rejection of the normality assumption. Moreover, the differences in mean and standard deviation also hint at the differences of consumption levels amongst the runs.

One-Sample Kolmogorov-Smirnov Test

		lag0	lag1	lag2	lag3	lag4
N		550	550	550	550	550
Normal Parameters [a,b]	Mean	-156,7278	18,6116	-160,1026	-40,3668	-161,6186
	Std. Deviation	1430,572	2202,015	1814,540	1346,988	1391,846
Most Extreme Differences	Absolute	,270	,316	,247	,310	,281
	Positive	,245	,282	,197	,305	,273
	Negative	-,270	-,316	-,247	-,310	-,281
Kolmogorov-Smirnov Z		6,341	7,422	5,790	7,270	6,592
Asymp. Sig. (2-tailed)		,000	,000	,000	,000	,000

a. Test distribution is Normal.

b. Calculated from data.

Table 17: Kolmogorov-Smirnov statistics for scenario C

The use of the Kolmogorov-Smirnov test on relative changes confirms the fact that the relative changes are not normal either, with all probabilities of the sample of origin being normally distributed effectively equal to zero.

5.2.2.4 Scenario D: Local Stewardship

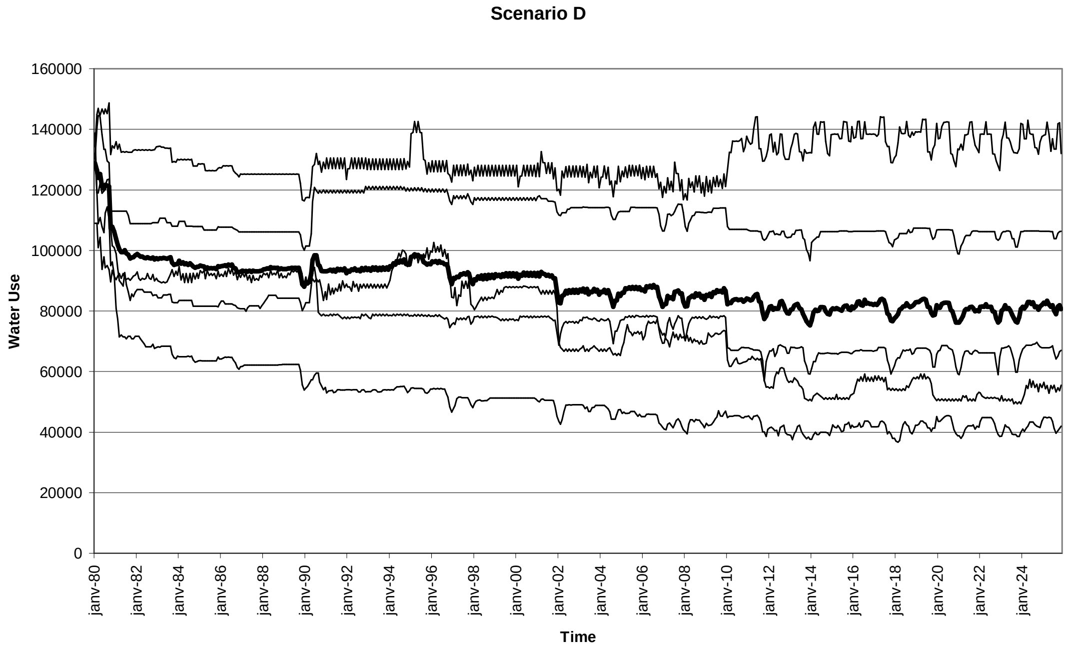

Figure 17: Scenario D

The noticeable increase in water use in the end of 1990, following a decrease a few months earlier can be explained by the events taking place then in the model. Towards the end of 1989, there are three consecutive months of relative drought, and the policy agent broadcasts its recommendations, which results in a decrease in water use. In 1990, the availability of power showers on the market is becoming clear, as their high volume per use translates into an upwards demand trend for all runs.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std.	Variance	Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error
serie0	551	36668,43	132069,60	51272,07	12545,27	1,6E+08	9,429	,208
serie1	551	116338,74	148685,10	130507,0	6435,298	4,1E+07	-,507	,208
serie2	551	49346,03	108936,60	74753,38	16780,64	2,8E+08	-1,517	,208
serie3	551	56920,26	138684,10	75792,09	9686,710	9,4E+07	8,381	,208
serie4	551	96523,20	146861,80	111127,7	6562,600	4,3E+07	3,536	,208
Valid N (listwise)	551							

Table 18: Descriptive statistics for scenario D

For the first time in assessing the scenarios, three of the runs have a positive kurtosis. This indicates that the observations cluster more and have longer tails than those in the normal distribution. The runs affected are the lowest one (series0), the second lowest one till 2002, which then becomes third lowest (series3), and the second to the highest (series4).

One-Sample Kolmogorov-Smirnov Test

		lag0	lag1	lag2	lag3	lag4
N		550	550	550	550	550
Normal Parameters [a,b]	Mean	-163,7762	2,9003	-97,0778	-130,3852	-50,4957
	Std. Deviation	1488,797	3456,891	1879,920	1826,011	1427,272
Most Extreme Differences	Absolute	,197	,126	,075	,266	,234
	Positive	,153	,117	,056	,193	,226
	Negative	-,197	-,126	-,075	-,266	-,234
Kolmogorov-Smirnov Z		4,619	2,951	1,766	6,232	5,493
Asymp. Sig. (2-tailed)		,000	,000	,004	,000	,000

a. Test distribution is Normal.

b. Calculated from data.

Table 19: Kolmogorov-Smirnov statistics for scenario D

Paradoxically, the first and only positive probability that a data set could come from a normally distributed sample, is one with a negative kurtosis, just as the scenarios A, B and C displayed. Nevertheless, the probability remains very low, and seems therefore reasonable to consider that it is not significant.

5.2.3 Comparison of simulation results and reference scenarios

When comparing the results obtained from simulations and those expressed by the Environment Agency, several differences are present. While the figures do not match well, the ranking of scenarios according to the evolution of demand they display is more accurate. The table below shows this evolution using the average of 24 values from the years 84-85 as a reference. Values for 2010 and 2025 are averages for the year indicated.

Scenario / Year	A	B	C	D
2010	-20 (+14)	-6 (+13)	-20 (+3)	-9 (+6)
2025	-26 (+33)	-14 (+19)	-38 (-28)	-11 (-20)

Table 20: Comparison of scenarios with reference

Amongst the reasons for the discrepancies are the fact that miscellaneous use is not taken into account, the fact that water use is mostly driven down by the new appliances never using more water than the previous ones, the lack of increase in population, and probably the characterisation of the scenarios via endorsements.

Scenarios A and B show an increase in water use in the Environment Agency, and the bias introduced by a steady population and the lack of miscellaneous uses can explain the failure to corroborate these scenarios. Scenarios C and D seem much closer to the Agency's estimates. Despite the absence of increase by 2010, the results for 2025 can be considered as reasonably close to the Agency's. This is encouraging, as these two scenarios include the diffusion of new technologies, and would tend to show that the method used to represent innovators in the model seem to be effective.

To better understand the causes of the changes in the different scenarios, one must look into the origin of specific behaviour, as well as investigate the sensitivity of the model to its parameters or structure.

5.3 Initial analysis

A qualitative analysis is now undertaken to study a particular phenomenon, such as a run with extreme values. Qualitative analysis is necessary when the numbers are less important than what they represent, or when differences are better expressed by words than by meaningful numbers (if they exist).

Sensitivity Analysis is necessary to understand the role of the multiple parameters in the model.

There are models that are simple enough so that the few parameters are meaningful ones with respect to the object of the modelling. It is for example the case when dealing with size and weight for a person in a sample. There are more complex models, which require many aspects of a problem to be taken into account. It is then possible that some parameters integrated into the model could influence the results significantly, while not being central to the modeller. Edmonds and Hales (2003) have given an example of modelling details that, although not really central to their issue, turned out to be decisive for the behaviour of the model, and the observed phenomenon. That was in an allegedly simple model. In the current case, there are many parameters and algorithms. The methods and values used are carefully selected as having appropriate characteristics and (in general a lack of) underlying assumptions. Nevertheless, their influence upon the results of the model needs to be understood, in order to improve comprehension of the model.

One needs to understand how the parameters that do not necessarily have direct links with the abstract model (*i.e.* that can be directly related to an artificial society) can be modified to change the behaviour of the whole system. This is the purpose of sensitivity analysis.

Sensitivity analysis is generally undertaken to assess the variability or stability of the outputs of a model or simulation with respect to the possible space of inputs. This is recommended when the computational burden is not too heavy. In this case, there are limiting factors that prevent standard sensitivity analysis. The first of these is the number of inputs and their possible values. The abstract model is based upon an existing description of scenarios. While some values can be debated and changed, most of the parameters would be set by the system that is being represented, and the values it explicitly provides. Also, there are many parameters in the model that are not thought to influence the end result, although demonstrating this would prove quite a challenge. So when sensitivity analysis is limited, it should focus on either (potentially) key variables, or explicit assumptions that cannot be backed up with evidence or reason.

Another difference from the standard approach is that generally, such tests aim to assess the sensitivity of the results to some input values. This research is more focused on the representation itself than its results. It is then only natural to assess the sensitivity of the model itself, to its assumptions and input values. Various indicators will be selected depending on the changes whose impact will be assessed.

Adopting this particular point of view regarding sensitivity also leads to the investigation of another aspect of the model. As already mentioned, it is common for scientific purposes to assess the impact of input values to a model. What can be left out is the study of the shape of the model itself, and of the parameters or processes representing assumptions its structure relies upon.

The parameters to analyse can be of different types. They can refer to single dimension (typically numerical) continuous values or sets of values, but also to discrete values or sets of values, as well as to the presence or not of some properties.

While models generally allow the input values to be changed, sometimes the outputs of the model also depend on how the model itself was though and implemented. This part will now investigate the impact of the input values and of the model structure upon its outcome.

First of all, the sample the investigation must rely on might not be composed of all the runs. It could be necessary to select some runs in particular, and have the analysis apply to a specific run, or to the representation of a set of runs. As presented earlier in this work, regrouping sets of runs could lead to statistical issues.

The literature provides some examples where the processes and internal structure of particular models are investigated.

Cohen, Riolo et al. (1999) present some interesting comparisons of methods. They represent a repeated prisoner’s dilemma using a Multi Agent System, for which they analyse various parameters.

The model has three key dimensions: the strategy space, the interaction process, and the adaptive process. Changes in these parameters have impacts upon the results (payoffs) of the agents represented, and hence the emergence of patterns of activity. Although some conclusions could be drawn upon well-known and understood phenomena, some observations were unexpected (such as the high levels of co-operation when mixing agents with random strategies between games).

The prisoner's dilemma, because of its simplicity and its diffusion, is an appropriate subject for which to investigate sensitivity to various parameters. Also, these parameters are not numerical changes, but qualitative changes. They investigate the influence of the model structure upon the model results.

Generating a model, there are implicit modelling methods, and explicit ones. The explicit ones are for example strategy spaces, or neighbourhood definitions, while implicit ones could be the representation of cognition, or environment perception. Sensitivity analysis in often undertaken assessing the impact of the most explicit or representative assumptions. The example of Cohen, Riolo et al. (1999) does just that, because of the restrictive settings of the prisoner's dilemma: the case that is represented is composed of one game, one partner, no geographical or social space.

To complement that qualitative approach, sensitivity analysis is often undertaken on a numerical aspect, *e.g.* the sensitivity of the result, or indicator, to a specific value.

In other cases, the importance of sensitivity analysis comes to understanding and explaining the consequences of parameter variations (Barreteau and Bousquet (2000)). There can be several reasons for not testing alternative structures.

The structure of the model is already understood, and its effects are known

The model's structural part is not important to the results

The model does not include an agent's location: *e.g.* Hales representation of agents only uses tags, and does not use situated agents

The analysis of the structure is not generally undertaken. In most cases, the parameters that are included in the sensitivity analysis are numerical. The few times when this analysis is done, one can see that the underlying structure could have important impacts. In Duboz, Ramat et al. (2001) for example, the Multi Agent System used is tested for boundary conditions, *i.e.* a change in the algorithms that are involved in the spatial behaviour of agents (namely the way the agent bounces off a wall). Also tested are the distribution algorithms and the size of the space, and the conclusion suggests that the choice of the bouncing algorithm is a more important parameter than the distribution or size of the population of agents.

Studied impacts of structure or algorithms are common when the point of the research is to address specifically that influence, as in Cohen, Riolo et al. (1999), where the interaction mechanism is under scrutiny, along with the strategies' dimensions, and the adaptation process of strategies with time.

As in many other studies, the literature shows the effects that a simple change in the way the interactions take place sometimes has, giving extreme and opposite results (Edmonds and Hales (2003)).

An additional problem in MAS is choosing a reference run to compare to the others, since it is a stochastic process.

In the various runs generated by a set of specific parameters for the model, one can certainly distinguish several categories. There are generally 2 or 3 different sets of runs with the current model: some that are very high, that could correspond to the fact that the highest users of water are taken as examples, some that could be qualified as average runs, and some that are lower than all others, sometimes corresponding to a diffusion of patterns copied from households using low levels of water. Because of the nature of agent based modelling, it is not appropriate to use only statistical tools to select a representative run. The qualitative aspects of the simulation cannot be captured easily by means of software. The selection of the run that is used in order to compare will be done by presenting the set of runs, with both graphical and statistical properties, and then extracting what seems to be an appropriate run to consider.

The extreme behaviours that can be observed in the various runs remind the users that the results of the simulations are not to be understood as forecasts, but as indicators, examples of what the interactions could generate.

The size of the network and the characteristics of the agents (and especially their cognition) are important parameters that might influence strongly the dynamics of the system.

A number of hypothesis are going to be investigated in the following sections. They are part of a sensitivity analysis process, and will shed some light upon the possible influence of some aspects of the model, either built-in characteristics, or critical values and processes.

They are:

- the grid structure
- The density of agents
- The visibility parameter
- The agent’s memory

5.3.1 The toroidal structure

One could assume that grids with different structures produce different results. This section will compare the outputs obtained running the model using an extended grid with those obtained from the often used 2D grid.

It is necessary to mention that the simulation runs performed in order to observe the consequences of a toroidal structure have been run with the frequency and volume generated according to a power law distribution. This explains why some runs seem very high, since this implementation can sometimes generate unlikely large values. The power law distribution is assumed to be underlying in the frequency and volume used per appliance. In most other simulation runs, the frequency and volume are initially normally distributed around the mean that has been provided from observed data. At a given point in time, this might well be the case, and it does not mean in any way that this distribution is assumed to hold with time. More specifically, further analysis will demonstrate that both alternatives (power law and not power law distributed initial values) have a negative kurtosis.

Differences in the number of links between agents when the grid is toroidal or not can be represented via a matrix. The two figures below display these matrices for a specific simulation.

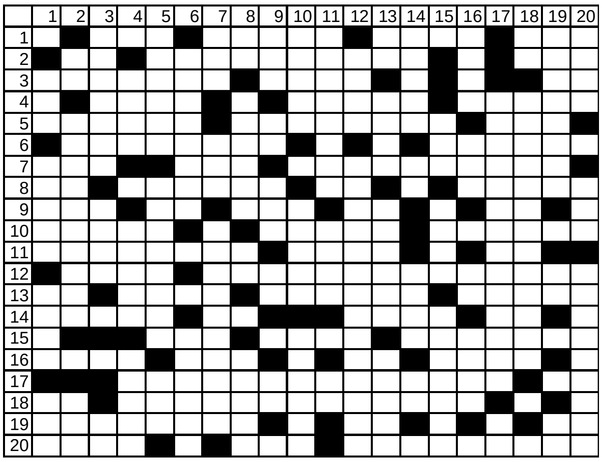

Figure 18: Matrix of links for a grid with a toroidal structure: in this case, the 20 agents are situated on a grid of size 8*8

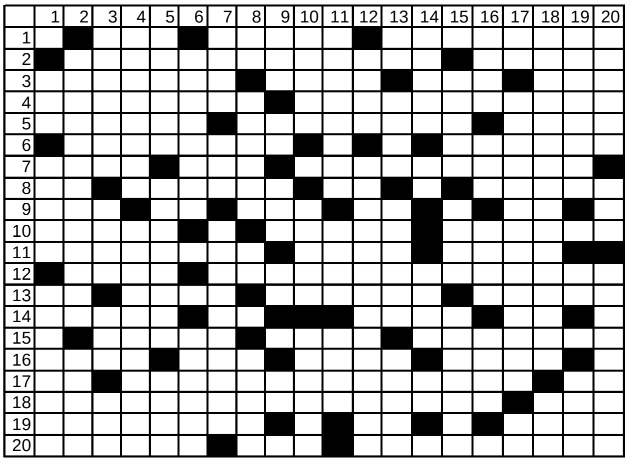

Figure 19: The equivalent matrix of links for the non-toroidal version

The black cells show the existence of an interaction between the agents listed horizontally and vertically, and it is easy to notice that the toroidal structure provides more contacts to each agent.

The diagrams below show the results of 46 reference runs.

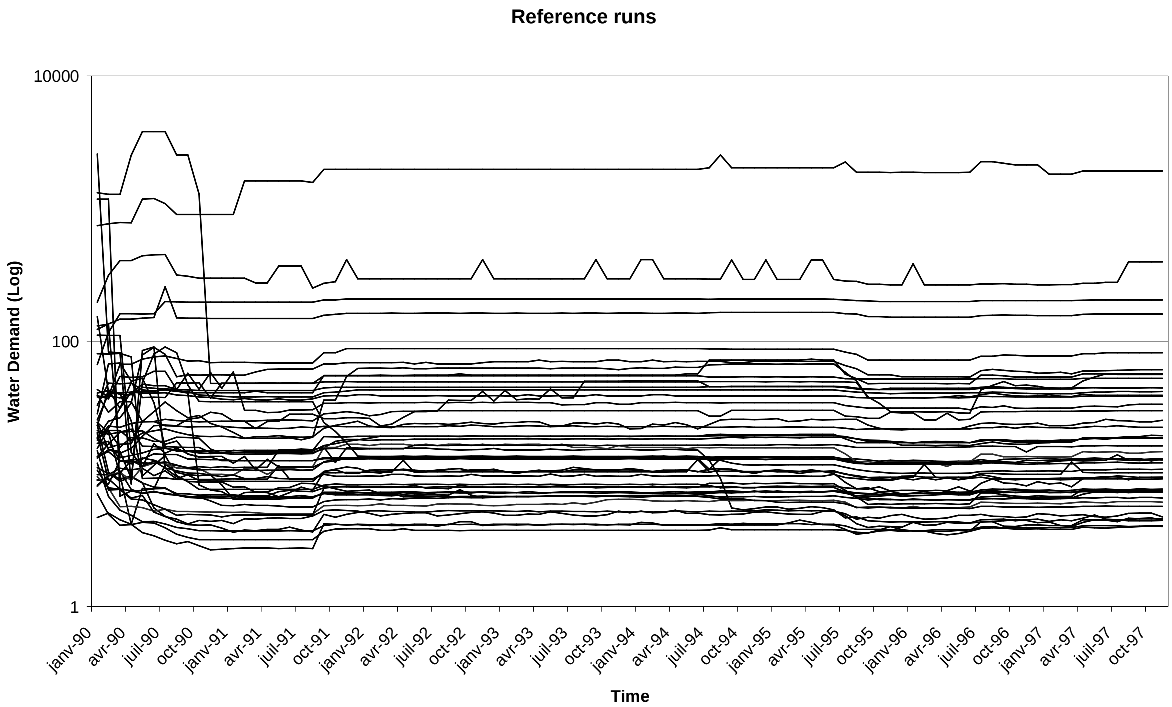

Figure 20: Multiple reference runs

This graph represents the total water demand for the system. It is here on a log scale, since this allows us to show all the runs, while there are some that are significantly different, with volumes being several orders of magnitude larger than the bulk of the others.

If the focus is upon that bulk of runs, the result is as follow.

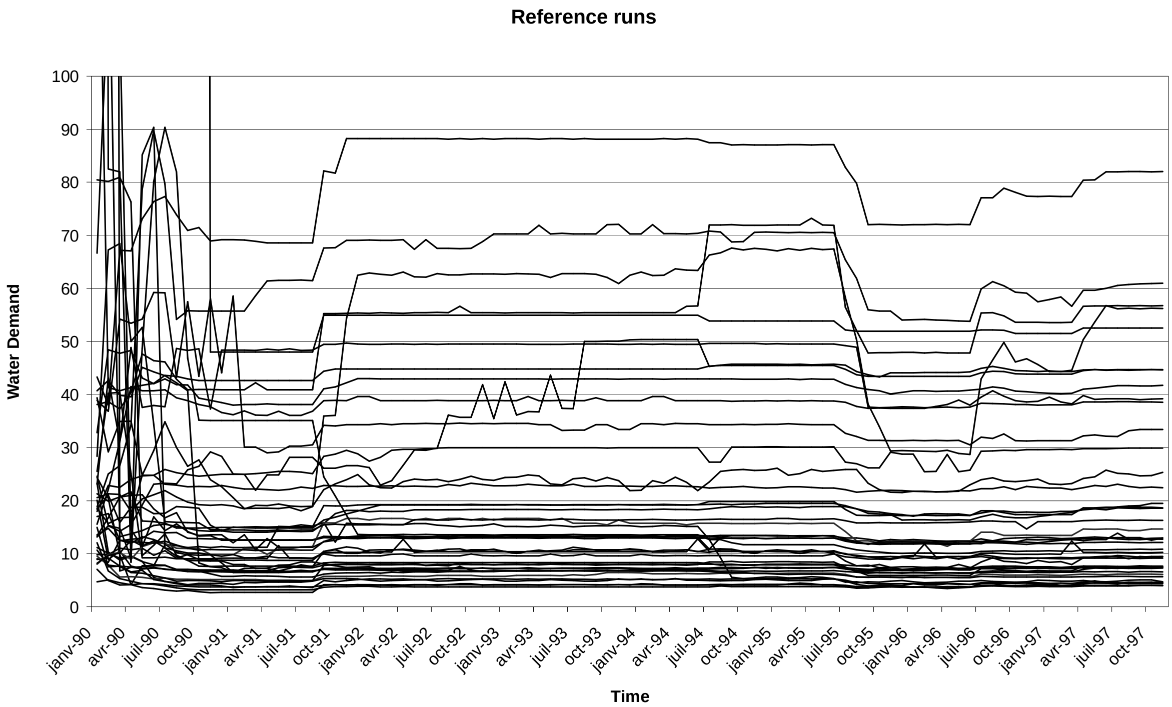

Figure 21: Focused reference runs

As it can be seen, the majority of the runs (29 of them) are below 20. That seems to indicate that a reasonable value would tend to be below this threshold.

By contrast, another set of runs, with the same parameters, just changing the structural property of having a finite (non-toroidal) space gives the following 34 runs.

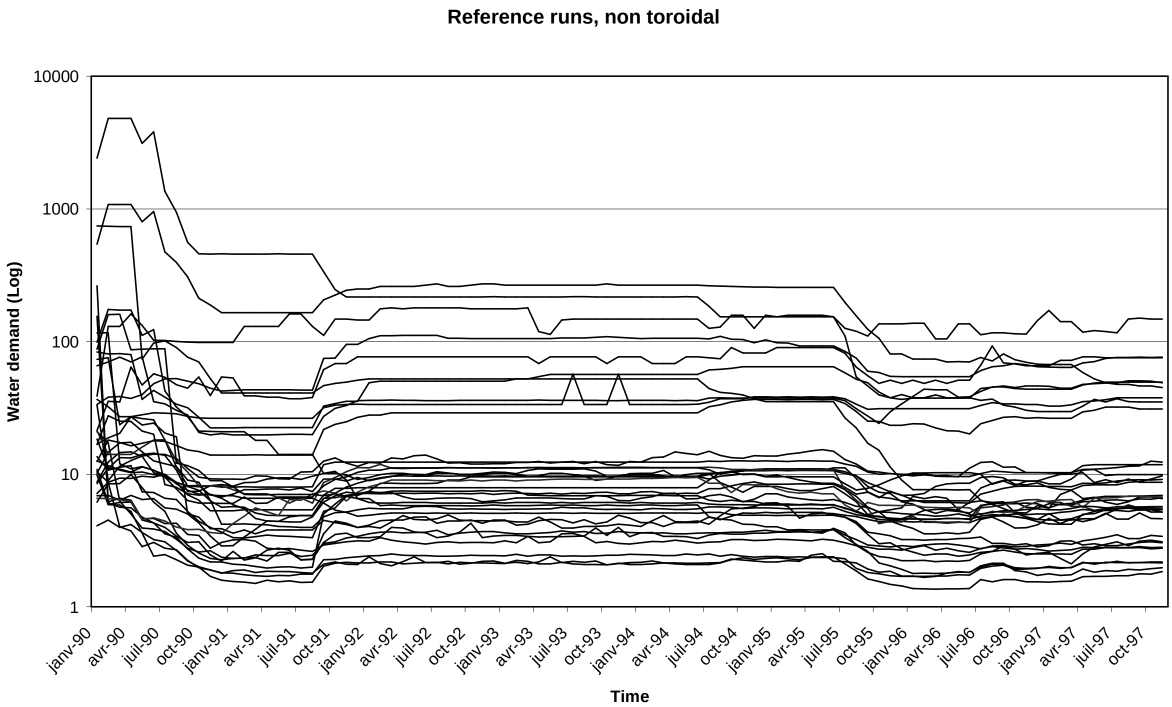

Figure 22: Reference runs, logarithmic scale

The same focus as before, gives the following:

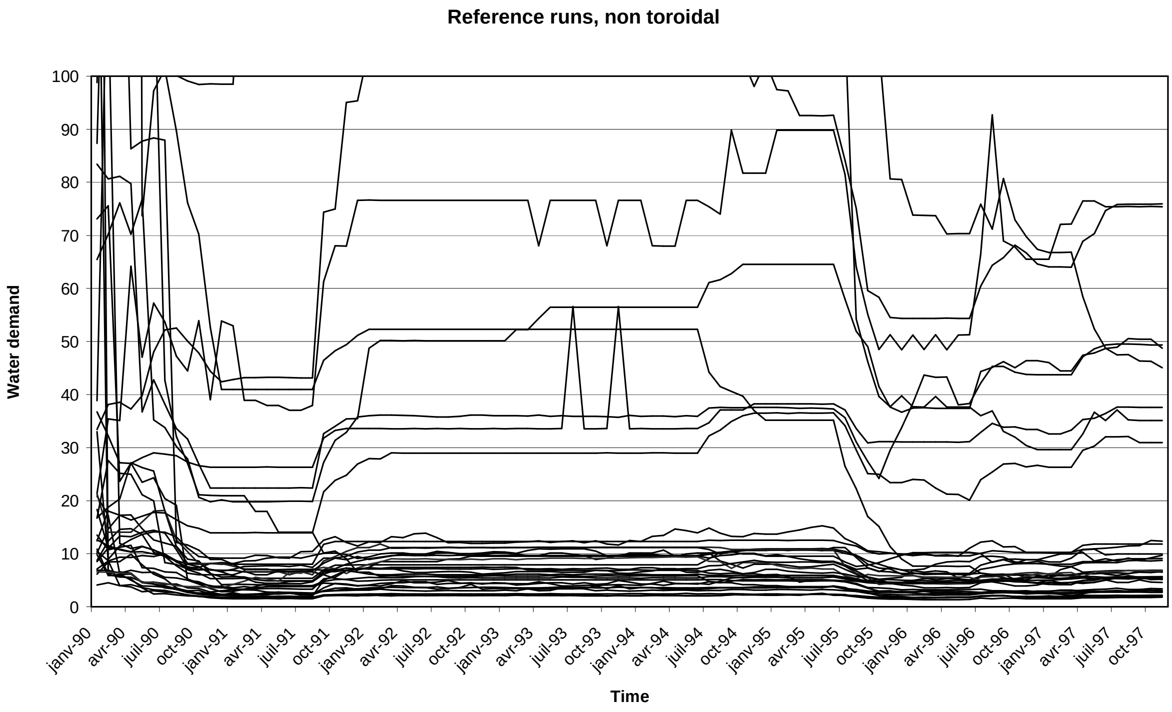

Figure 23: Focused reference runs

This time, it is 25 runs of the 34 that are concentrated within the [0 – 20] values. That is 75% of them. It seems that the space structure could have some effects upon the global dynamics of the model.

By extending the visibility (to 6 instead of 4 by default) on a finite grid, the proportion changes, as it reaches about 57% of runs only (51 upon 89) below that threshold.

If the month of December 1990 is taken as a reference, then the following dynamics can be observed.

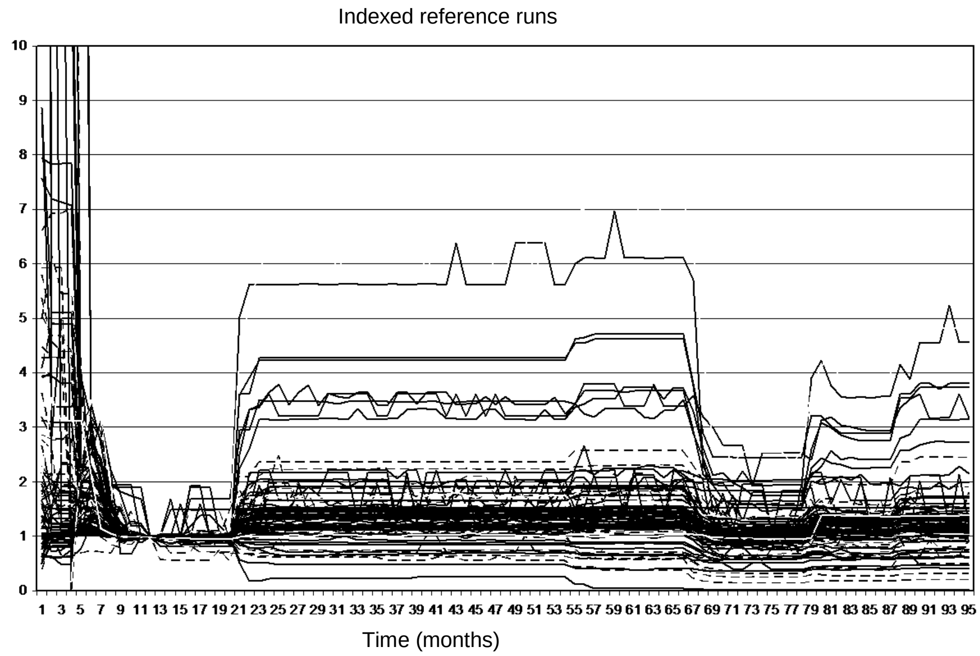

Figure 24: Reference runs, indexed December 1990

One can see that the variations of water demand have all a value of 1 for the 12th month. It is also visible that there seems to be a most likely dynamics, or a set of most likely dynamics, generating similar relative changes for the majority of the runs.

By using the particular case of a system with 10 agents on a 20*20 grid, that have no visibility, the following result is reached:

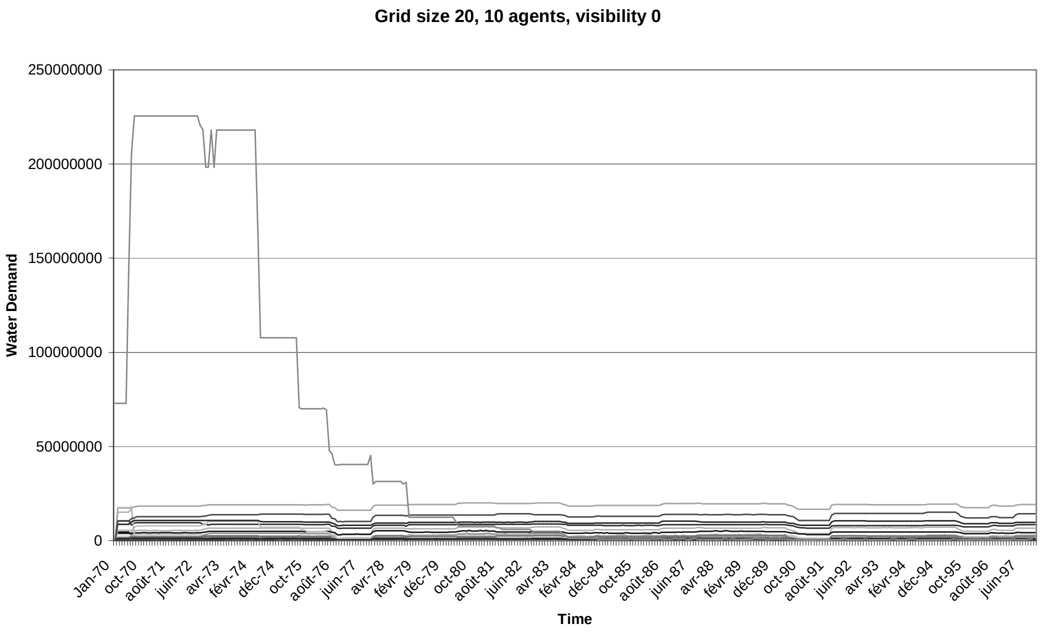

Figure 25: 4 agents, grid size 20, visibility 0

The topmost run displays an example of extreme behaviour. Removing it from this graph allows a more detailed view of the values for remaining runs. Focusing on the lower part of the diagram can further identify the similarities of some runs.

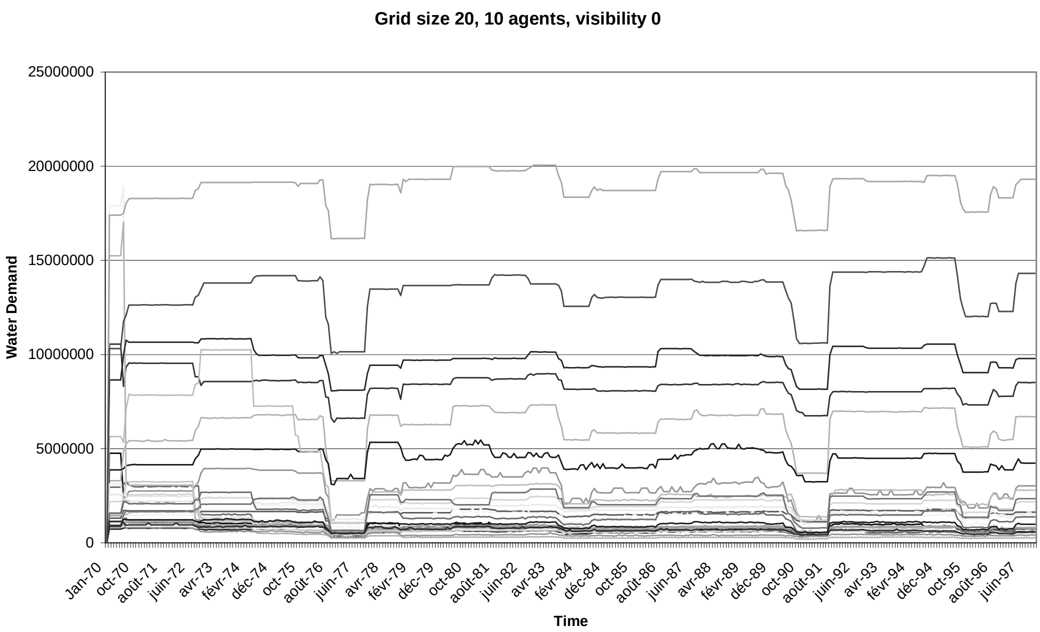

Figure 26: Detailed view, agents, grid size 20, visibility 0

The similarities of patterns one can observe on the figure below are applicable to all scenarios, regardless of the network structure. An example with a reduced number of agents on a toroidal grid tends to show that some runs seem to behave identically.

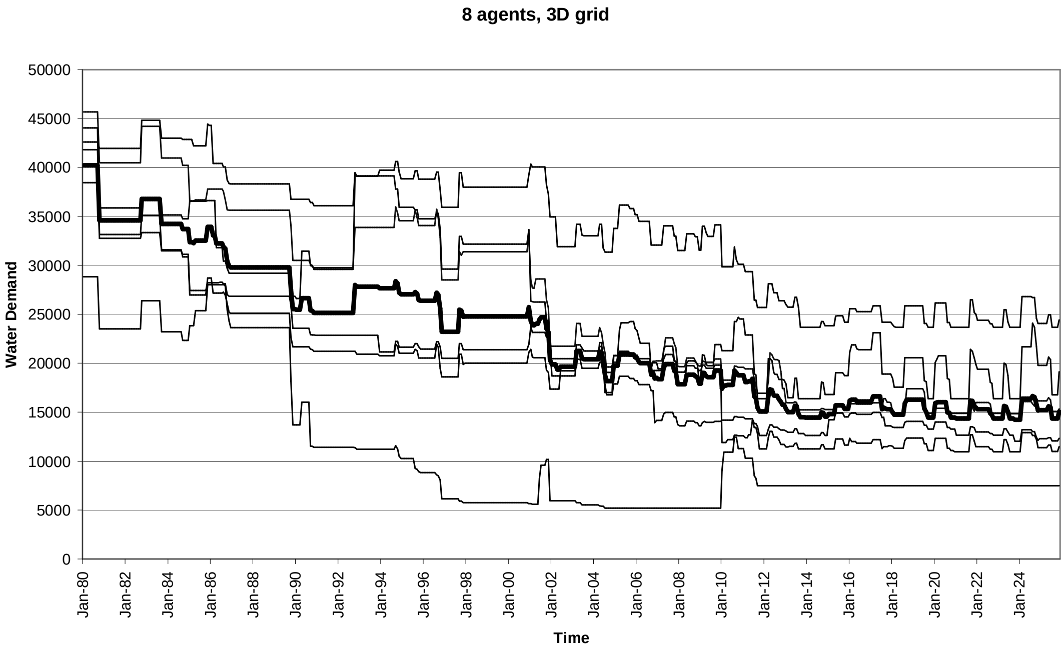

Figure 27: Similarities of runs on a toroidal grid

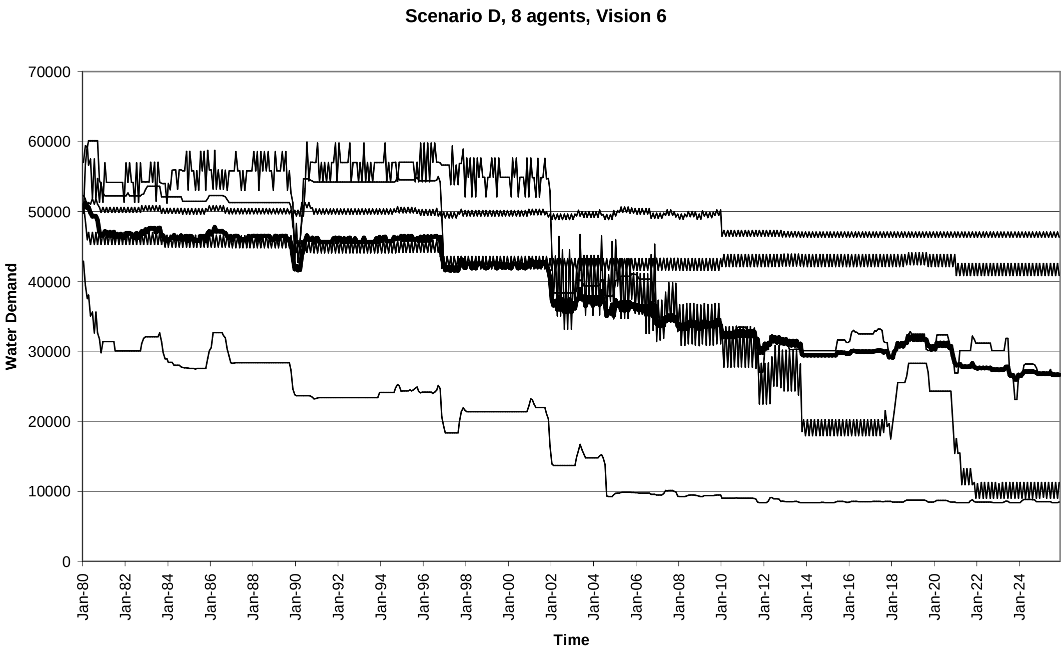

Figure 28: Runs on a non-toroidal grid

To investigate this idea, a formal analysis of the distributions involved is done in SPSS.

Testing the averages for both simulation results with SPSS, the results are not clear-cut, as shown in the table below.

Test Statistics[a]

	lag
Mann-Whitney U	146589,0
Wilcoxon W	298114,0
Z	-.901
Asymp. Sig. (2-tailed)	.367

a. Grouping Variable: VAR00008

Table 21: Testing sample independence (relative change)

The probability that the two distributions are extracted from an identical sample is not zero as was the case in earlier tests, but is now close 0.367. This means that the two distributions do have similarities. Nevertheless, it is not possible to assert with confidence that the averages are extracted from the same sample.

However, when using raw data instead of relative changes, the figures seem to improve. In several comparisons of specific series, the probability that the two sets of data are extracted from the same sample reaches values higher than 0.8. This value is high enough so the doubt is the opposite way, and it would be likely that the underlying distributions of both sample might be identical.

Test Statistics[a]

	lag
Mann-Whitney U	150384,0
Wilcoxon W	301909,0
Z	-.172
Asymp. Sig. (2-tailed)	.864

a. Grouping Variable: VAR00008

Table 22: Testing sample independence (raw data)

This could imply that there is a technical issue with the averages, and that the dimensions of the grid supporting the agents seem of no great influence upon the results.

Considering that the support itself has little influence, the number of agents present and the number of interactions taking place in the model must be looked into.

Altogether, as a rule, it is not clear that the dimensions of the underlying space make a difference in the way the processes take place and the results at a macro level. Nevertheless, some cases have been observed, when the positioning of agents upon the grid has generated a situation in which the links were so few that changing the toroidal space into a non-toroidal one did change in quite a radical way the shape of the network involved. Despite this, the overall patterns observed did not seem significantly sensitive to this parameter.

In such extreme cases, it appeared that a more critical index of how sensitive a specific set-up would be to changes was the density of agents.

The conclusion of such analysis is not clear-cut. On one hand, when both simulation results were compared using the standard output (*i.e.* in this case the water demand figure), the structure seemed to make a difference. On the other hand, when the relative changes of these two simulations were analysed, the statistics seemed to indicate that there was not a significant difference between them.

One could think that this could be explained by the fact that the absolute figures obtained can be very variable, due to the inclusion of randomness at the start of the simulation run. But the non-parametric statistics should not be assessing the values themselves, but rather the structure their hypothetical sample of origin would have.

Yet, the results are opposite when analysing the changes within these water demand figures.

It is debatable whether they both are the consequence of the same component of the model. The structure of the grid will have an impact upon the households that communicate with each other, and this might be a main driver for levels of water demand in this model. Similarly, the process that is embedded within every agent to describe its decisions and choices does not change when the grid structure changes. Consequently, one could associate the relative changes, which do not seem to differ, with the decision making process, while the absolute values would be more influenced by the amount of information that is available to an agent.

Also playing a part in the innovation diffusion, the network structure can intuitively be considered as a major parameter during the set-up of a simulation run. The fact that a network with a higher number of links seems to be associated with rapid uptake of innovation would tie in with the explanation suggested above regarding the different impacts of communication and decision making processes.

5.3.2 The density of agents

One could suppose that the density of agents on the grid can influence the outcomes of the simulation. This section will investigate whether there is a critical density below which some phenomenon do not emerge, or some conclusions do not hold.

The nature of the model makes it very sensitive to the amount of interactions that can take place. If the social environment of an agent is limited, what is the impact on that agent's behaviour and why?

The method used to answer this question is the following. For an equivalent grid size, different numbers of households are simulated. The runs generated can then be compared, and help to provide insight into this possible influence.

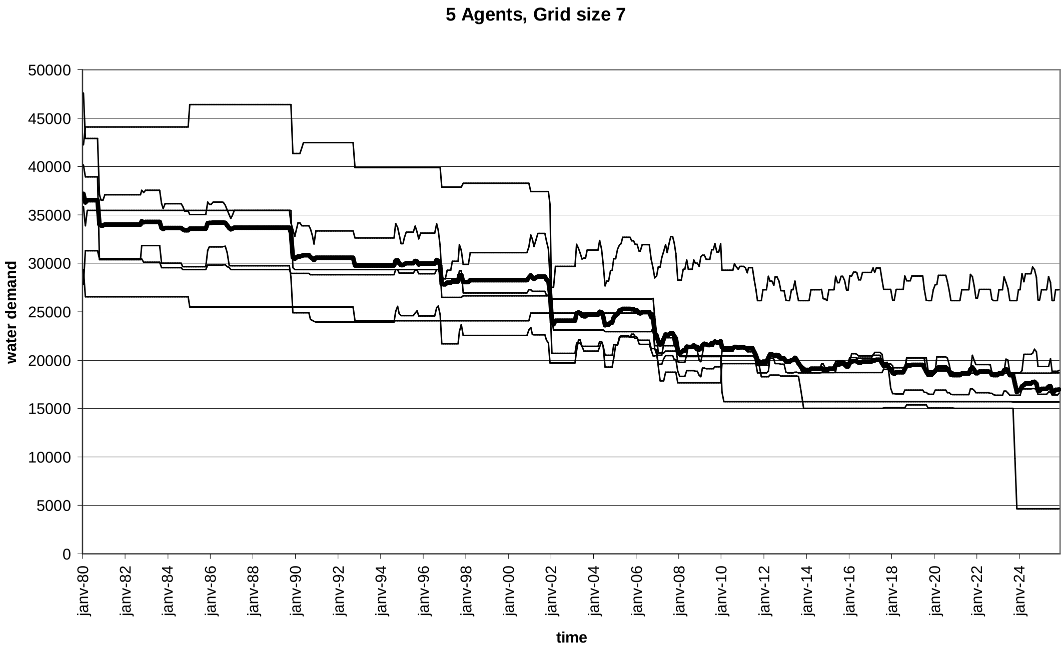

Figure 29: Water demand, agent density 0.1

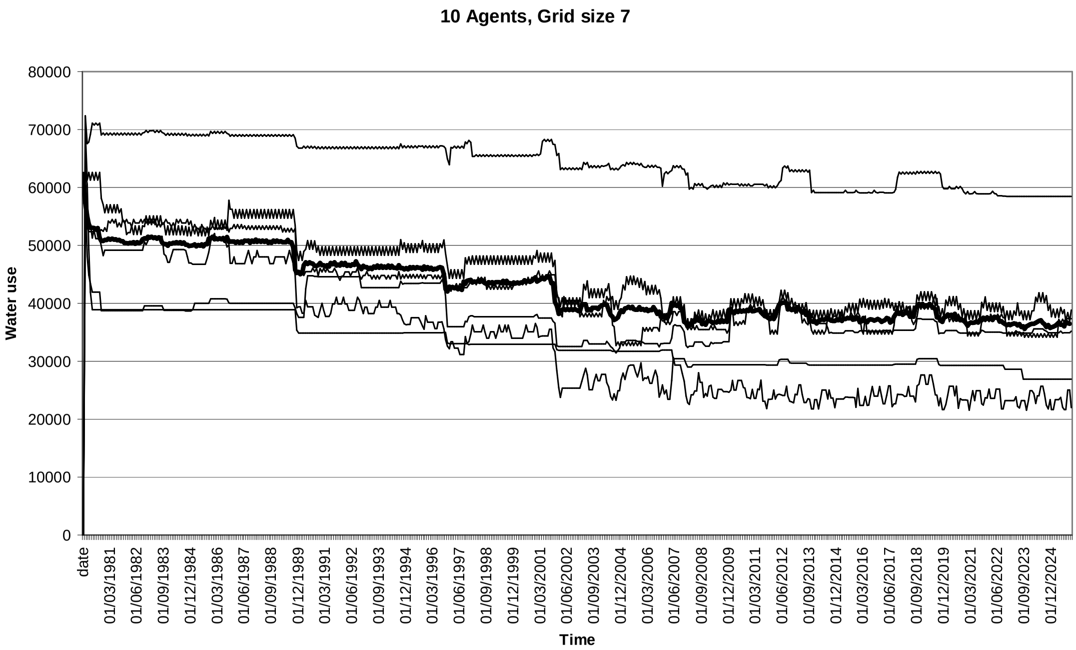

Figure 30: Water demand, agent density 0.2

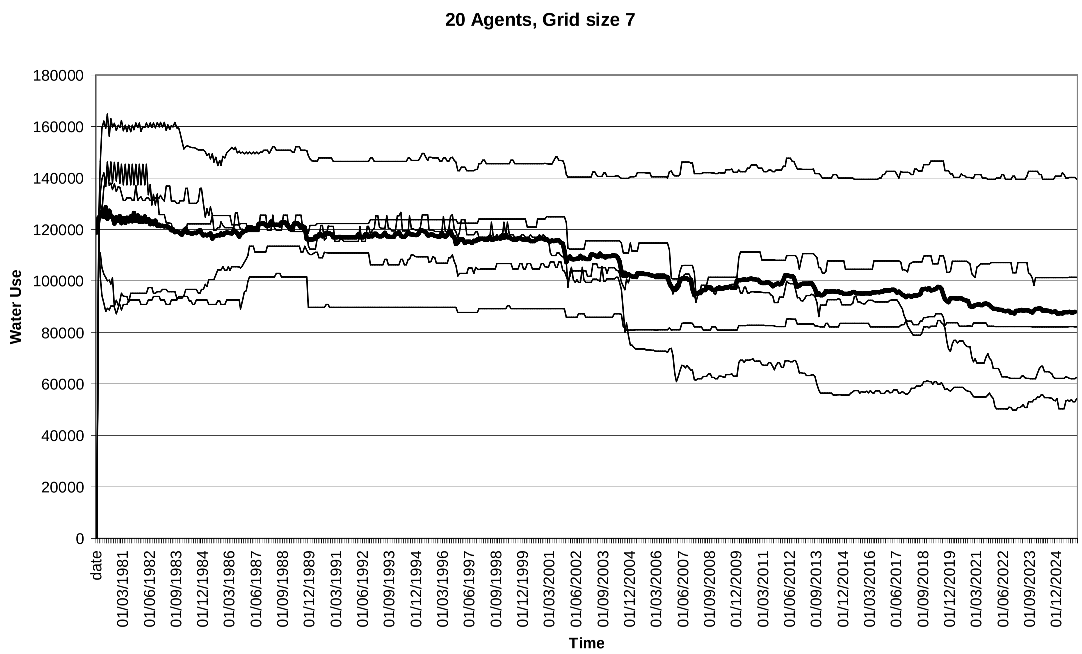

Figure 31: Water demand, agent density 0.4

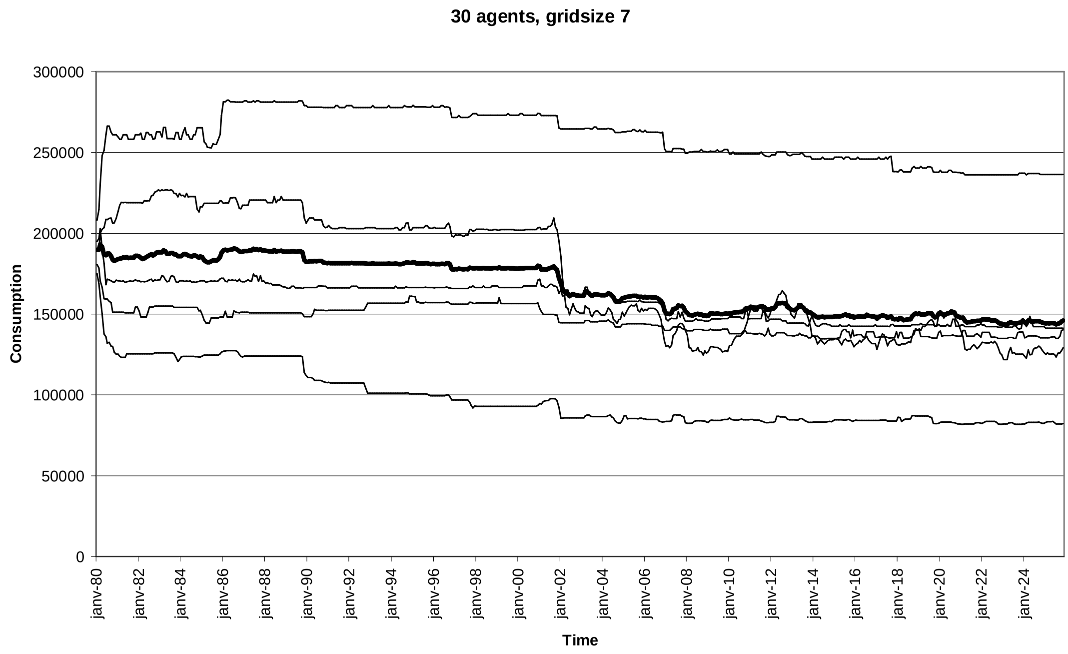

Figure 32: Water demand, agent density 0.6

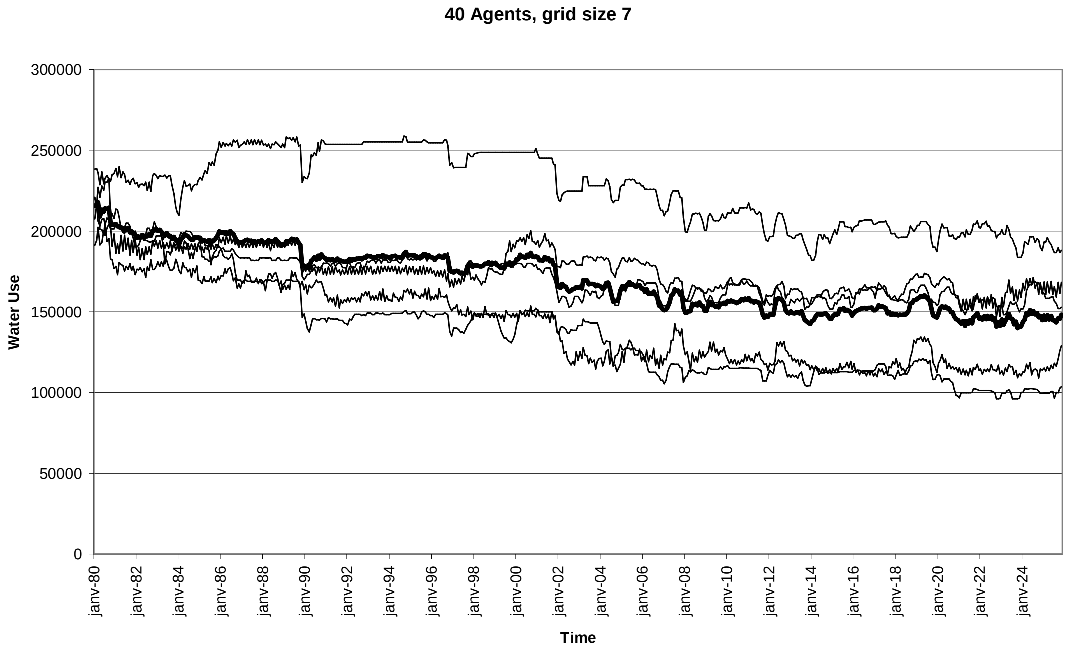

Figure 33: Water demand, agent density 0.8

The size of the grid can either be finite, or infinite. In this particular case, if the grid is actually a mapped 3D space, the size can be thought of as infinite (every agent has the same number of cells in its neighbourhood). Several important points must be made in order to explain the following assumptions and tests.

1) The size could be not important in itself

2) The number of agents could be not important in itself

3) The ratio agents / size, *i.e.* the density could be important

4) The social environment will define the extent to which an agent can see other agents.

Assertion number 1 is expressing the fact that the influence of the size of the grid cannot be evaluated as a single parameter. Changing it also impacts on the agents' density, as well as the communication paths. The same meaning is in assertion number 2. Number 3 and 4 represent the assumptions that will be tested below.

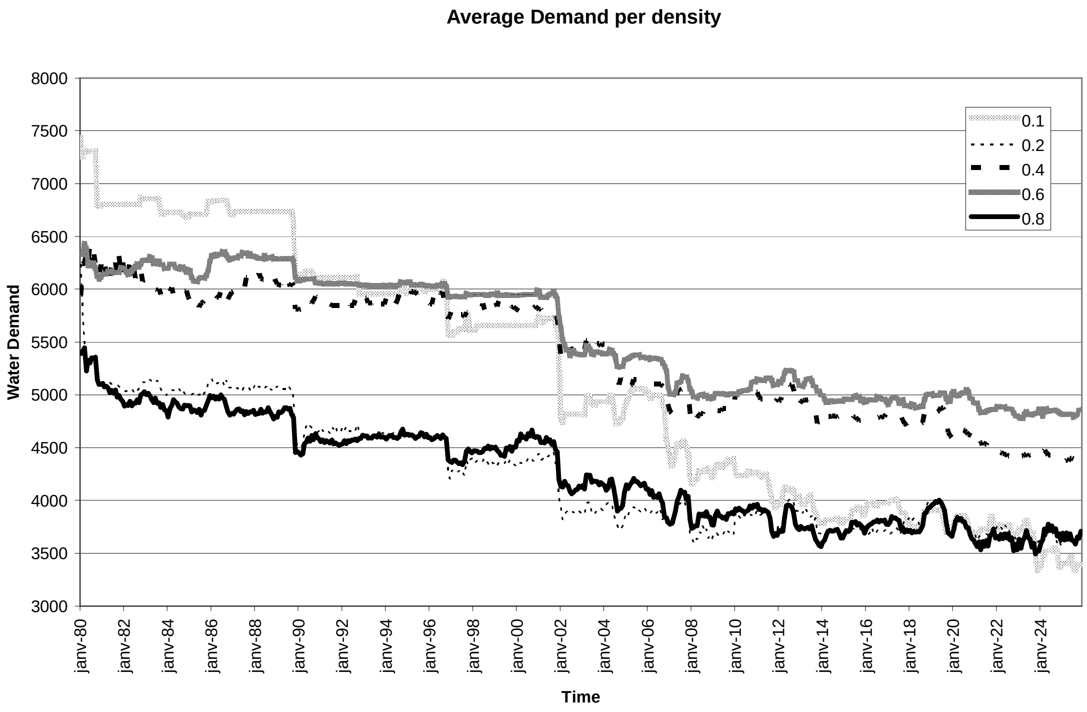

Figure 34: Average water demand with respect to agent density on the grid

One can observe in the above graph that, while the general trend is a decrease in water demand, there are differences according to the density of agents on the grid. A low density displays the most important variations, for example in 1990 and 2002. Due to this sensitivity, it is also the demand that falls the most quickly. There seem to be two different groups for the remaining densities, with the evolution of the simulations for densities of 0.4 and 0.6 close to each other, as are 0.2 and 0.8.

The tools used in this case are simple and descriptive. It would be interesting to assess more rigorously similarities amongst different sets of simulations, but currently, there does not seem to be any available software that can be used for treating the amount of data generated by the model.

Focusing on the different number of agents in a simulation, SPSS can be used in order to assess whether all sets of results might have similar statistical properties, and the conclusion is not equivocal. As shown in the tables below, when studying the relative differences in every series, the results are considered to be from the same sample with a probability superior to 0.96.

Test Statistics[a,b]

	lag
Chi-Square	.573
df	4
Asymp. Sig.	.966

a. Kruskal Wallis Test

b. Grouping Variable: VAR00008

Table 23: Kruskal-Wallis statistics for runs with various densities

An initial conclusion of this test could be that the density of agents does not matter. Intuitively, though, one can understand that the density is linked with the amount of interactions, and therefore this result would be surprising. But the non parametric method used is based on the ranking of data, and not their absolute value (see table below, displaying the mean rank of every run in the series). This could mean that the studied object would more likely be the process itself, leading to the interpretation that the process generates data with similar properties regardless of the size of the population. By increasing this size, the results themselves are changed, due to the increase in possible interactions, but their underlying distribution is not.

Ranks

Run	N	Mean Rank
0	55	1360.5
1	55	1375.1
2	55	1365.5
3	55	1390.5
4	55	1385.6
Total	275	

Table 24: Mean rank for runs with various densities

In fine, it seems that changes in density within a set of assumptions do not significantly impact on the output's distribution. Provided that the density is high enough to enable a minimum amount of communication amongst households, further increase would only lead to potential changes in absolute value of the output, but not leading to a change in the underlying distribution.

Since density as such does not appear to be a crucial parameter in this model, one then wonders whether this role could be played by the extent to which agents can see each other on the grid, and that is now the object of study.

5.3.3 The visibility parameter

One can consider visibility as a crucial parameter, with values at which the model's output differ. This section will study the potential consequences various ranges of visibility.

Different simulations were undertaken to assess the importance of the visibility parameter. This first set uses the standard simulation parameters, and is composed of 10 agents. The representation of the runs is as follows:

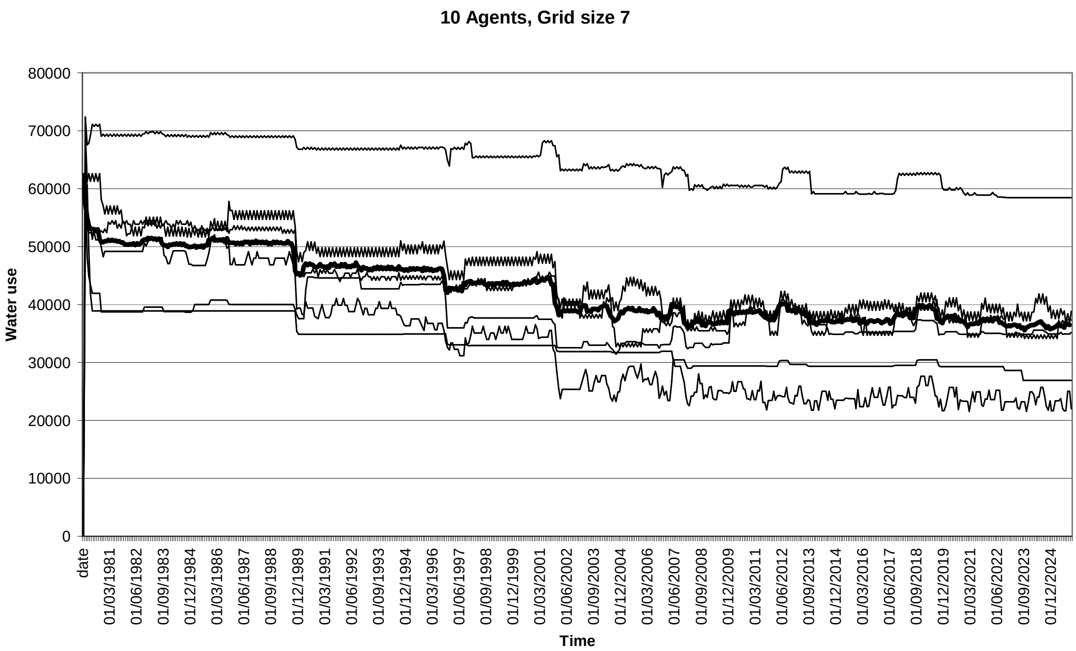

Figure 35: Reference run, visibility = 6

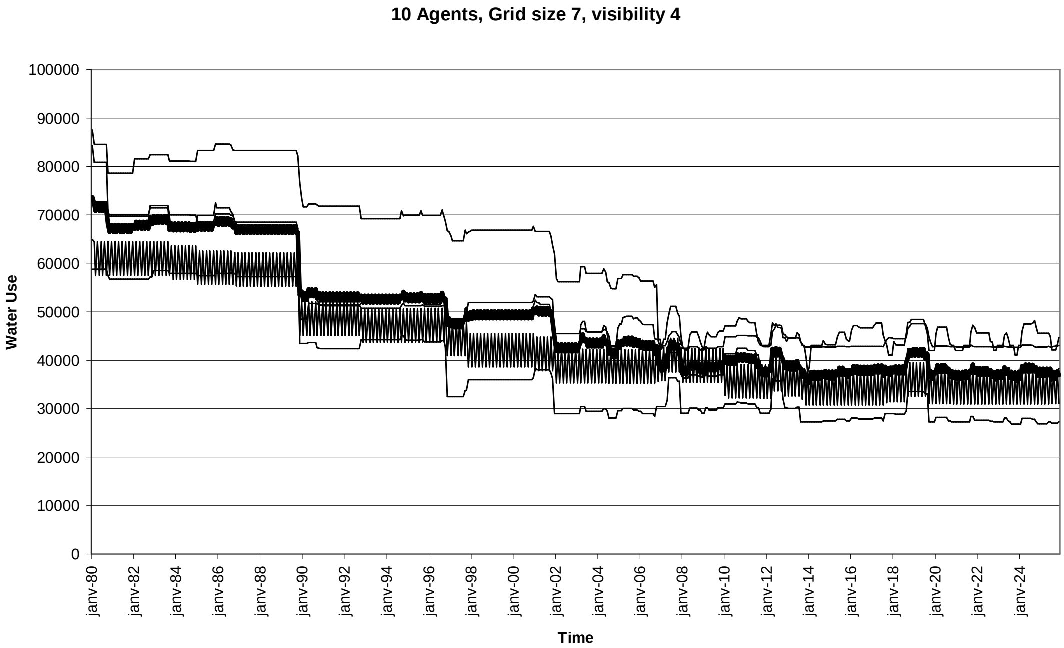

Figure 36: Reference run, visibility = 4

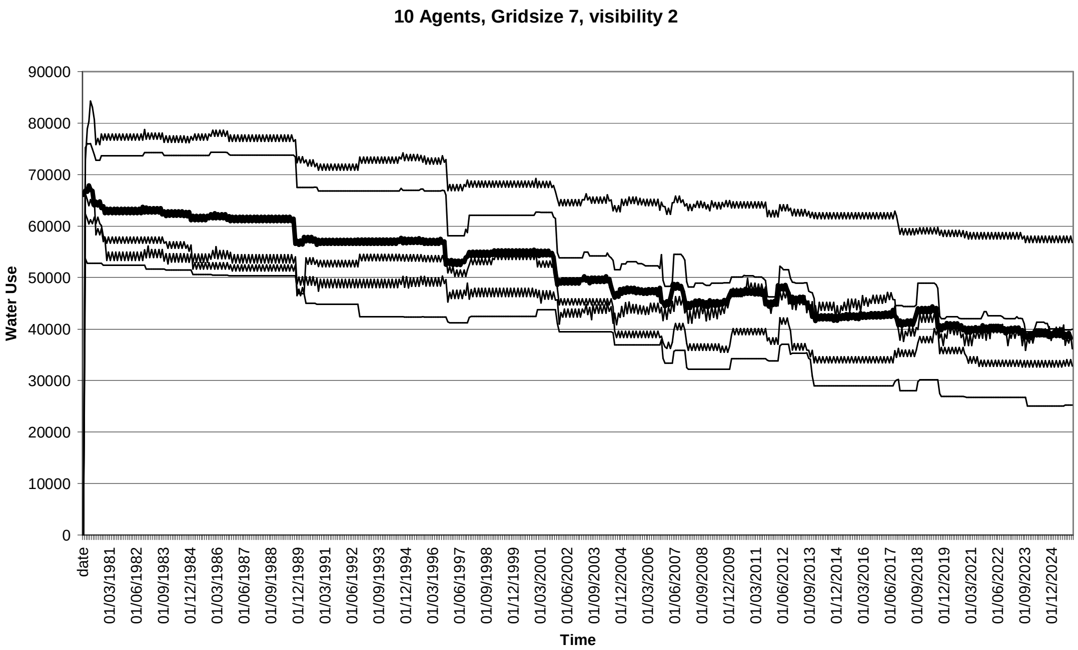

Figure 37: Reference run, visibility = 2

While there is only a single run showing micro instabilities with simulations whose vision is 6 or 4, there are 3 when it is equal to 2. This could lead us to assume that stability relies on a relatively high level of communication.

But some other simulations could cast a doubt upon this theory.

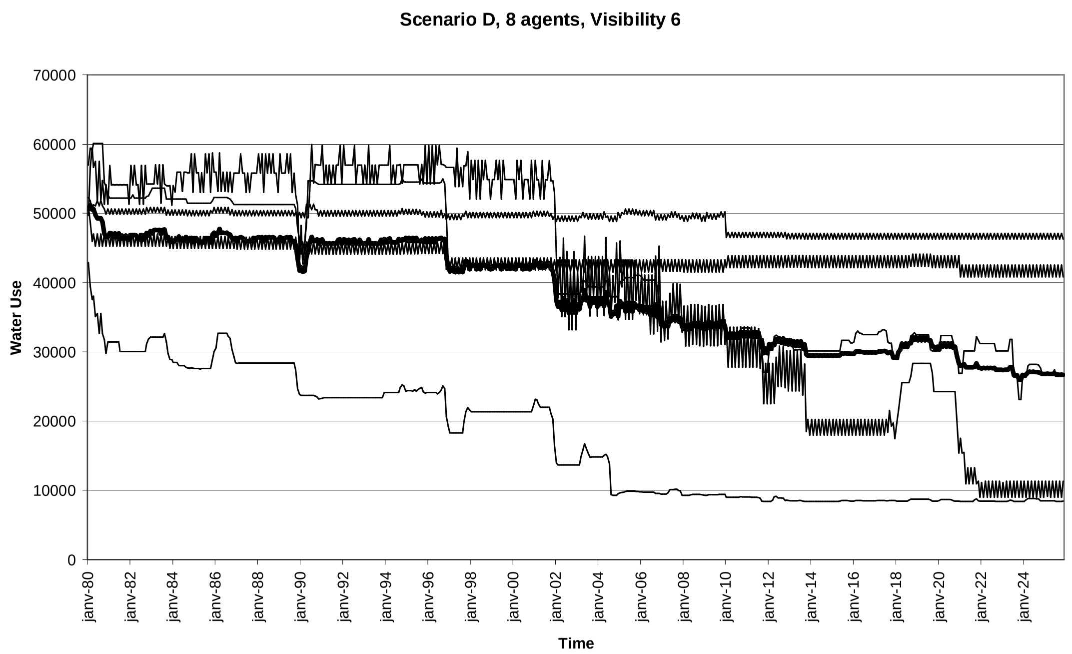

Figure 38: Scenario D, visibility = 6

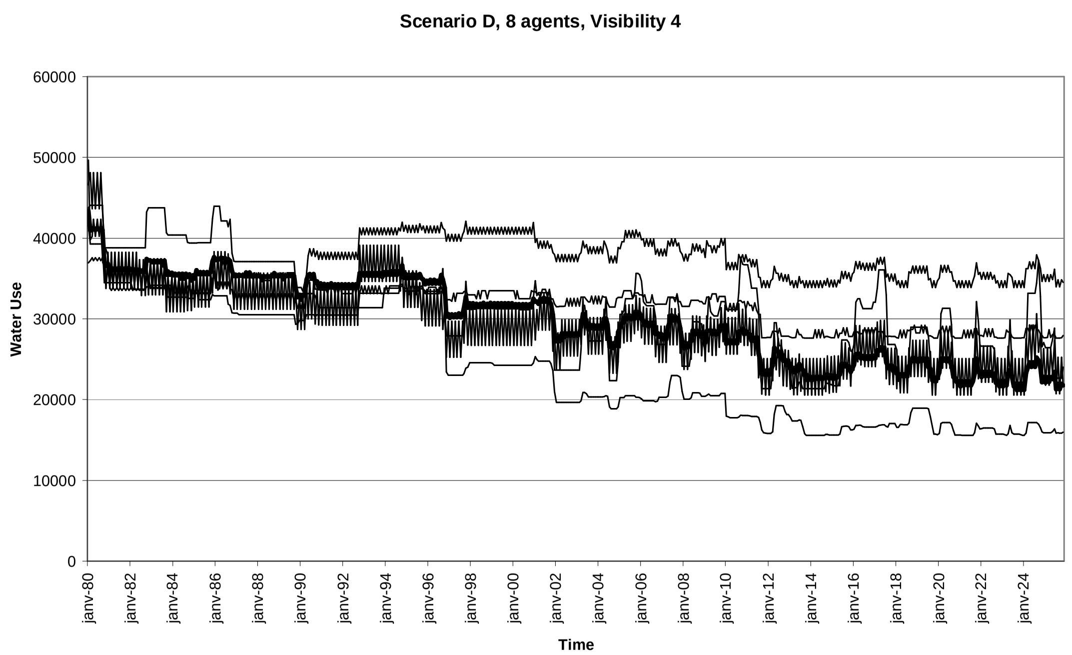

Figure 39: Scenario D, visibility = 4

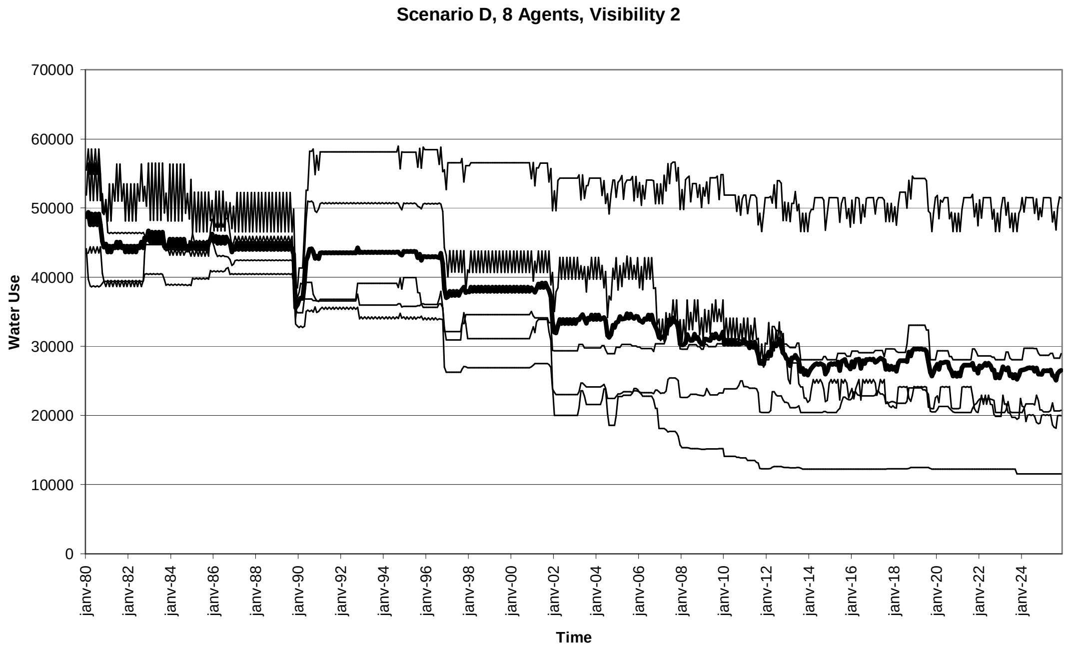

Figure 40: Scenario D, visibility = 2

In this case, the parameters used are those of scenario D. As one can see, the simulations with a larger vision parameter seem to show more micro instabilities than those with lower values.

In order to test this, a complete set of simulations was run that kept all previous scenario parameters, apart from a reduced visibility of 2. The aim is to analyse the behaviour of the changes. The most significant indicator is then the behaviour of the relative changes happening in the series, as well as their frequency and statistical properties.

Also, the results presented include a representation of the normal distribution with equivalent parameters to the sample used. It is obvious then that these are not normal and that they show the unmistakable fat tailed and high peaked distribution that is associated with positive kurtosis.

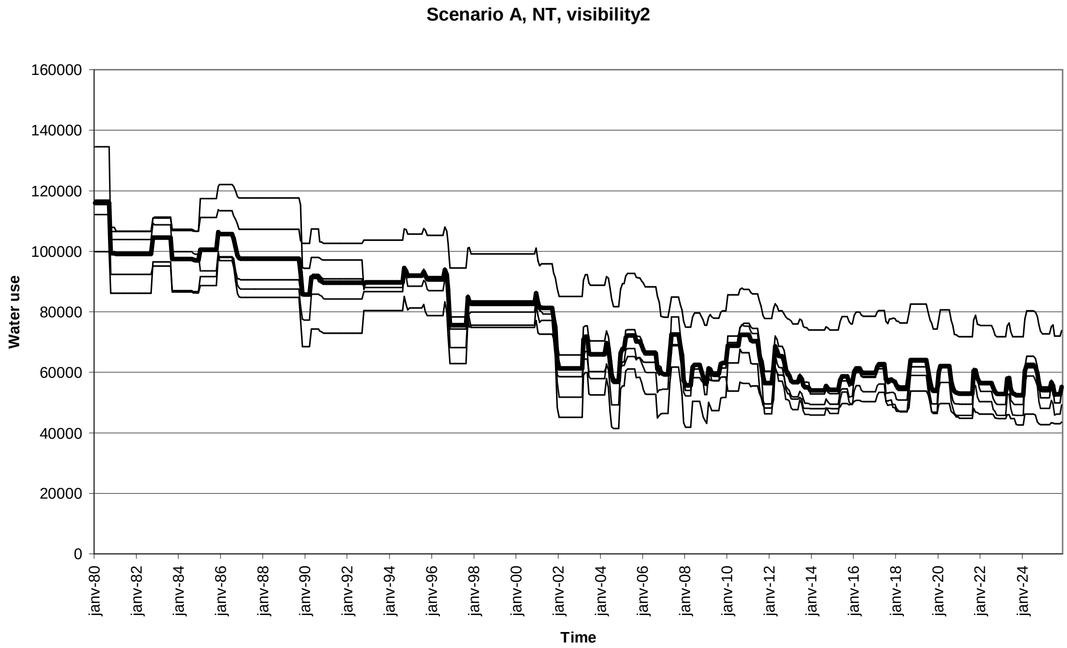

Figure 41: Scenario A, non-toroidal grid, visibility = 2

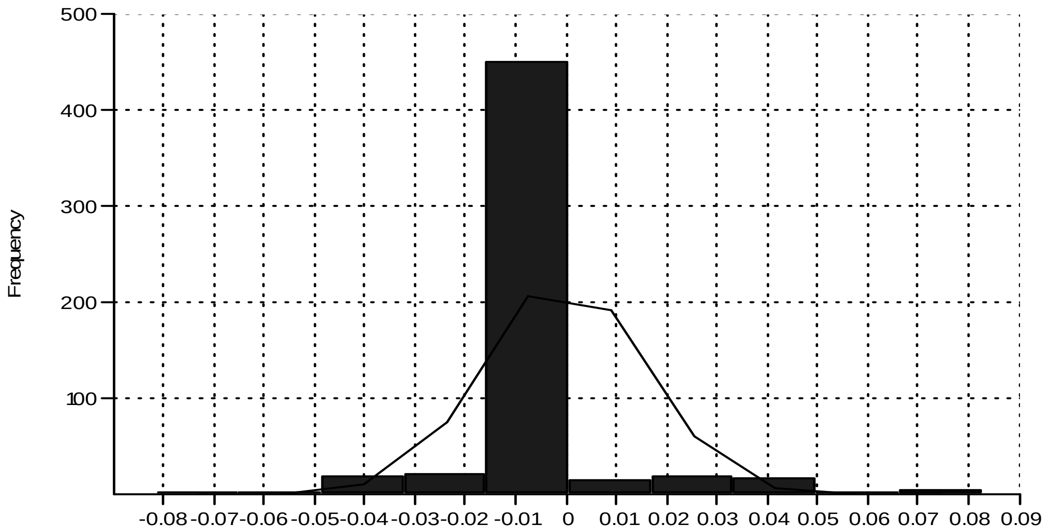

Figure 42: Comparison with normal distribution, Scenario A, non-toroidal grid, visibility = 2

The graph above displays relative changes for scenario A, with reduced visibility. The curve represents the normal distribution with equivalent parameters (mean and variance) to the relative changes.

Now looking at scenario B, the changes are as follows:

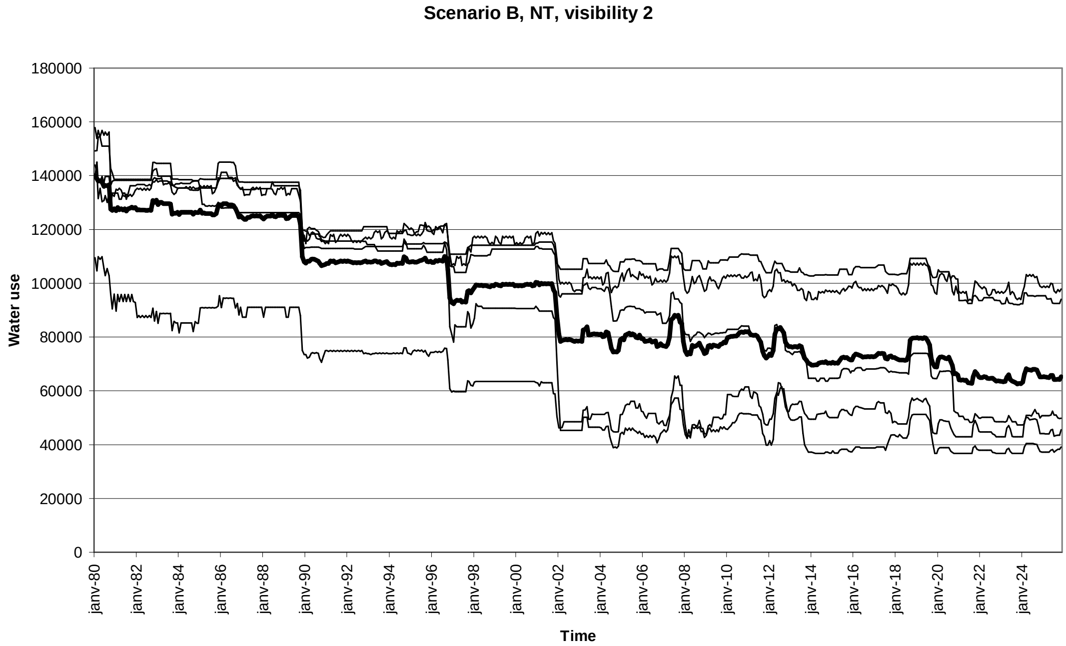

Figure 43: Scenario B, non-toroidal grid, visibility = 2

With respect to the standard simulation undertaken with parameters corresponding to scenario B, one can notice a more common reduction of water use in the simulations. The importance of self-endorsements in this scenario, coupled with a lower visibility tended to weaken the community-based endorsements, and resulted in several agents adopting new technologies.

The histogram of relative changes for scenario B with reduced visibility still demonstrates the presence of non-normally distributed changes, as shown below.

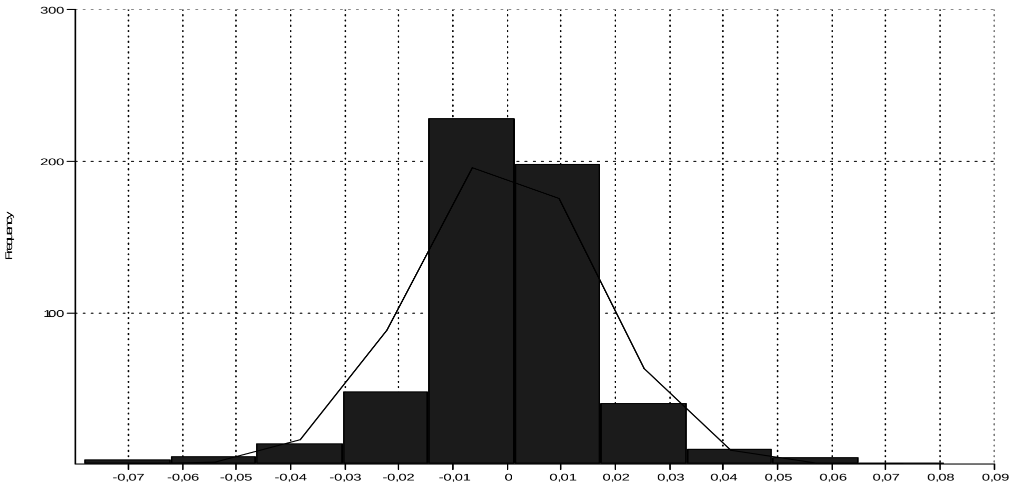

Figure 44: Comparison with normal distribution, Scenario B, non-toroidal grid, visibility = 2

The same type of analysis is now undertaken for scenario C.

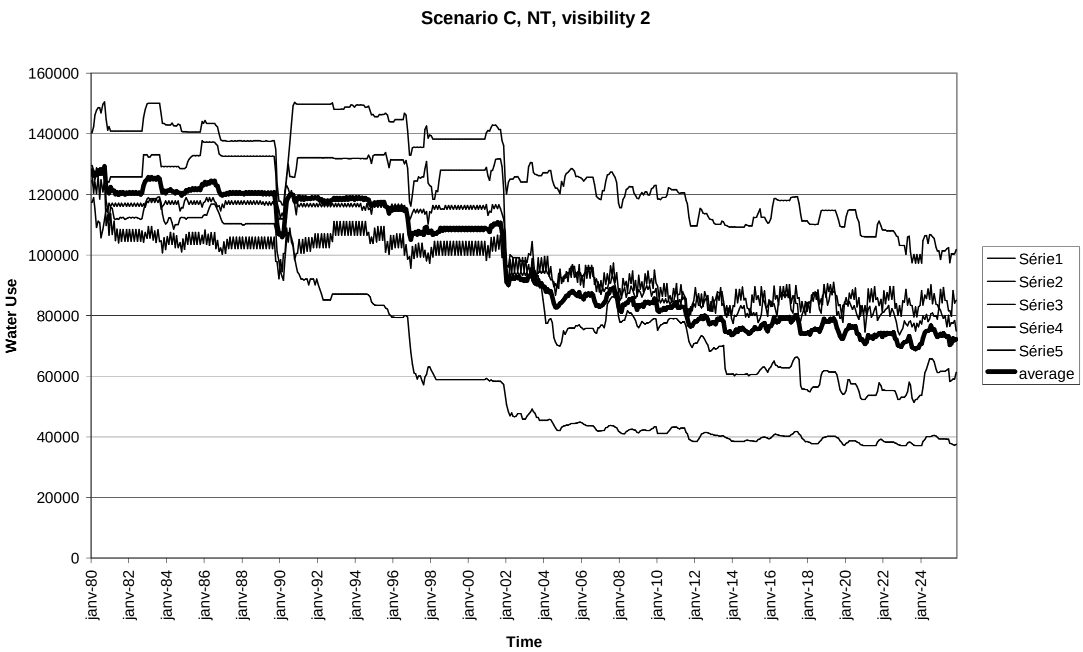

Figure 45: Scenario C, non-toroidal grid, visibility = 2

One can notice that the decreasing effect seen in scenario B does not seem to hold here, as the levels of water consumption are higher in this case than in the case of scenario C with standard parameters. Two series stand out in this set of runs, both presenting small repeated variations, both with fairly similar patterns to each other, but one with a smaller range of variations than the other. It is mostly visible in the period from 1990 to 2002.

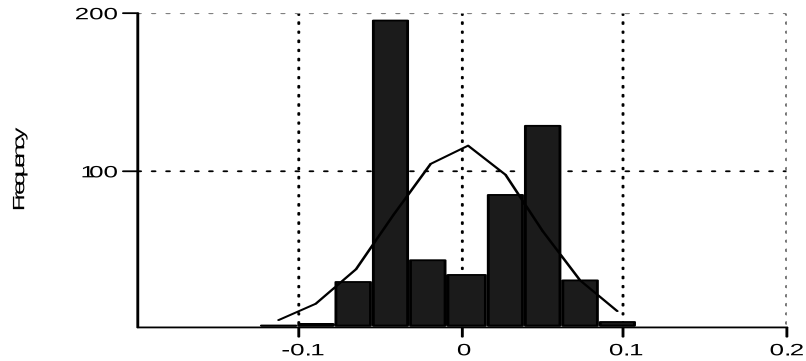

Figure 46: Comparison with normal distribution, Scenario C, non-toroidal grid, visibility = 2, series with small micro variations

The graph above represents the plotting of the higher of the two series, the one showing what could be denoted as small “micro variations”

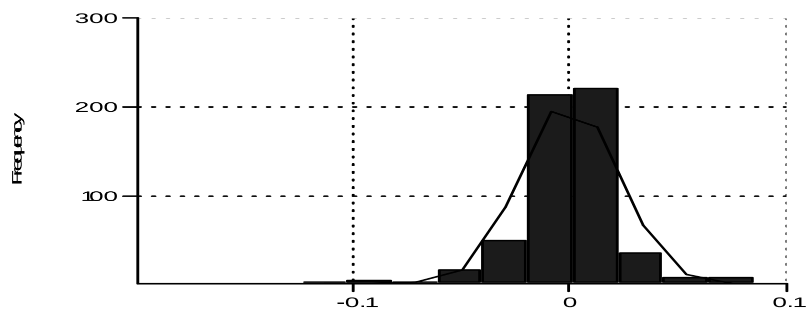

Figure 47: Comparison with normal distribution, Scenario C, non-toroidal grid, visibility = 2, series with large micro variations

This graph represents the result for the series displaying the lower of the series, the one showing larger “micro variations”.

As one can see, in both cases the normal curve does not match the histogram shape, a phenomenon confirmed by the visible higher peaks and fatter tails.

For scenario D, as showed in the graph below, the main change is the fact that a decreasing trend is also present. As seen with scenario B, the cause lies in the endorsement value. The high value of local endorsements results in a relatively stronger influence of one neighbour on the other. One could understand this phenomenon as a compensation of visibility reduction by the increased importance of neighbours' activities in an agent's decision process.

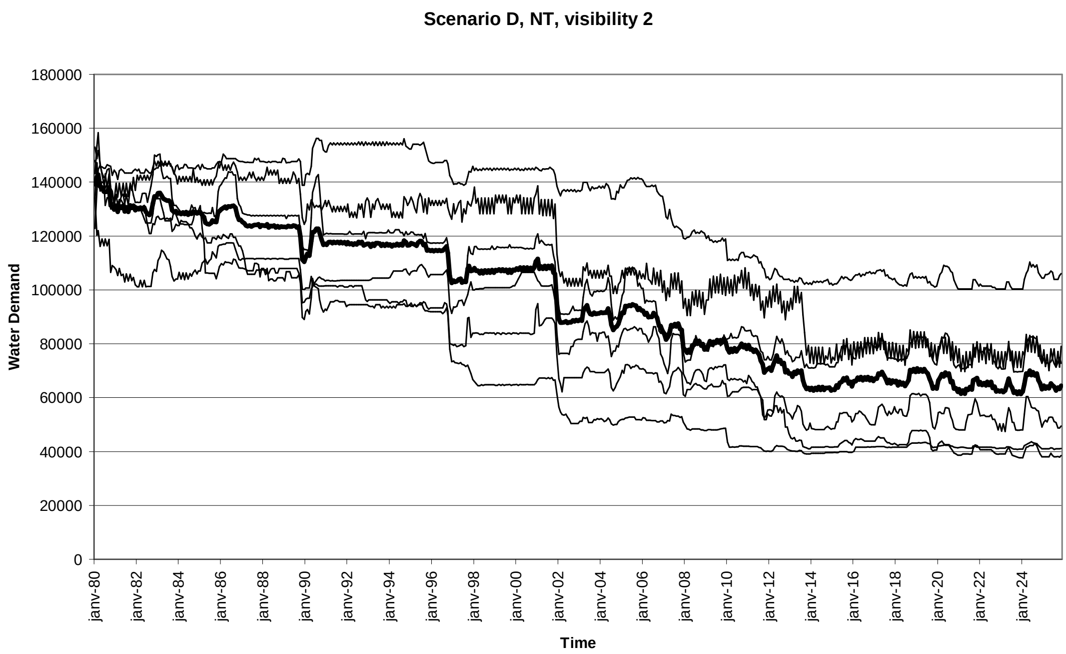

Figure 48: Scenario D, non-toroidal grid, visibility = 2

Still, as with previous scenarios, the relative changes are not normally distributed, and show the common characteristics, the distribution being fat tailed and high peaked, as the graph below demonstrates.

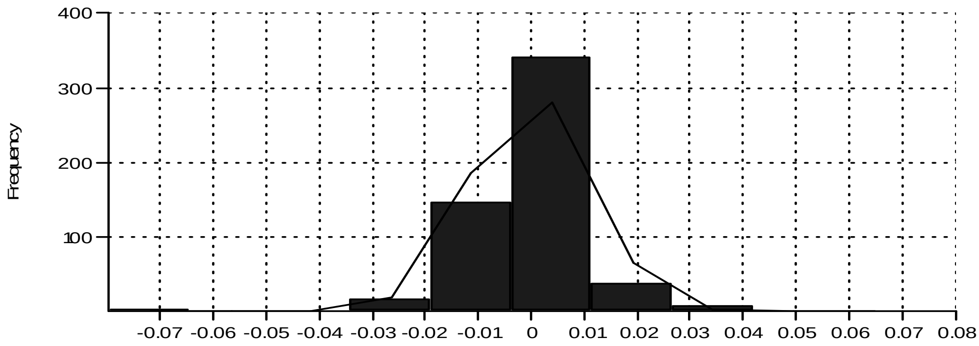

Figure 49: Comparison with normal distribution, Scenario D, non-toroidal grid, visibility = 2

In this case, the average relative variations have a mean of -0.000507754, and a standard deviation of 0.0285293. Also, the median is 0, and the skewness and kurtosis are respectively 0.123833 and 2.69326.

In the end, by enhancing the vision range of an agent, one increases the amount of information available to this agent. One of the conclusions from such an increase is equivalent to the comment made regarding the network structure, with potentially statistically significant changes between simulation runs. Also, the different values for the vision of an agent seem to have another effect. When associated with a low density, ensuring a minimal amount of connections, there seems to be another phenomenon, with what has been labelled in the previous chapter micro-variations. This could be justified by the fact that the subjective evaluation of this minimum amount of information would be very sensitive to changes in one endorsement value, such as the memorised ones.

Another parameter that one might argue plays an important role in the determination of a simulation's output is the extent to which an agent can remember what happened in the past.

5.3.4 The memory

Memory can be judged as a critical factor. By referring to events further into the past, can agents show distinct behaviours? This section will analyse this, comparing outputs from simulations with short and long memory.

One would expect that a “better” memory would yield different results, maybe inferring a more stable consumption, due to the greater amount of choice in an agent’s action, and the eventual probability it would reproduce its own pattern through the repetition of self endorsed actions.

There are other possibilities obviously, and the following simulations intend to assess the effect of an increased memory.

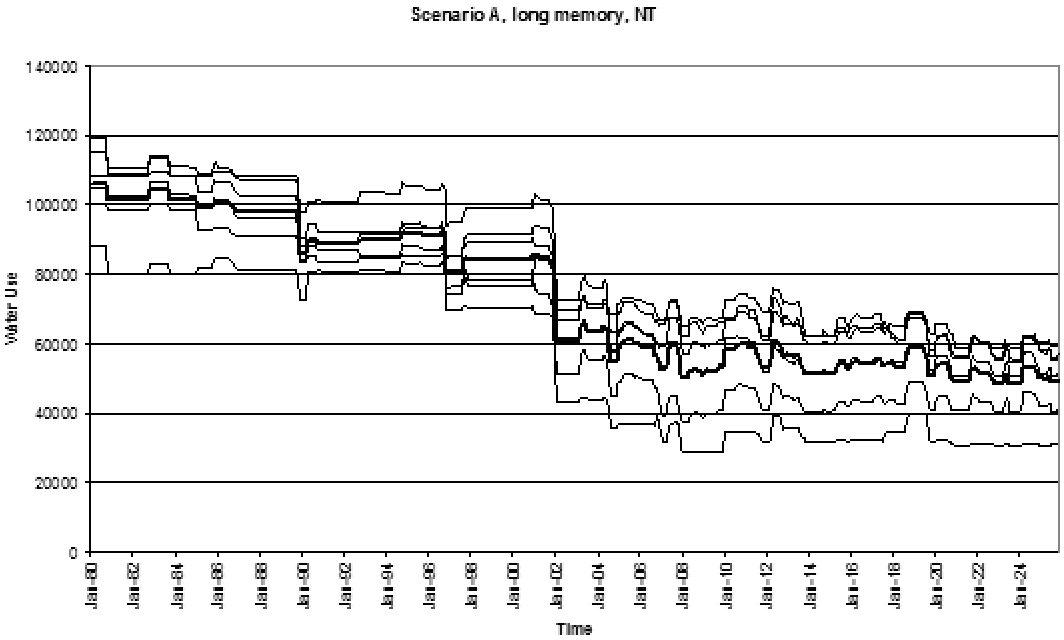

Figure 50: Scenario A, long memory, non-toroidal grid

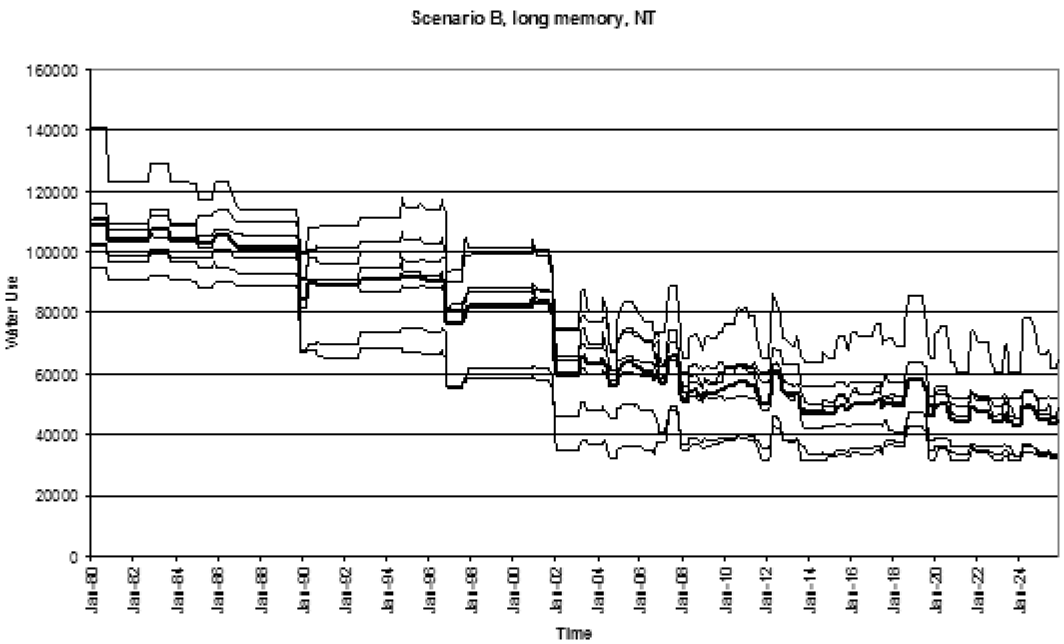

Figure 51: Scenario B, long memory, non-toroidal grid

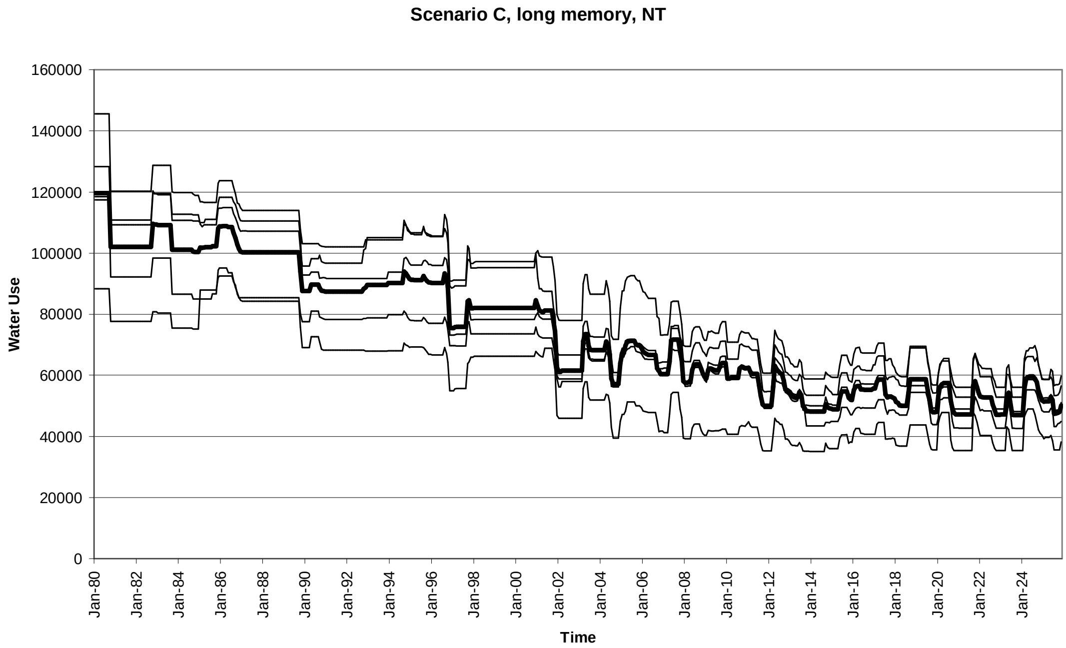

Figure 52: Scenario C, long memory, non-toroidal grid

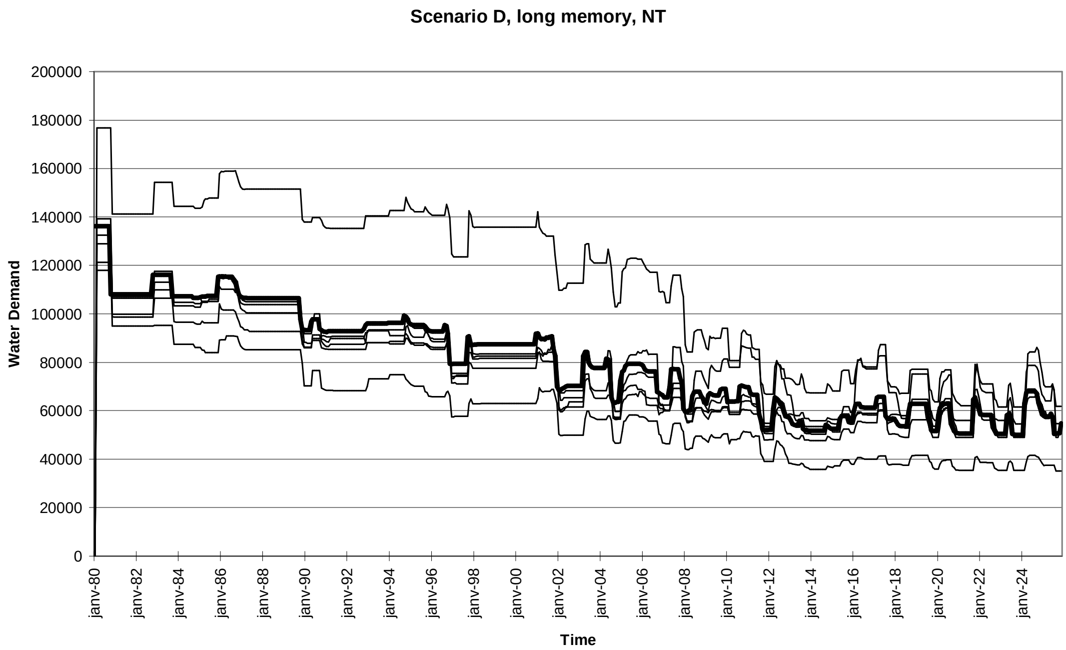

Figure 53: Scenario D, long memory, non-toroidal grid

One can compare the graphs above with the original ones from the four scenarios in section 5.2.2. The trends seem quite different as the better the memory (or the more the agents can remember) the more marked the decrease in water use over the period. The reason for this phenomenon is that they not only remember previous water use, but also previous drought periods when the policy agent was communicating on water use reductions.

Therefore memory allowing the agents to increase the amount of information available to them seems, in this particular case, to increase the decreasing trend of water consumption.

The explanation for this is that when remembering past uses, agents also remember past droughts, and their consequences. This seems consistent with a more sensible approach in the real world regarding the use of natural resources, as well as the building of a household’s patterns of use from one year, or one season to another.

One could hence draw several conclusions from this change of behaviour as a consequence of a better memory.

The additional memory actually results in more information available to the agent. It could be argued that it is that additional information itself that drives the water consumption down, as this seems a behaviour that could be qualified of “reasonable” in the real world. Nevertheless, this relies on the assumption that increased information leads to the wisdom of reducing one’s use, and also implies knowledge of (in this case) natural resources, as well as an awareness of at least financial and environmental issues.

This is obviously not the explanation for such a phenomenon. The actual reason for this trend is implied in the model itself. The memorable events are by definition of the memory algorithm those with the highest endorsement. At a time step corresponding to a normal (as opposed to drought) situation, the endorsements are regarding oneself, and the social environment. But at a time of drought, the endorsements also include those regarding the message broadcast by the policy agent. As there is a chance that this preached behaviour will be adopted, the actions / activities with lower water use will also be given endorsements from oneself, and the environment.

As the endorsements are superior in numbers, the chances that the values of the specific actions selected are higher increase. The consequence is that the memory of agents is likely to contain more patterns of low use at anytime and therefore is driving the overall consumption down.

It is worth considering that in a theoretical grid where no agent can see any other, this trend should happen anyway. The agents which are sensitive to the policy agent's message will decrease their water consumption while all others will only change as the replacement of old devices becomes a necessity.

Concluding this analysis, it is clear that the set up of a better memory has an impact upon the behaviour of the system. On a methodological side, this test showed that the implementation of an agent's memory is consistent with intuition and observation: more extreme events are likely to be remembered for longer than common ones, provided that the endorsement mechanism is set up appropriately. On a qualitative side, this demonstrates that the model tends to be built in such a way that the natural general tendency it demonstrates is a decreasing trend. The explanation for this lies in the fact that the only changes described in the Environment Agency's scenarios that do not depend upon the agent's own behaviour are embedded in the innovation and diffusion of new appliances.

A further analysis of this diffusion is the subject of the following section.

5.4 Detailed analysis of innovation diffusion

As detailed in chapter 3, for every household, appliances are available from the start of the simulation period. During the time interval, some become available to replace already present ones, or could emerge as new water use activities. At the same time, and to represent the assumptions about the changes of regulations, some appliances will not be available anymore for the households to replace or add to their endowments, as described in the first section of this chapter.

The process of adoption can then be, for increased convenience, presented as composed of several stages: observation, evaluation of current state, availability, endorsement, and decision.

In the observation stage, the agent gathers all the information regarding its environment, both geographical and social. The information collected refers to its own ownership and use of water, as well as its neighbours. It also refers to the situation of the neighbour with respect to his own characteristics, as to how similar they are in structure or pattern of use.

During the evaluation stage, the agent assesses whether any of its own appliances need replacing. First, a probability is used, taken from a Weibull distribution, which will determine if any appliance is broken. If it is not, then another probability is used to infer whether the agent has decided to replace the appliance anyway, as often people do not wait for appliances to break before they replace them, but do so at their will, for example for comfort or to update their installation.

If an appliance needs to (or is considered to) be replaced, the agent then checks which appliances are available on the market. The list of available appliances is updated every month, with new technologies or regulations having an immediate effect upon it. Once this list is known, the agent classifies the appliances into equivalent ones, *e.g.* considering all toilet-flushing technologies as responding to one particular activity. The list from which the agent will select its future appliances is therefore tailored to its current situation.

Every appliance is then endorsed. The agent gathers from its own observations some indication of who uses which technology, what is said about it, and how it is used. These qualitative assessments are transformed into a quantitative measure, which allows a direct comparison of appliances with each other (provided they are equivalent in the agent's activity list). The appliance with the higher endorsement is selected. Endorsements are described in a previous chapter, and are related to the product itself, to its users, and to the way they use it, as well as the way the observing agent can relate to the observed ones.

The way innovation is implemented in this model is not a typical use of the literature available (*e.g.* the implementation of a common diffusion process). It is drawn from observation, with properties of the process tailored for the representation of the model, and not implemented from a theory present in the general innovation diffusion literature.

Technologies in general have within the model, as in real life, three important stages in their lifecycle: their emergence, their diffusion, and their disappearance.

Emergence and disappearance, at least with respect to the availability to the households, are set exogenously, using specific variables. The diffusion itself is an endogenous process, based on endorsements of some components of the model by an agent, namely the other visible agents, their activities, and the policy agent.

In most innovation theories, the level of penetration follows an S-shaped curve with time, with the corresponding marginal adoption being a bell-shaped curve, as shown in chapter 3. The implementation of innovation in this case provides an opportunity to assess whether the process described would generate such shapes.

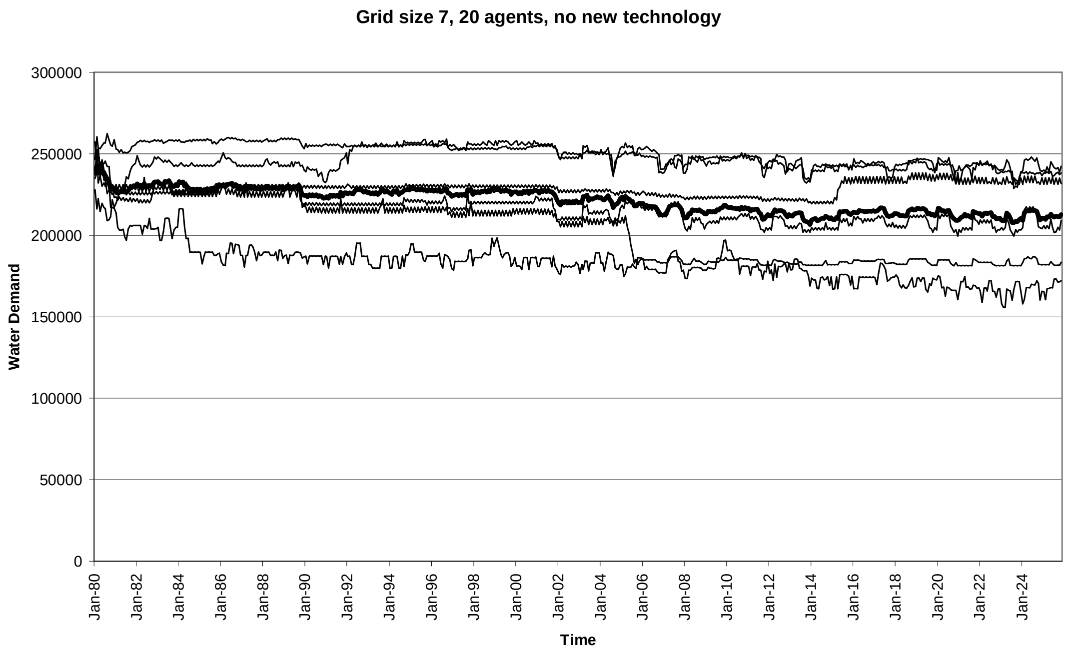

Figure 54: Scenario D, in the absence of new technologies

The graph below represents the diffusion of power showers in two runs with the parameters from the scenario delta.

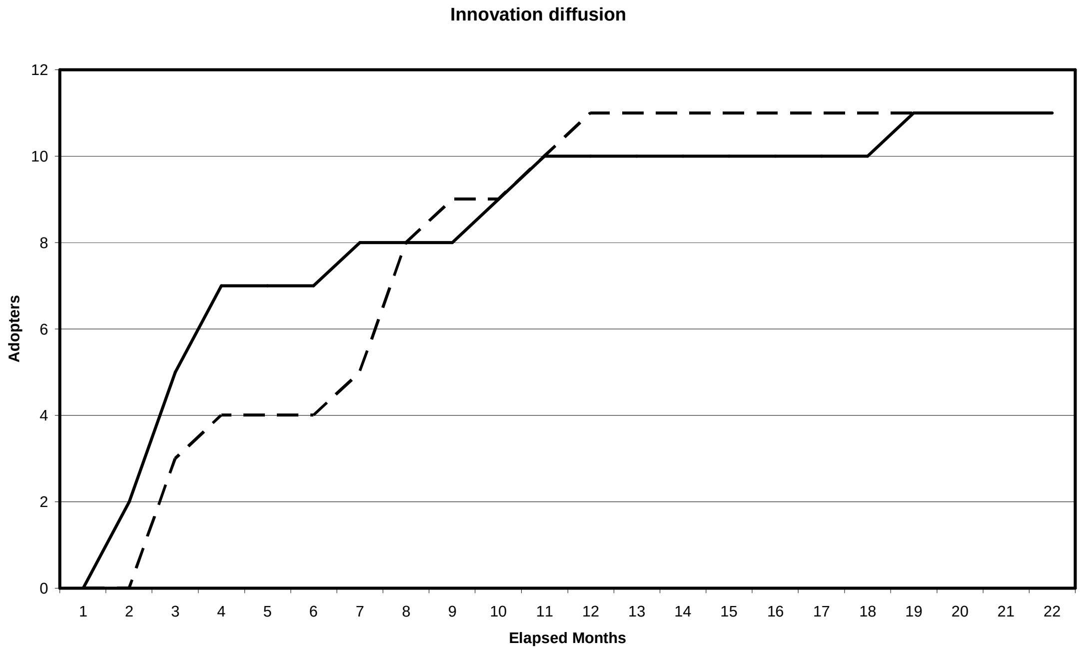

Figure 55: Diffusion of innovation

There are several patterns of diffusion that can be observed in a simulation, as shown in the graph above. While some can be considered as matching the sigmoid shape mentioned above, others show a rapid uptake that is difficult to consider equivalent.

As nearly all parameters are equivalent between simulations, the only justifications for this difference seem to be part of the network composed of the agents, and how linked they are.

The analysis of the network does not show any significant difference. The density of links is on average 5.5 per agent.

In the fifth run of scenario C, the adoption pattern for power showers is the most contradictory to a sigmoid. In this case, the network is composed of 9 cliques, which contain on average 4.11 agents.

For the first run of scenario C, which presents a pattern of adoption for power-showers which is sigmoid-shaped, there are also 9 cliques, but this time with an average size of 3.8 agents.

These kind of values seem to be consistently present when the density of agents and the size of the grid do not vary. Similar properties can be observed for the other runs: when the average size of the clique is low (around 3.8), the pattern observed is more similar to a sigmoid than when the value is high (4 and over).

Intuitively, one could assume that a lower average clique size, would limit the influence from the neighbours, and therefore allow for more innovative behaviour, due to the lower formal constraints upon the endorsements (as there are more households within an agent's neighbourhood, the absolute value the endorsement of a new appliance must reach gets higher).

Referring to scenario A, with agents that are relatively self centred, one could expect to observe agents less likely to be influenced by their immediate neighbourhood, and therefore a link between patterns of adoption and average clique size of the network that would not be as consistent. Unfortunately, the analysis of scenario A, in which the take up of new technologies is quite limited, does not confirm this hypothesis, as the main changes appear when appliances break and need to be replaced with their current equivalent, which is more water efficient and therefore reduces the water demand.

5.5 Detailed study of a particular set of runs

Some simulation results, although following standard rules, appear to generate extreme behaviours. The simple interactions in the model can lead to the adoption of very high or very low patterns, with no distinction. This certainly depends upon the randomisation system, as well as upon the initial values and attributes given to the households.

A representative example of such an extreme run is shown in the following diagram. The level reached for consumption is such that the other runs are not visible on a standard scale.

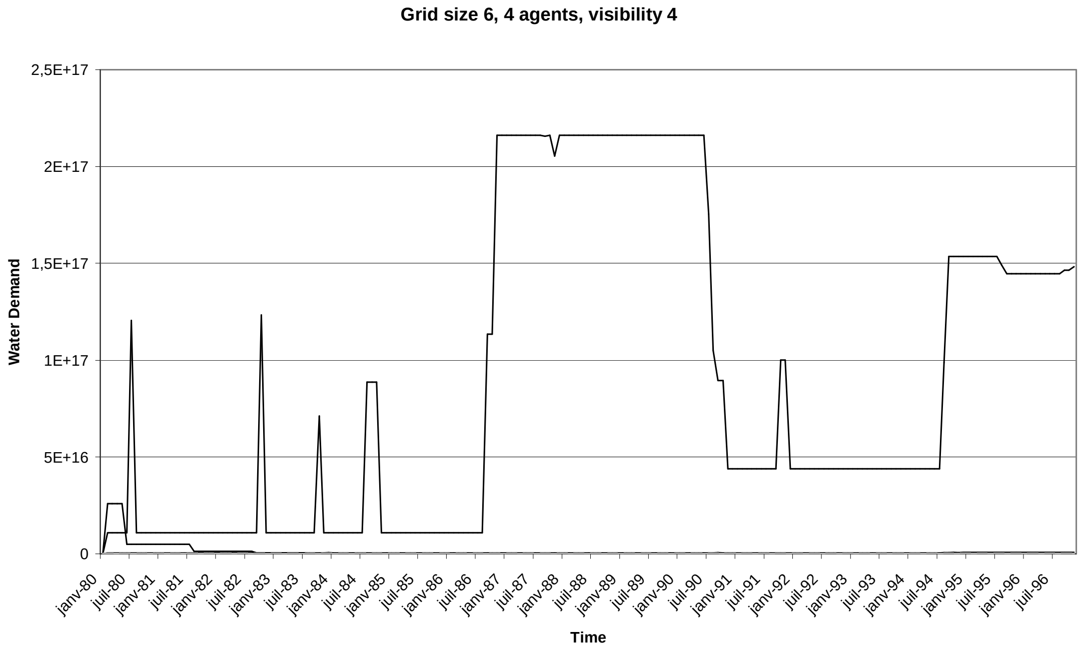

Figure 56: Standard scale representation of multiple simulation runs

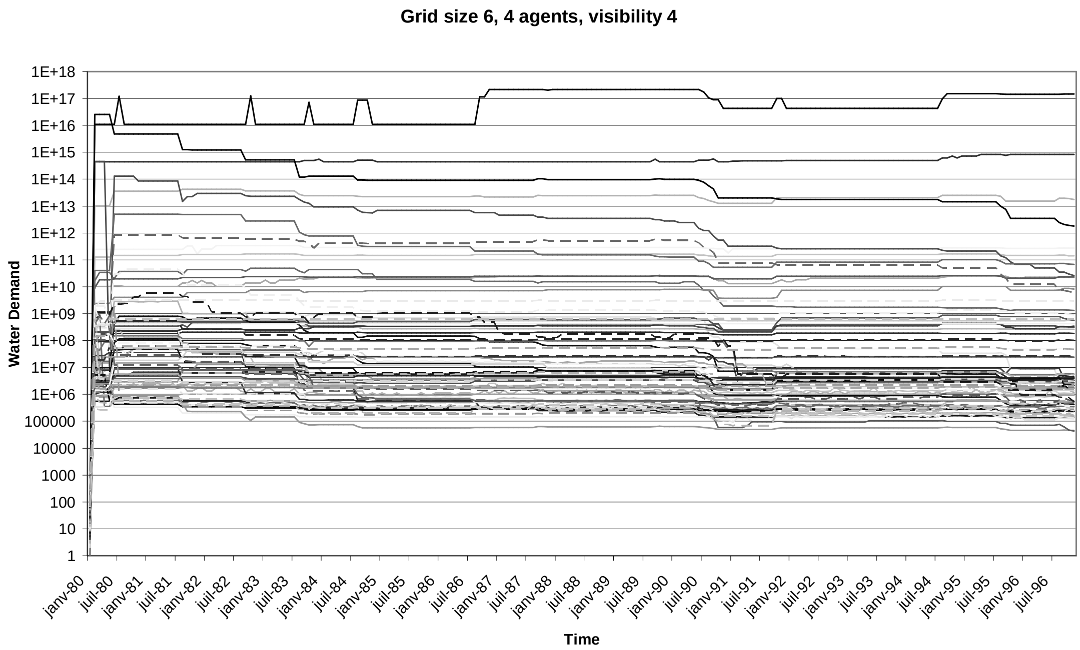

Figure 57: Logarithmic representation of multiple simulation runs

Only the transformation to a logarithmic scale allows the display of all the runs.

Obviously, the variations observed are well aligned within that set of runs, and referring to the external data that are input to the model shows the correlation for some of them. It is therefore worth remembering the global drought duration associated with this set of climatic data, and more precisely, stripping the data to the relevant timescale gives us the following.

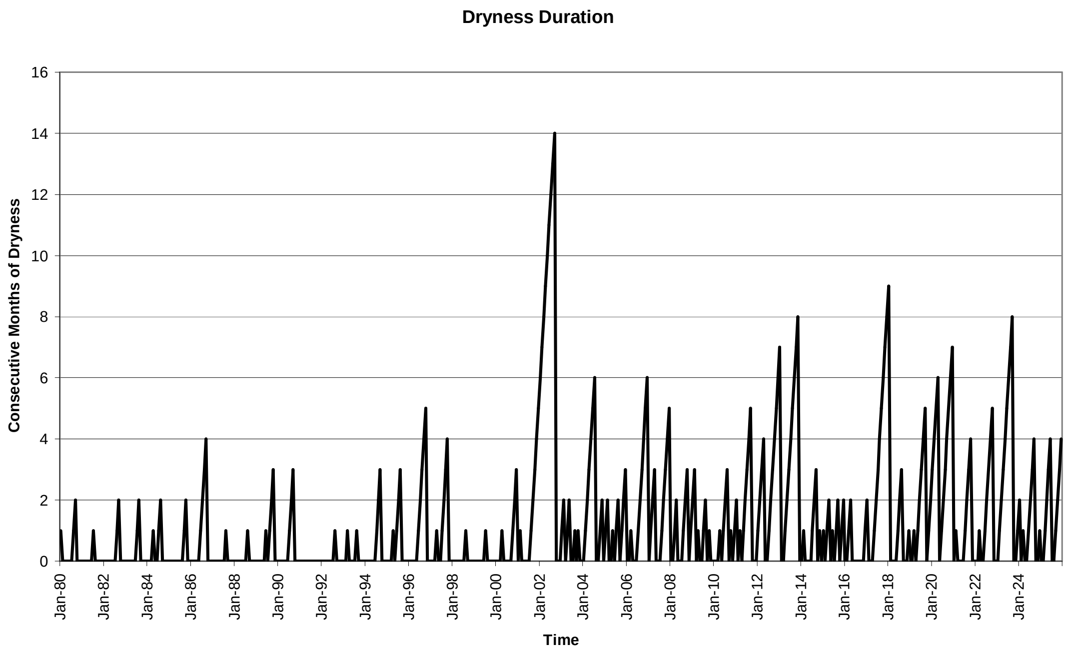

Figure 58: Dryness duration

Integrating the charts together one obtains:

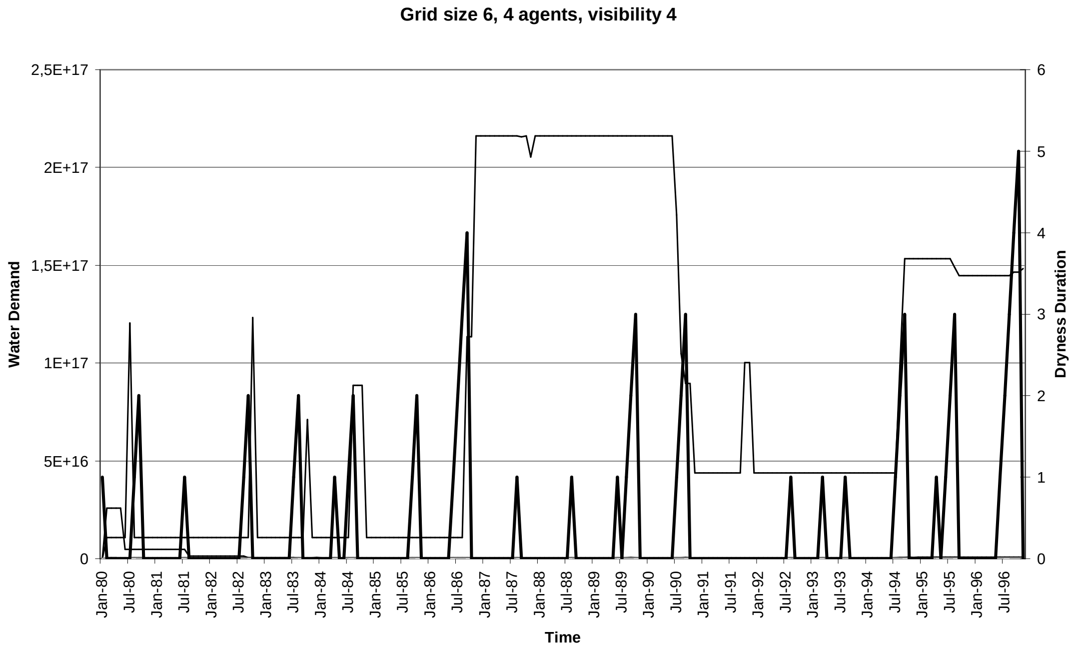

Figure 59: Multiple simulation runs and drought duration

One could expect that the effect of drought would drive consumption down. The matching of these visual indications reveals that the reaction to an exhortation from the policy agent is not always producing the expected effect. Only the major drought period lasting for 9 months in 1991 had an important and significant effect upon the water consumption. The other drought events do not seem to have any effect.

This demonstrates that either the behaviour of the agents is not implemented properly, or that there are other method related issues.

Although this behaviour does not seem to affect the vast majority of the runs, it requires investigation to understand what the cause of such variance within the simulations is.

The detailed study of this run shows exactly what is happening. As expressed in the description of the model, the policy agent uses a kind of average of the observed frequency and volume data from the households. Due to the initial conditions, the policy agent could then be biased by some extreme randomised value for the households.

It would therefore broadcast a message that would lead households to adapt by using patterns whose recommended values are higher than those in use by the households themselves.

5.6 Conclusion

This chapter is intended to provide simulation results for every scenario and a comparison amongst them. It is also intended to investigate the effects of parameters or structural changes upon the stability of the result.

Section 5.2 contained the detailed transcription and set-up of the different scenarios used by the Environment Agency. It also describes and justifies the values selected for the structure of the population for a set of simulations. It includes a detailed study of runs for each of the scenarios and is accompanied by a brief presentation of the results, both qualitatively and quantitatively. The quantitative analysis particularly demonstrates that the simulated data does not comply with the frequently encountered normality assumption.

Section 5.3 focuses upon the sensitivity of the model to some of its components. As Multi Agent Systems have been used after acknowledging the presence of complexity, and concluding that standard techniques presented limitations that made them impossible to use, this section presents a particular analysis of the sensitivity of the model. There were no thresholds to analyse, or derivatives to calculate. So in order to assess which changes they might induce, this section also includes an investigation of the effect of variations of parameters (or algorithms) associated to components deemed of importance.

Section 5.4 provides a detailed analysis of how innovation spread amongst the agents. The innovation diffusion relies upon a representation based on observation and evidence, and for which different tools such as endorsements have been used. The conjunction of endorsements as a means to evaluate subjectively another agent’s activities and a social location via grid coordinates is not present in the current literature. The first tests have demonstrated that it can represent correctly a process of innovation diffusion, as the discrete graph presented can be compared with a standard sigmoid generally observed.

In section 5.5 is an example of particular runs, providing the reason behind the emergence of extreme patterns, which contradict initial beliefs.

The next chapter will detail how these findings can be used, and their validity, as well as the opinions of the Environment Agency on the impact of this type of modelling, in the perspective of forecasting.