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1 **Dynamic Bayesian Networks as a Decision Support Tool for assessing** 2 **Climate Change impacts and adaptation of groundwater systems**

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16

17 **Abstract**

18 Bayesian Networks (BNs) are powerful tools for assessing and predicting consequences of water
19 management scenarios and uncertain drivers like climate change, integrating available scientific
20 knowledge with the interests of the multiple stakeholders. However, among their major limitations, the
21 non-transient treatment of the cause-effect relationship stands out. A Decision Support System (DSS)
22 based on Dynamic Bayesian Networks (DBN) is proposed here aimed to palliate that limitation through
23 time slicing technique. The DSS comprises several classes (Object-Oriented BN networks), especially
24 designed for future five years length time steps (time slices), covering a total control period of 30 years
25 (2070-2100). The DSS has been developed for assessing impacts generated by different Climate Change
26 (CC) scenarios (generated from several Regional Climatic Model (RCM) under two emission scenarios,
27 A1B y A2) in an aquifer system (Serral-Salinas) affected by intensive groundwater use over the last 30
28 years. A calibrated rainfall-runoff model was used to generate hydrological CC scenarios, and then a
29 simulation groundwater flow model (MODFLOW) was employed in order to analyze the aquifer
30 behaviour under CC conditions. Results obtained from both models were used as input for the DSS,
31 considering rainfall, aquifer recharge, variation of piezometric levels and temporal evolution of aquifer
32 storage as the main hydrological components of the aquifer system. Results show the evolution of the
33 aquifer storage for each future time step under different climate change conditions and under controlled
34 water management interventions. Furthermore, results also reveal the economic cost of the different land

35 use scenarios under such CC conditions. The DBN application is seen to be effective in propagation of
36 probabilities into the future to represent impacts generated by different hydrological scenarios. This type
37 of applications would allow establishing adaptation strategies for aquifer systems as the CC comes into
38 effect.

39 **Key words:** Dynamic Bayesian Networks, Climate Change, Decision Support Systems, Aquifers
40 management, Adaptation, Groundwater Intensive Use

41 **1. Introduction**

42 The prediction of hydrological impacts generated by Climate Change is an appealing
43 and emerging research area. However, research studies about climate change impacts on
44 groundwater systems are still relatively scarce (Scibek et al., 2007; Roosmalen et al.,
45 2007, Barron et al., 2010; Pulido-Velázquez et al., 2011; Green et al., 2011). Predicted
46 changes on meteorological variables such as temperature or rainfall can provoke
47 significant changes on aquifer recharge rates (Jyrkama and Sykesa, 2007), which can
48 drive to important piezometric level variations. Consequently, water resource
49 availability can be reduced, modifying stream-aquifer interaction, pumping cost rates
50 and, eventually, leading to aquifers contamination. The aforementioned scarcity of
51 research studies about the influence of Climate change on groundwater resources has
52 been shown by the Intergovernmental Panel on Climate Change (IPCC) (Parry et al.,
53 2007).

54 A methodology for assessing the potential impacts produced by Climate Change is
55 proposed in this study. These impacts are made up of different nature and produce
56 results on the different aspects involved in the management of aquifer systems. This
57 analysis has been developed from the regional scenarios of Climate Change developed
58 for Europe through the research projects Prudence (2004) and Ensembles (2009).
59 Furthermore, the study is aimed to analyze the sensitivity of the results when a change
60 in intensity in the climatology series (rainfall and temperature) takes place, but also in

61 the frequency of the events. This aspect could be of great interest in arid and semi-arid
62 regions due to the increment in rainfall variability and intensity that should be related
63 with an increment in aquifer recharge rates, while greater variability in humid regions
64 would decrease aquifer recharge rates as more water is lost to runoff (WRF, 2009).

65 In this study, a 30 year time series (2070-2100) is used as the period for the predictions
66 of long-term Climate Change. The year 2070 is taken as the starting time point,
67 assuming existing hydrological and economic conditions from 2011. The methodology
68 has been applied to the overexploited Serral-Salinas aquifer (Molina et al., 2009). An
69 exhaustive analysis of the potential hydrological impacts of Climate Change has been
70 developed, considering two emission scenarios (A2 y A1B) resulting from the assemble
71 of different models.

72 The paper is mainly aimed to show the utility of Dynamic Bayesian Networks as a
73 modeling tool for analyzing long-term hydrological impacts on aquifers generated by
74 Climate Change. Secondly, this paper is aimed to show the utility of this type of
75 methodologies and tools for providing strategies of adaptation, especially for vulnerable
76 aquifers systems mainly located in arid and semiarid regions.

77 The paper is structured as follows. First, the state of the art on Dynamic BNs related to
78 water management and hydrology is is discussed, followed by the description of the
79 case study. Then, the explanation of the methodology and the results drawn from this
80 application are shown. Finally, two sections are dedicated for discussion and for
81 conclusions respectively.

82

83 **2. Tool and Methods: Dynamic Bayesian networks as a modeling tool for**
84 **integrated water resources management**

85 All real world systems change over time. Modeling their equilibrium states or ignoring
86 change altogether, when it is sufficiently slow, can be enough for solving a wide
87 spectrum of practical problems. In some cases, however, it is necessary to follow the
88 change that the system is undergoing and introduce time as one of the model variables

89 This research is focused on models that belong to the class of probabilistic graphical
90 models, with their two prominent members, Bayesian Networks (BNs) (Pearl, 1988)
91 and dynamic Bayesian networks (DBNs) (Dean and Kanazawa, 1989). BNs are widely
92 used practical tools for knowledge representation and reasoning under uncertainty in
93 equilibrium systems.

94 A BN consists of three main elements; a set of variables that represent the factors
95 relevant to a particular environmental system or problem; the relationships between
96 these variables that quantify the links between variables and the set of conditional
97 probability tables (CPTs) that quantify the links between variables and are used to
98 calculate the state of nodes. The first two elements form a Bayesian Diagram and the
99 addition of the third forms a full network.

100 BNs are probabilistic graphical models that offer compact representations of the joint
101 probability distribution over sets of random variables. Formally, a BN is a pair (ζ, Θ) ,
102 where ζ is an acyclic directed graph in which nodes represent random variables
103 X_1, \dots, X_n and edges represent direct dependencies between pairs of variables. Θ
104 represents the set of parameters that describes the probability distribution for each node
105 X_i in ζ , conditional on its parents in ζ , i.e., $P(X_i \mid \text{Pa}(X_i))$. Often, the structure of the
106 graph is given a causal interpretation, convenient from the point of view of knowledge
107 engineering and user interfaces. BNs allow for computing probability distributions over
108 subsets of their variables conditional on other subsets of observed variables.

109 A BN can be run as a standalone network, but it is possible to link together a number of
110 networks to produce an Object-Oriented Bayesian Network (OOBN) model (Koller and
111 Pfeffer, 1997). OOBNs are based on the Object-Oriented Programming paradigm
112 (OOP) and thus adopt the same attributes used in OOP languages (Koller and Pfeffer,
113 1997; Molina et al., 2010; Weidl et al., 2005). OOP techniques and languages include
114 features such as encapsulation, modularity, polymorphism, and inheritance (defined
115 below) (Armstrong, 2006). The traditional programming approach tends to separate data
116 from behaviour, whereas in OOP this separation is not necessary; the result is that real-
117 world phenomena can be represented in a much more realistic way (Booch, 1996). As
118 Wirth (2006) states “this paradigm closely reflects the structure of systems in the real-
119 world, and it is, therefore, well suited to model complex systems with complex
120 behaviour”.

121 A conventional BN is a single system that is unable to receive or transmit information
122 from outside the network. In contrast an OOBN represents a number of networks that
123 can be linked together such that it is possible to transfer information from one to the
124 other. The transfer of information is accomplished through the creation of output and
125 input nodes in each network. These types of node are able to import and export
126 information outside individual networks; these linking nodes are called interface nodes.
127 Together the interface nodes form what in Object-Oriented programming terminology is
128 known as an ‘instance node’, which in effect represents an ‘instance’ of another network
129 (Fig. 1). In object-oriented terms each network becomes equivalent to a class. OOBNs
130 are a hierarchical description (or model) of real-world problems that mirror the way in
131 which humans conceptualize complex systems. To cope with complexity humans think
132 in terms of hierarchies of different classes. When considering this problem the human
133 mind will abstract selectively from this hierarchy of class types. The use of instance

134 nodes provides support for working with these different levels of abstraction in the
135 construction of object-oriented network models.

136 OOBNs can be utilized in two ways. First, they can be used for “time slicing” for
137 problems in which processes take place over multiple time periods (Kjaerulff, 1995).
138 This is how Dynamic BNs (DBNs) are built. Because BNs are not intended for transient
139 analysis, time slicing provides one way to generate predictive simulations. This is the
140 approach that has been adopted for the current study where networks representing
141 different time domains are linked to outputs nodes to produce a dynamic model for the
142 period 2070-2100. The second way in which OOBNs can be used is to form Sub- and
143 Master-Networks, referred to here as an “organizational” application (Molina et al.,
144 2010).

145 To summarize, an OOBN is a network that in addition to the usual network nodes,
146 contains instance nodes. Instance nodes represent an instance or representation of
147 another network, and provide the means by which networks are linked. The links are
148 made via interface (input and output) nodes that are embedded within the instance
149 nodes. Note that instance nodes should be viewed as a copy of the network of which it
150 is an instance. Instance nodes only comprise a subset of the nodes (interface nodes) in
151 the master network, while nodes that are not directly connected to other networks are
152 said to be hidden.

153 DBNs extend them to time-dependent domains by introducing an explicit notion of time
154 and influences that span over time (Nodelman and Horvitz, 2003). Most practical uses
155 of DBNs involve temporal influences of the first order, i.e., influences between
156 neighboring time steps. This choice is a convenient approximation influenced by
157 existence of efficient algorithms for first order models and limitations of available tools.

158 After all, introducing higher order temporal influences may be costly in terms of the
 159 resulting computational complexity of inference, which is NP-hard even for static
 160 models. Limiting temporal influences to influences between neighboring states is
 161 equivalent to assuming that the only thing that matters in the future trajectory of the
 162 system is its current state. Many real world systems, however, have memory that spans
 163 beyond their current state

164 DBNs (Dean and Kanazawa, 1989) are an extension of BNs for modeling dynamic
 165 systems. The term dynamic means that the system's development is modeled over time
 166 and not that the model structure and its parameters change over time, even though the
 167 latter is theoretically possible. In a DBN, the state of a system at time t is represented by
 168 a set of random variables $X^t = X_1^t \dots X_n^t$. The state at time t generally depends on the
 169 states at previous k time steps. There is nothing in the theory that prevents k from being
 170 any number between 1 and $t - k$. When each state of the model only depends on the
 171 immediately preceding state (i.e., $k = 1$, the system is called first-order Markov (Markov
 172 Chains), often assumed in practice), we represent the transition distribution $P(X^t | X^{t-1})$.
 173 This can be done using a two-slice BN fragment (2TBN) β^t , which contains variables
 174 from X^t whose parents are variables from X^{t-1} and/or X^t , and variables from X^{t-1} without
 175 their parents. A first order DBN is often defined as a pair of BNs ($\beta^0, \beta^{\rightarrow}$) where β^0
 176 represents the initial distribution $P(X^0)$, and β^{\rightarrow} is a two time slice BN, that defines the
 177 transition distribution $P(X^t | X^{t-1})$ as follows:

$$178 \quad P(X^t | X^{t-1}) = \prod_{i=1}^n P(X_i^t | P_a(X_i^t)) \quad (1)$$

179 BNs can become a type of DSS based on a probability theory which implements Bayes'
 180 rule (Jensen, 1996, 2001; Pearl, 1988). A BN can also be defined as 'nodes' used to

181 represent random variables that interact with others (Cain, 2001). Bayesian Networks
182 have been used as decision support systems for many years in fields such as road safety,
183 medicine and artificial intelligence. During the last decade Bayesian networks (BNs)
184 have become a worldwide modeling tool for dealing with Environmental problems. It
185 has been in the last 5 years when BNs have been increasingly used to deal with
186 problems framed within the Integrated Water Resources Management (IWRM)
187 paradigm. In this sense, BNs have been used for many purposes and from different
188 perspectives that are explained as follows: BNs have been used as a modeling tool for
189 water planning and management of catchments in an overall way (Varis and Fraboulet-
190 Jussila, 2002; Castelletti and Soncini-Sessa, 2007), they have been also used for
191 integrated aquifers management from the groundwater perspective from a hydraulic
192 view (Henriksen and Barlebo, 2007; Molina et al., 2010 and 2011), or from an
193 agroeconomic perspective (Carmona et al., 2011). Furthermore, BNs have been applied
194 for Coastal Lake Assessment and Management (Ticehurst et al., 2008) or for the study
195 and management of groundwater contamination (Farmani et al., 2009). BNs have been
196 also useful for studies on water domestic supply (Bromley, 2005) or for the
197 management and assessment of the hydrology on forest fires (Wisdom, 2011).
198 Additionally, BNs are also applied in reservoirs management with operating rules for
199 flooding control (Malekmohammadi, 2009), in Limnology with application in
200 eutrophication models (Borsuk et al., 2004) or in management of fishing vessels (Little
201 et al., 2004).

202 **3. Case Study**

203 The present study is focused on the Serral-Salinas aquifer, between Murcia and Alicante
204 provinces (SE Spain; Fig. 1). This area is bounded to the east by the Alto and Medio
205 Vinalopó (which belong to the province of Alicante), to the south by the Oriental and

206 Vega Alta de Segura (in Murcia), and to the north by the province of Albacete. The
207 region experiences a mild Mediterranean climate. Water demand is at its highest in the
208 summer months, when availability is lowest. In general, current demand greatly exceeds
209 available supplies, and water is an issue of paramount importance. The main economic
210 activity in the area is agriculture, which is characterized by its high profitability, partly
211 due to the effective marketing of its products (Molina et al. 2009). From a hydrologic
212 standpoint, the area has no permanent surface water bodies, and the only available water
213 is that obtained from exploitation of the Serral-Salinas aquifer. The impacts of pumping
214 from this aquifer extend to the regional scale, well beyond the boundaries of the aquifer
215 area (Molina and García-Aróstegui 2006, 2007). Responsibilities for the monitoring of
216 the aquifer are shared by the Júcar and Segura River Basin authorities. Finally, note that
217 to date this region has been historically excluded of the large hydraulic projects that
218 have been carried out in SE Spain like Tajo-Segura water transfer. The historical
219 overexploitation of the Serral-Salinas aquifer has severely affected its hydraulic
220 behavior. Mean renewable water resources in the aquifer are estimated to be about 5
221 Mm^3 per year, these being derived exclusively from the infiltration of precipitation onto
222 permeable outcrops (Molina et al. 2009). Pumped abstraction can only be estimated
223 indirectly, as very few boreholes are fitted with volumetric control meters. In this study,
224 the volume and rate of water abstraction is estimated by studying bibliographic records
225 and from field surveys of the main water users. Consequently, the average rate of
226 exploitation over the last 10 years amounts to some 18 Mm^3 per year.

227 The water budget calculated from the above data is clearly negative, which is evidenced
228 as a notable consumption of water reserves (-13 Mm^3 per year and an accumulated
229 drawdown exceeding 350 Mm^3). In some parts, groundwater heads have fallen by up to

230 200 m over a period of 30 years with a depletion rate over 10 m/year in some sectors of
231 the aquifers (Fig. 1).

232 All of this has raised the cost of water extraction, and has induced negative effects on
233 the related environment such the drying up of springs that represented the eastern
234 aquifer sector natural discharge. On the other hand, it must also be recognized that this
235 intensive exploitation has produced positive effects too, by increasing agricultural
236 income, which in turn has enabled demographic stability or even an increase in some
237 regions, as well as other socio-economic benefits. Recently measures have been
238 proposed aimed to alleviate the water problems of the region and specifically, aimed to
239 alleviate the imbalance of aquifer water budgets MIMAM (2001 and 2004). Among
240 others, stands out the import of domestic water through a pipe from the Segura Basin
241 headwaters reservoirs to supply the main cities (Jumilla and Yecla) that have an urban
242 demand of about 6 Mm³ per year. This intervention has been stopped or slowed down
243 and only Jumilla has asked for the inclusion on the Mancomunidad de los Canales del
244 Taibilla (MCT). Another important proposed intervention is the consideration of
245 replacing groundwater extraction rights by water rights from desalination. However, the
246 possibility of returning the aquifers to their original condition have yet to be assessed, as
247 well as the required time scales or the costs and benefits involved.

248 **Figure 1. Location of Case Study.**

249

250 **4. Methodology**

251 The methodology comprises two main branches (Fig. 2). On one hand the Climate
252 Change procedure made up of several phases described in the next section. On the other
253 hand, the land use change procedure described in section 4.2. The outputs from both
254 methodologies become inputs to the Non-transient Bayesian network model. Then, once

255 this model is calibrated and tested, is fragmented in different time steps. Thus, the
256 previous model becomes a Dynamic Bayesian Network which is able to analyze the
257 temporal evolution of the model for that period.

258 **Figure 2. General Methodology**

259 **4.1 Climate Change procedure**

260 Future groundwater recharge scenarios for the period 2071-2100 under 2 emission
261 scenarios [A2, A1B] were generated with the information available about several CRM
262 simulations previously developed in the European PRUDENCE [2004] and
263 ENSEMBLES [2009] projects. The approach involves generating future rainfall and
264 temperature series by modifying mean and standard deviation of the historical series in
265 accordance with the estimation of the increment or decrement produced by climate
266 change (obtained from the differences between the control and future series provided by
267 Climate Regional Models (CRM). The corresponding future groundwater recharge
268 series is generated by simulating the new daily rainfall and temperature series through a
269 calibrated soil water balance model (Samper et al., 1999). We have also developed a
270 multi-objective analysis to propose an ensemble predictions by giving more value to the
271 information obtained from the best calibrated models (those that provide better
272 approximations to the historical period). The scheme of the methodology is summarized
273 in Figure 3.

274 **Figure 3. Climate change methodology**

275 This paper is not aimed to describe in detail the different steps of the methodology to
276 generate the future climate change scenarios (the reader is referred to Pulido-Velazquez
277 et al., 2011) (the objective of this paper is to show the applicability and utility of
278 Dynamic Bayesian Networks to analyze future climate change impact scenarios).

279 Therefore, in this section we will just show the scenarios finally obtained that will be
280 used as input in the Bayesian Network.

281 Figure 4 shows the future recharge obtained for the period 2071-2100 with an ensemble
282 of 5 RCM for the scenario A2 and for the scenario A1B. This ensemble of predictions
283 estimates a reduction in mean annual recharge of 14% for the A2 scenario and 57.7% in
284 the A1B scenario derived from the infiltration of precipitation onto permeable outcrops.

285 **Figure 4. Expected and Historical annual Series for Rainfall and Recharge. Figure 4a: Scenario**
286 **A1B; Figure 4b: Scenario A2**

287 Natural recharge from rainfall infiltration was the only source of recharge considered
288 and it was estimated by using the Visual Balan model (Samper et al., 1999) (Molina et
289 al., 2010) which is a soil water balance model that consider the main parameters of the
290 root zone: a root zone thickness of 0.5 m; total porosity (8%), wilting point (3%), field
291 capacity (7%), permeability (0.08 m/day) and a Useful Water Reserve (UWR) rate of 20
292 mm. Recharge was evaluated from daily hydrometeorologic (Rainfall and Temperature)
293 records from Ensemble data series under both CC scenarios (A1b and A2) from 30
294 years period of Climate Change (2070-2100). The model calibration was done by
295 comparing observed and simulated groundwater heads of a neighbor aquifer (El Cantal)
296 that remains unexploited and consequently, it is behaving in natural regime, so the
297 piezometric level variations uniquely are due to natural recharge impulses. Hydraulic
298 parameters were obtained from the literature and pumping tests, in the absence of
299 sufficient data, hydraulic conductivity values were assumed to be isotropic (Table 4; K_x
300 = K_y = K_z). The assumption of equal K in all directions is not realistic, however, due to
301 the calibration method and shifting layers of aquitards/aquifers this may not have
302 importance in the present case. The considered aquifer area is 65.5 km² with a storage
303 coefficient of 0.02 an initial aquifer level of 475 m. This recharge data were introduced

304 in a calibrated Groundwater Flow Model (Modflow) (Molina et al., 2010), based on an
305 existing hydrogeological conceptual model. Regarding the aquifer geometry, the aquifer
306 was represented by up to 17 layers in the model; these layers represent the various
307 lithological units of the Serral-Salinas aquifer. The geometry and nature of the aquifer
308 was obtained through the interpretation of over 100 borehole logs and geological
309 sections, as well as the results of geophysical studies. Topography details were taken
310 from digital maps at a scale 1:25,000. Spatially, the model defined the aquifer within a
311 finite difference grid covering an area of approximately 690 km². The grid contained
312 2,760 cells (60 horizontal, 46 vertical) with a cell size of 500 × 500 m. For the transient
313 version of the model calibration was made using data from October 1956 to September
314 2006 (50 years) at monthly time steps. Boundary conditions were defined by two types
315 (no flow and drain). No flow conditions (Cheng and Cheng 2005) have been applied to
316 the base substrate, as well as to the main boundaries of the model. On the other hand,
317 drain or flow conditions were used to simulate discharge through the Salinas' spring in
318 a non-influenced (natural) regime. Further explanation of this GFH may found at
319 Molina et al. 2010.

320 The output from this GFM can be seen in figure 5 in the form of the evolution of
321 piezometric levels. Accordingly with the recharge rates for CC scenarios A1B and A2
322 the water table depletion is larger under scenario A1B where a lower rainfall and
323 recharge rates take place. Historical evolution of piezometric levels follows an
324 intermediate tendency between CC A1B and A2 scenarios.

325 **Figure 5. Piezometric levels Evolution under Climate Change scenarios in representative boreholes.**
326 **Historical, A1B and A2**

327

328 **4.2 Land uses changes procedure**

329 The previous Serral-Salinas aquifer OOBN model (Molina et al., 2010) did not deal
330 with Climate or Land Use changes. In order to deal with expected changes in land uses
331 (section 4.3), specifically in the irrigated area, the original network has been expanded
332 with new variables such as “Irrigated Area Scenarios”, “New Agricultural Net Profit”,
333 “New Water Abstraction for Irrigation”, “New Water Abstraction”, “New Aquifer
334 Water Budget” and, “New Natural discharge recovery (years)”.

335 The new variable “Irrigated Area Scenarios” allows considering four scenarios in the
336 analysis, depending on the increasing or reduction of the current irrigated area. These
337 scenarios are defined as 10% increase, 20% increase, 10% decreasing and 20%
338 decreasing of the current (baseline) Irrigated area. Obviously, the profits coming from
339 the agriculture will change depending on the land use scenarios.

340 **4.3 Stationary or time aggregated CC-BN modeling**

341 Two DBNs DSS have been developed, one for each climate change scenario (A1B y
342 A2) previously described in the previous part of the methodology. These models have
343 identical structure but differ in the information provided by the soil water balance
344 model, introduced in the DBN model as the relationship between rainfall and the
345 corresponding aquifer recharge.

346 The BN or class used to modelize the aquifer system is divided into two main sections;
347 one deals with the hydrology, the other with social and economic variables (Fig. 6).
348 Figure 6 and Table 1 reveal all the 38 variables introduced in the aquifer network (Class
349 1). The variables of the second class, the module that implement the dynamic process,
350 are shown in Figure 7 and Table 2. The BN model of Molina et al. (2011) has been
351 modified for incorporating the Climate and Land use changes conditions. The reader is

352 referred to the cited previous studies to find a deeper explanation of those invariant parts
353 of the BN model.

354 The probability distributions for the hydrological variables, under each CC scenario,
355 were derived from the calibrated soil water balance model and from the previous
356 hydrological flow model developed for this research. The CPTs for hydrological
357 variables were entered automatically via the Learning Wizard module of the Hugin
358 software (HUGIN 2011). This module automatically discretizes data by transforming
359 continuous distributions into discrete counterparts (i.e. get into groups or intervals with
360 its resultant probability). Automatically entered hydrological variables were “Rainfall”,
361 and “Recharge”. Then, the variable “Water abstraction” is coming from the historical
362 pumping data for agricultural and domestic uses and finally, “Annual Water Budget” is
363 calculated as the difference between Recharge to the aquifer and Water abstraction.

364 The socioeconomic variables were defined in agreement with the stakeholders based on
365 two general meetings. An agro-economic simulation model was used to define these
366 main variables: “Crop distribution”, “Market Trend”, “Variable Costs” “Agricultural
367 Net Profit”, and “Total number of Agricultural Direct Employment”. Then, from an
368 economic study of non-agricultural activities in which the land market price is the key
369 factor (“Sale of land” variable) we derive the following variables: “Total Income from
370 alternative activities” ,“Sale of land for Tourist activities”,” Income from sale land”,
371 “Sale Land Offer Price (Rustic)”and finally ” Total Income” that is the sum of both
372 ways. For socioeconomic variables, the CPTs were also derived in two ways; firstly, by
373 using an agro economic simulation model of the irrigated area; secondly, non-
374 agricultural variables were defined by the economic study of land and properties.

375 Variables are divided into five groups according to their function in the network (Table
376 1). (1) Parent nodes: these are not subject to changes in the states of other nodes; in this
377 study most parents represent proposed strategies that may or may not be implemented;
378 (2) Intervention actions: these are actions that follow from the strategies selected
379 through the parent nodes; (3) Intermediate variables: represent simulation of the
380 intermediate processes that take place between action and objective; (4) Partial
381 objectives: intermediate objectives that contribute toward final objectives; (5) Final
382 objectives: represent the variables that are of key importance to the system; it is the
383 states of these variables that are of most concern to stakeholders. Here, two variables
384 have been added, representing the number of year that the aquifer would take to be
385 restored its natural regime. One variable “Natural discharge recovery (years)”, dealing
386 just with Climate Change Conditions and second one “New Natural discharge recovery
387 (years)” including also the effects of Land Uses change.

388 Finally, ‘interface’ variables in the system include “Agricultural Net Profit”, “New
389 Agricultural Net Profit”, “Aquifer Water Budget” and “New Aquifer Water Budget”,
390 connect to the second class or network which represents the dynamic module (Section
391 4.4, Table 2).

392 **Figure 6. Stationary BN DSS Structure**

393

394

GROUP	NAME	EXPLANATION	STATES CC SCENARIO A1B	STATES CC SCENARIO A2
1. Parents	Rainfall	Annual Average Rainfall under CC scenario (mm/year)	45 – 156; 156 - 267; 267 - 378; 378 - 489; 489 - 600	80-176; 176-272; 272-368; 368-464; 464-560
	*HDCR (Coercive Tools)	% Reduction of Agriculture Water Demand Applying Coercive Tools	No Reduction; 0-25; 25-50; >50	No Reduction; 0-25; 25-50; >50
	*HDRV (Incentive Tools)	% Reduction of Agriculture Water Demand Applying Incentive Tools	No Reduction; 0-25; 25-50; >50	No Reduction; 0-25; 25-50; >50
	*External irrigation water resource income TJV	Mm3 y-1	0; 0-5; 5-10	0; 0-5; 5-10
	*External irrigation water resource income Desalinitation	Mm3 y-1	0; 0-5; 5-10	0; 0-5; 5-10
	*Purchase of WR Offer price	€/ha	3000-6000; 6000-9000; 9000-12000	3000-6000; 6000-9000; 9000-12000
	*External domestic water resource income JV Transfer	Boolean (False/True)	False; True	False; True
	*External domestic water resource income TS Transfer	Boolean (Y/N)	False; True	False; True
	*Reduction in water concession or quotas	% Reduction in total water quotas assigned	0; 0-25; 25-50; 50-100	0; 0-25; 25-50; 50-100
2. Intervention Action	Sale Land OfferPrice (Rustic)	€/ha	10000-20000; 20000-50000; >50000	10000-20000; 20000-50000; >50000
	Price of External Irrigation Water Resource	€/m ³	0.2-0.4; 0.4-0.6; 0.6-0.8	0.2-0.4; 0.4-0.6; 0.6-0.8
	External Irrigation water resource Income or Availability	Mm3 y-1	0; 0-5; 5-10	0; 0-5; 5-10
	Purchase of water rights	% Water Rights sold by the farmers	0; 0-25; 25-50; 50-100	0; 0-25; 25-50; 50-100
	Sale of land for Tourist activities	% Irrigated Crop Area sold	0-33; 33-66; 66-100	0-33; 33-66; 66-100
	Income from sale land	€/ha	0-1000; 1000-5000; 5000-10000; 10000-20000	0-1000; 1000-5000; 5000-10000; 10000-20000
	Recharge (mm/year) ENSAMBLE	Annual Average Recharge from rainfall under CC scenario (mm/year)	0 – 32; 32 - 64; 64 – 96 ;96 - 128; 128 - 160	0-30; 30-60; 60-90; 90-120; 120-150
	Recharge (Mm3/year) ENSAMBLE	Annual Average Recharge from rainfall under CC scenario (Mm3/year)	0-2; 2-4; 4-6; 6-8; 8-10; 10-12	0-2; 2-4; 4-6; 6-8; 8-10; 10-12
	Irrigation Water Need After Rainfall	Mm3 y-1	<7.5; 7.5-10; >10	<7.5; 7.5-10; >10
3. Intermediate Nodes	Water irrigated abstraction 1	Mm3 y-1	0-5; 5-10; 10-15; 15-20	0-5; 5-10; 10-15; 15-20
	Water irrigated abstraction 2	Mm3 y-1	0-5; 5-10; 10-15; 15-20	0-5; 5-10; 10-15; 15-20
	Water irrigated abstraction 3	Mm3 y-1	0-5; 5-10; 10-15; 15-20	0-5; 5-10; 10-15; 15-20
	Water domestic abstraction	Binary (Current Abstraction/None)	None; Current Abstraction	None; Current Abstraction
	New Water Abstraction for Irrigation 1	Mm3 y-1	0-5; 5-10; 10-15; 15-20; 20-25; 25-30	0-5; 5-10; 10-15; 15-20; 20-25; 25-30
	Water abstraction	Mm3 y-1	0-5; 5-10; 10-15; 15-20	0-5; 5-10; 10-15; 15-20
	New Water abstraction	Mm3 y-1	0-5; 5-10; 10-15; 15-20; 2-25; 25-30; 30-35; 35-40	0-5; 5-10; 10-15; 15-20; 2-25; 25-30; 30-35; 35-40
	Annual Water Budget	Mm3 y-1	-30--25; -25--20; -20--15; -15--10; -1--5; -5-0; 0-5; 5-10; 10-15	-30--25; -25--20; -20--15; -15--10; -1--5; -5-0; 0-5; 5-10; 10-15
	New Aquifer Water Budget	Mm3 y-1	-40--35; -35--30;-30--25; -25--20; -20--15; -15--10; -1--5; -5-0; 0-5; 5-10; 10-15	-40--35; -35--30;-30--25; -25--20; -20--15; -15--10; -1--5; -5-0; 0-5; 5-10; 10-15
	Crop distribution	% Crop surface	D1;D2;D3;D4	D1;D2;D3;D4
	Current Dotation for Irrigation	m ³ ha ⁻¹	0; 1073; 2243.51; 4850.5	0; 1073; 2243.51; 4850.5
	IRRIGATED AREA SCENARIOS	% Changes in the irrigated area based on Baseline Irrigated Area=5000 ha	-0.2; -0.1; 0; 0.1; 0.2	-0.2; -0.1; 0; 0.1; 0.2
	Market Trend	Trend of crops prices in the last 5 years	Strong decrease prices; Light decrease prices; Steady; Light Increase price; Strong increase prices	Strong decrease prices; Light decrease prices; Steady; Light Increase price; Strong increase prices
	Variable Costs	% Increasing above Retail Price Index (RPI) RPI: 4,5 %	No increasing; 5; 10	No increasing; 5; 10
	4. Partial Objectives	Total Income from alternative activities	€ ha-1	0-1000; 1000-5000; 5000-10000; 10000-20000
Agricultural Net Profit		€ ha-1	0-1000; 1000-5000; 5000-10000	0-1000; 1000-5000; 5000-10000
Agricultural Net Profit		M €	0-10; 10-20; 20-30; 30-40; 40-50	0-10; 10-20; 20-30; 30-40; 40-50
Agricultural Net Profit		M €	0-10; 10-20; 20-30; 30-40; 40-50; 50-55; 55-60	0-10; 10-20; 20-30; 30-40; 40-50; 50-55; 55-60
5. Final Objectives	Total Income	€ ha-1	0-1000; 1000-5000; 5000-10000; 10000-20000	0-1000; 1000-5000; 5000-10000; 10000-20000
	Natural discharge recovery	Years	Never; 100-200; 70-100	Never; 100-200; 70-100
	New Natural discharge recovery	Years	Never; 100-200; 70-100	Never; 100-200; 70-100
	Total number of Agricultural Direct Employment	Number of employments/ha	0-0.1; 0.1-0.3; 0.3-0.4	0-0.1; 0.1-0.3; 0.3-0.4

396 **4.4 Dynamic CC-BN modeling**

397 The DSS has been designed considering 6 identical time steps (time slice technique) of
398 5 years length for the 30 years period (2070-2100). This was done aimed to develop a
399 dynamic analysis and to prove how OOBN can deal with a dynamic or transient
400 behavior. 6 identical networks or classes have been developed, populated with the
401 corresponding data of each time step. Those 6 networks are linked to a final seventh
402 network or class that link each time step and allows developing the dynamic analysis.
403 This final network comprises 6 instance nodes belonging to each time step aquifer class
404 and other variables for each time step: “Agric Net Profit Variation”, “Agric Net Profit
405 Variation IAC”, “Annual Average Storage Variation”, “Total Accumulated Storage
406 Variation”, “Annual Average Storage Variation IAC” and “Total Accumulated Storage
407 Variation IAC”.

408 The variable “Agric Net Profit Variation” describes the temporal variation of the
409 economic variable Agricultural Net profit. The variable “Agric Net Profit Variation
410 IAC” describes the same but including the effects of Land Uses Changes. The variable
411 “Annual Average Storage Variation” represents the temporal variation of the annual
412 aquifer storage and the variable “Total Accumulated Storage Variation” represents the
413 aggregated previous value for the entire time step. Finally, “Annual Average Storage
414 Variation IAC” and “Total Accumulated Storage Variation IAC” represent the same but
415 taking into account the effects of Land Uses Changes.

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VARIABLE NAME	EXPLANATION	STATES CC SCENARIO A1B	STATES CC SCENARIO A2
Agric Net Profit Variation (TIME STEPS 1,2,3,45,6)	Variation of Agricultural Net profit per Time Step (M €/year)	-80—40; -40-0; 0-40; 40-80	-80—40; -40-0; 0-40; 40-80
Agric Net Profit Variation IAC (TIME STEPS 1,2,3,45,6)	Variation of Agricultural Net profit per Time Step Including Irrigated Area changes (M€/year)	-80—40; -40-0; 0-40; 40-80	-80—40; -40-0; 0-40; 40-80
Annual Average Storage Variation (TIME STEPS 1,2,3,45,6)	Variation of Annual Average Storage Variation (Mm ³ /year)	-30--20; -20--10; -10-0; 0-5; 5-10	-30--20; -20--10; -10-0; 0-5; 5-10
Total Accumulated Storage Variation (TIME STEPS 1,2,3,45,6)	Variation of Accumulated Average Storage Variation per Time Step (Mm ³)	-1100--900; -900--700; -700--500; -500--300; -300--100; -100-0; 0-50; 50-100; 100-150; 150-200; 200-250; 250-350	-1100--900; -900--700; -700--500; -500--300; -300--100; -100-0; 0-50; 50-100; 100-150; 150-200; 200-250; 250-300
Annual Average Storage Variation IAC (TIME STEPS 1,2,3,45,6)	Variation of Annual Average Storage Variation including Irrigated Area Change (Mm ³ /year)	-40--30; -30--20; -20--10; -10-0; 0-5; 5-10	-40--30; -30--20; -20--10; -10-0; 0-5; 5-10
Total Accumulated Storage Variation IAC (TIME STEPS 1,2,3,45,6)	Variation of Accumulated Average Storage Variation including Irrigated Area Change (Mm ³)	-1200--1000; -1000--800; -800--600; -600--400; -400--300; -300--100; -100-0; 0-50; 50-100; 100-150; 150-200; 200-250; 250-300; 300-350	-1200--1000; -1000--800; -800--600; -600--400; -400--300; -300--100; -100-0; 0-50; 50-100; 100-150; 150-200; 200-250; 250-300

425

426 **Table 2. Extended list of variables and their states for the second class (Dynamic module)**

427

428 **Figure 7. Dynamic BN DSS Structure**

429

430

431 5. Results

432 5.1 Stationary or time aggregated analysis

433

434 The climate change scenarios, which provoke a reduction in the rainfall and
435 consequently, in the groundwater recharge rates, affect the results of the hydrological
436 and economic variables. In this sense, in order to keep the current crop distribution, the
437 aquifer abstraction rater will be higher to compensate by irrigation the lower rainfall
438 rates. This will produce hydrological and economic impacts quantified and analyzed in
439 this study.

440 All these impacts are quantified and shown through the use of this specific DSS based
441 on OOBNs. Several scenarios are defined. The first scenario (“Scenario A1B_No Land
442 Use Changes) considers climate change conditions under emission Scenario A1B
443 without land use change; then, the second scenario (“Scenario A1B_Land Use
444 Changes”) considers climate and land use changes together. The third scenario
445 (“Scenario A2_ No Land Use Changes”) deals with climate change conditions under
446 emission Scenario A2 without considering land use change; finally, the fourth scenario

447 (“Scenario A2_Land Use Changes”) considers climate and land use changes
448 simultaneously.

449 **1.- Scenario A1B_No Land Use Changes**

450 Under this CC scenario, the annual average rainfall for the whole control period is 160
451 $\text{mm}\cdot\text{year}^{-1}$, producing an annual average recharge of $33 \text{ mm}\cdot\text{year}^{-1}$ ($2.2 \text{ Mm}^3\cdot\text{year}^{-1}$)
452 according to the soil water balance model. In contrast, the historical average values for
453 rainfall is $281 \text{ mm}\cdot\text{year}^{-1}$, producing an average recharge rate of about $74 \text{ mm}\cdot\text{year}^{-1}$
454 ($4.9 \text{ Mm}^3\cdot\text{year}^{-1}$). Consequently, under this scenario, the recharge rate is reduced in
455 more than half of the situation without CC conditions. This makes the water budget (-
456 $12.1 \text{ Mm}^3\cdot\text{year}^{-1}$) even more unbalanced, reducing the chances of the long-term
457 sustainable groundwater exploitation (aquifer budget equilibrium) in about 4%, what
458 means a practical absence of chances for reaching the long-term sustainable
459 groundwater exploitation (0.4%).

460 With regards to the economic variables, there are not significant changes under this
461 scenario due to the non-annual (woody crops) nature of the crops in this area. Thus,
462 reducing the rainfall and recharge rates due to A1B CC scenario, just would involve a
463 slight increase of groundwater pumping and the abstraction costs does not increase
464 significantly (Fig. 8a).

465 **2.- Scenario A1B_Land Use Changes**

466 **Sub-scenario Increase 10% Irrigated Area**

467 This sub-scenario establishes an increase of 10% in the irrigated area for the whole
468 control period. This will produce a slight increase of the groundwater abstraction of
469 about $0.3 \text{ Mm}^3\cdot\text{year}^{-1}$. In contrast, this would produce an increase in the total
470 agricultural profits of about 1.54 M€ (Fig. 8b).

471 **Sub-scenario Increase 20% Irrigated Area**

472 This scenario establishes an increase of 20% in the irrigated area for the whole control
473 period. According to the agronomic model and the BN model this increase will not
474 produce a relevant increase of groundwater abstraction. Additionally, this would
475 produce an increase in the total agricultural profits of about 0.83 M€ over the previous
476 scenario (Fig. 8c).

477 **Sub-scenario Decrease 10% Irrigated Area**

478 Decreasing the irrigated area in 10% would produce a reduction of 1.50 M€ in total
479 agricultural net profits in comparison with the scenario without land uses change. On
480 the other hand, the hydrological variables will not change significantly (Fig. 8d).

481 **Sub-scenario Decrease 20% Irrigated Area**

482 Decreasing the irrigated area in 20% would produce a reduction of 3.33 M€ in total
483 agricultural net profits. On the other hand, the hydrological variables will change
484 significantly. Thus, groundwater abstraction will be reduced in $5 \text{ Mm}^3 \cdot \text{year}^{-1}$ which
485 makes the chance for the aquifer restoration increase in 3.3% (Fig. 8e).

486 **3.- Scenario A2_ No Land Use Changes**

487 Under this Climate Change scenario, the annual average rainfall for the whole control
488 period is $256 \text{ mm} \cdot \text{year}^{-1}$, producing an annual average recharge of $62 \text{ mm} \cdot \text{year}^{-1}$ (4.1
489 $\text{Mm}^3 \cdot \text{year}^{-1}$), according to the previous calibrated rainfall-runoff model. In contrast, the
490 historical average values for rainfall is $281 \text{ mm} \cdot \text{year}^{-1}$, producing an average recharge
491 rate of about $74 \text{ mm} \cdot \text{year}^{-1}$ ($4.9 \text{ Mm}^3 \cdot \text{year}^{-1}$). Consequently, under this scenario, the
492 recharge rate to aquifer is reduced in about 12 mm the situation without climate change
493 conditions. This makes the water budget more balanced ($-10 \text{ Mm}^3 \cdot \text{year}^{-1}$) than the
494 previous scenario but more negative than the historical behavior ($-8.9 \text{ Mm}^3 \cdot \text{year}^{-1}$).
495 Despite this more balanced aquifer budget, the chances for an aquifer restoration
496 remains similar than for the previous scenario.

497 In regards to the economic variables, there are not significant changes under this
498 scenario due to the same reason than for the previous scenario (Figure 9a).

499 **4.- Scenario A2_Land Use Changes**

500 **Sub-scenario Increase 10% Irrigated Area**

501 This scenario establishes an increase of 10% in the irrigated area for the whole control
502 period. This will produce a slight increase of the groundwater abstraction of about 0.2
503 $\text{Mm}^3 \cdot \text{year}^{-1}$. In contrast, this would produce an increase in the total agricultural profits
504 of about 1.54 M€ (Figure 9b).

505 **Sub-scenario Increase 20% Irrigated Area**

506 This scenario establishes an increase of 20% in the irrigated area for the whole control
507 period. According to the agronomic model and the BN model this increase will not
508 produce a relevant increase of the groundwater abstraction. Additionally, this would
509 produce an increase in the total agricultural profits of about 0.81 M€ over the previous
510 scenario (Figure 9c).

511 **Sub-scenario Decrease 10% Irrigated Area**

512 Decreasing the irrigated area in 10% would produce a reduction of 1.8 M€ in total
513 agricultural net profits in comparison with the scenario without land uses change. On
514 the other hand, the hydrological variables will not change significantly (Figure 9d).

515 **Sub-scenario Decrease 20% Irrigated Area**

516 Decreasing the irrigated area in 20% would produce a reduction of 3.31 M€ in total
517 agricultural net profits. On the other hand, the hydrological variables will change
518 significantly. Thus, groundwater abstraction will be reduced in $4.9 \text{ Mm}^3 \cdot \text{year}^{-1}$,
519 producing a more balanced aquifer budget ($-5.19 \text{ Mm}^3 \cdot \text{year}^{-1}$) which makes the chance
520 for the aquifer restoration increase in almost 9 % (Figure 9e).

521

522 **Figure 8. Compiled BN as DSS as a Stationary or Time Aggregated analysis (Scenario A1B)**
523 **8a,b,c,d,e**

524 **Figure 9. Compiled BN as DSS as a Stationary or Time Aggregated analysis (Scenario A2)**
525 **9a,b,c,d,e**

526

527 **5.2 Dynamic analysis**

528 As mentioned before, in order to analyze the behavior of these variables dynamically,
529 the time horizon has been discretized in 6 time steps (slices) of 5 year length each one.
530 This was done mainly for a methodological purpose, in order to probe the suitability of
531 OOBN for dealing with this type of analysis. Furthermore, interesting information from
532 this dynamic analysis has been drawn, mainly regarding the hydrological variables, such
533 the dynamic evolution of the aquifer storage under these scenarios.

534 **Scenario A1B_No Land Use Changes**

535 Under this scenario, the total aquifer storage drawdown is around 405 Mm^3 with an
536 average drawdown rate for each time step of around $13 \text{ Mm}^3 \cdot \text{year}^{-1}$. However, not all
537 the time slices have the same loss of storage. In this sense, the beginning of the period is
538 where the maximum drawdown takes place ($13.4 \text{ Mm}^3 \cdot \text{year}^{-1}$). On the other hand the
539 last years if the time series (sixth time slice) is where the minimum drawdown rate
540 occurs ($12.3 \text{ Mm}^3 \cdot \text{year}^{-1}$).

541 Regarding the economic variables, there is a continuous slight increase of agricultural
542 profits over the time period at a variant rate. However, it is not possible to define a clear
543 tendency or any pattern over the time. Furthermore, the inherent uncertainty of the
544 economic variables can be so high that any prediction on this, become too risky and
545 erroneous.

546 **Scenario A1B_Land Use Changes**

547 **Sub-scenario Increase 10% Irrigated Area**

548 Under this scenario, the total aquifer storage drawdown (around 412 Mm³) is bit larger
549 than in the previous scenario, with an average drawdown rate for each time step over 13
550 Mm³·year⁻¹. The beginning of the period is where the maximum drawdown takes place
551 (13.7 Mm³· year⁻¹). On the other hand the last years if the time series (sixth time slice) is
552 where the minimum drawdown rate occurs (12.5 Mm³· year⁻¹).

553 **Sub-scenario Increase 20% Irrigated Area**

554 Under this scenario, the total aquifer storage drawdown remains the same than in the
555 previous simulation (around 412 Mm³).

556 **Sub-scenario Decrease 10% Irrigated Area**

557 Under this scenario, the total aquifer storage drawdown remains the same than in the
558 Scenario A1B_No Land Use Changes (around 405 Mm³).

559 **Sub-scenario Decrease 20% Irrigated Area**

560 Under this scenario, there is an important reduction of the total aquifer storage
561 drawdown with a value of (around 223 Mm³). This makes perfect sense and can be an
562 intervention to address in order to balance the aquifer water budget or even restore the
563 aquifer natural regime.

564 **Sub-scenario Scenario A2_ No Land Use Changes**

565 Under this scenario, the total aquifer storage drawdown is around 376 Mm³ with an
566 average drawdown rate for each time step of around 11 Mm³· year⁻¹. However, there are
567 some differences between time slices. In this sense, the beginning of the period is where
568 the maximum drawdown takes place (11.8 Mm³·year⁻¹). On the other hand the last years
569 if the time series (sixth time slice) is where the minimum drawdown rate occurs (10.4
570 Mm³· year⁻¹).

571

572 Regarding the economics variables, there is a continuous increase of agricultural profits
573 through the time period at a variant rate. However, as for A1B_No Land Use Changes
574 scenario, it is not possible either to define a clear tendency or any pattern over the time.

575 **Scenario A2_Land Use Changes**

576 **Sub-scenario Increase 10% Irrigated Area**

577 Under this scenario, the total aquifer storage drawdown (around 383 Mm³) is bit larger
578 than in the previous scenario, with an average drawdown rate for each time step over 11
579 Mm³·year⁻¹. The beginning of the period is where the maximum drawdown takes place
580 (12.1 Mm³· year⁻¹). On the other hand the last years if the time series (sixth time slice) is
581 where the minimum drawdown rate occurs (10.6 Mm³· year⁻¹).

582 **Sub-scenario Increase 20% Irrigated Area**

583 Under this scenario, the total aquifer storage drawdown remains the same than in the
584 previous simulation (around 383 Mm³).

585 **Sub-scenario Decrease 10% Irrigated Area**

586 Under this scenario, the total aquifer storage drawdown remains almost the same than in
587 the Scenario A2_No Land Use Changes (around 375 Mm³).

588 **Sub-scenario Decrease 20% Irrigated Area**

589 Under this scenario, there is an important reduction of the total aquifer storage
590 drawdown with a value of (around 200 Mm³). This makes perfectly sense and can
591 become an intervention to address in order to balance the aquifer water budget or even
592 restore the aquifer natural regime if a larger reduction of irrigated area is established.

593 **Figure 10. Compiled DSS for the Dynamic or transient Analysis (Scenario A1B)**

594 **10a,b,c,d,e**

595 **Figure 11. Compiled DSS for the Dynamic or transient Analysis (Scenario A2)**

596 **11a.b.c.d.e**

597

598 **6. Discussion**

599 OOBNs have been recently considered and applied in a non-transient manner due to
600 their flexible and modular nature. This has caused that OOBNs have been used only for
601 structuring those complex problems in terms of organization (Molina et al., 2010),
602 especially in environmental problems. Thus, the use of OOBNs for the study of
603 dynamic processes is an innovative application of this tool. This research has proven the
604 utility of Dynamic BNs (DBNs) for those studies that involve a transient analysis of the
605 probability distributions or functions. The evolution of those probability distributions
606 over time can become very important, especially regarding the coupling between
607 OOBNs and physical models (groundwater flow models, hydraulic models, agronomic
608 models, etc).

609 Dynamic BNs should be seen as a structure for the propagation of probabilities over the
610 time. Each instance node represents a time step that likewise can represent a whole set
611 of classes or domains (BNs). Thus, Dynamic BNs play a double role; on one hand, the
612 way the problem is structured and then, the dynamic implementation of the problem. In
613 this sense, DBNs extend them to time-dependent domains by introducing an explicit
614 notion of time and influences that span over time. Most practical uses of DBNs involve
615 temporal influences of the first order, i.e., influences between consecutive time steps.
616 After all, introducing higher order temporal influences may be costly in terms of the
617 resulting computational complexity, which is NP-hard even for static models. Limiting
618 temporal influences to influences between neighboring states is equivalent to assuming
619 that the only thing that matters in the future of the system is its current state. Many real
620 world systems, however, have memory that spans beyond their current state

621 According to many authors, DBNs are an extension of BNs for modeling dynamic
622 systems. The term dynamic means that the system's development is modeled over time

623 and not that the model structure and its parameters change over time, even though the
624 latter is theoretically possible. In a DBN, the state of a system at time t is represented by
625 a set of random variables which are probability distributions or functions $X^t = X_1^t, \dots, X_n^t$
626 The state at time t generally depends on the states at previous k time steps. When
627 each state of the model only depends on the immediately preceding state (i.e., $k = 1$, the
628 system is called first-order Markov (Markov Chains), often assumed in practice), we
629 represent the transition distribution $P(X^t | X^{t-1})$. This can be done using the technique
630 called Time Slicing (Kjaerulff, 1995).

631 This application has been developed for analyzing the impacts produced by Climate and
632 Land-Use Changes in a historically overexploited aquifer system (Serra-Salinas
633 aquifer), located in SE Spain. This aquifer has been supplying groundwater for all the
634 uses since 1960's. High profitable agriculture is the main consumer, but also domestic
635 as well as recreational uses have been supplied by this aquifer during the last 5 decades
636 (Molina et al. 2009).

637 This research is focused on the analysis of hydrological and economic impacts produced
638 by two emission scenarios of Climate Change (A1B, and A2). Despite both scenarios
639 forecast an important reduction in average annual rainfall and consequently in the
640 recharge rate to the aquifers, there are important differences between them. Thus,
641 Scenario A1B estimates a reduction in the rainfall in more than the half comparing with
642 the historical situation. This makes the water budget ($-12.1 \text{ Mm}^3 \cdot \text{year}^{-1}$) even more
643 unbalanced, reducing the chances of the aquifer restoration in about 4%, what means a
644 practical absence of restoration chances (0.36%). On the other hand, Scenario A2
645 estimates a lower decrease of rainfall and consequently, the impacts on the hydrological
646 functioning of the system are less important.

647

648 Furthermore, an analysis of different scenarios of land use changes has been done with a
649 double goal; first, in order to analyze the important of these changes in the water
650 management of the aquifer and secondly, to compare the importance of land use
651 changes regarding with CC impacts. Attending to this second goal, it is clear that a
652 reduction of only 20% of the irrigated would produce a larger impact to the aquifer
653 hydrological functioning than the climate change effects. This result would allow
654 palliating and adapting the situation as the climate change effects revealed. Finally, it is
655 remarkable to mention that the fact that this aquifer system is so far away from the
656 hydrological equilibrium makes the results obtained less attractive. In this sense, those
657 aquifer systems with a water budget close to the equilibrium allow obtaining more
658 attractive results for reaching a long-term sustainability.

659

660 **7. Conclusions**

661 DBNs have been used for the assessment of impacts produced by climate and land use
662 changes in an extremely overexploited aquifer system in SE Spain. Results from
663 different Climate Change models and scenarios (A1B and A2) probe the high variability
664 in the forecast of the main meteorological variables such as rainfall and temperature.
665 This high uncertainty in the predictions condition the right water planning and
666 management, especially for those water systems located in arid and semiarid regions
667 where the impacts associated with CC are expected to be the largest. Furthermore, the
668 satisfactory results obtained from this research prove the usefulness of this technique
669 when a propagation of information (conditional probability) is required. Also, this
670 research can become a starting point for further studies that comprise coupling between
671 physical transient models and DBNs. Results obtained can be also useful for
672 establishing strategies for the adaptation of water systems to climate change effects. In

673 this sense, the development and use of this kind of tools can help to assess and
674 implement in advance adaptive management strategies aimed to palliate future potential
675 negative effects to be produced by climate and land use changes.

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684

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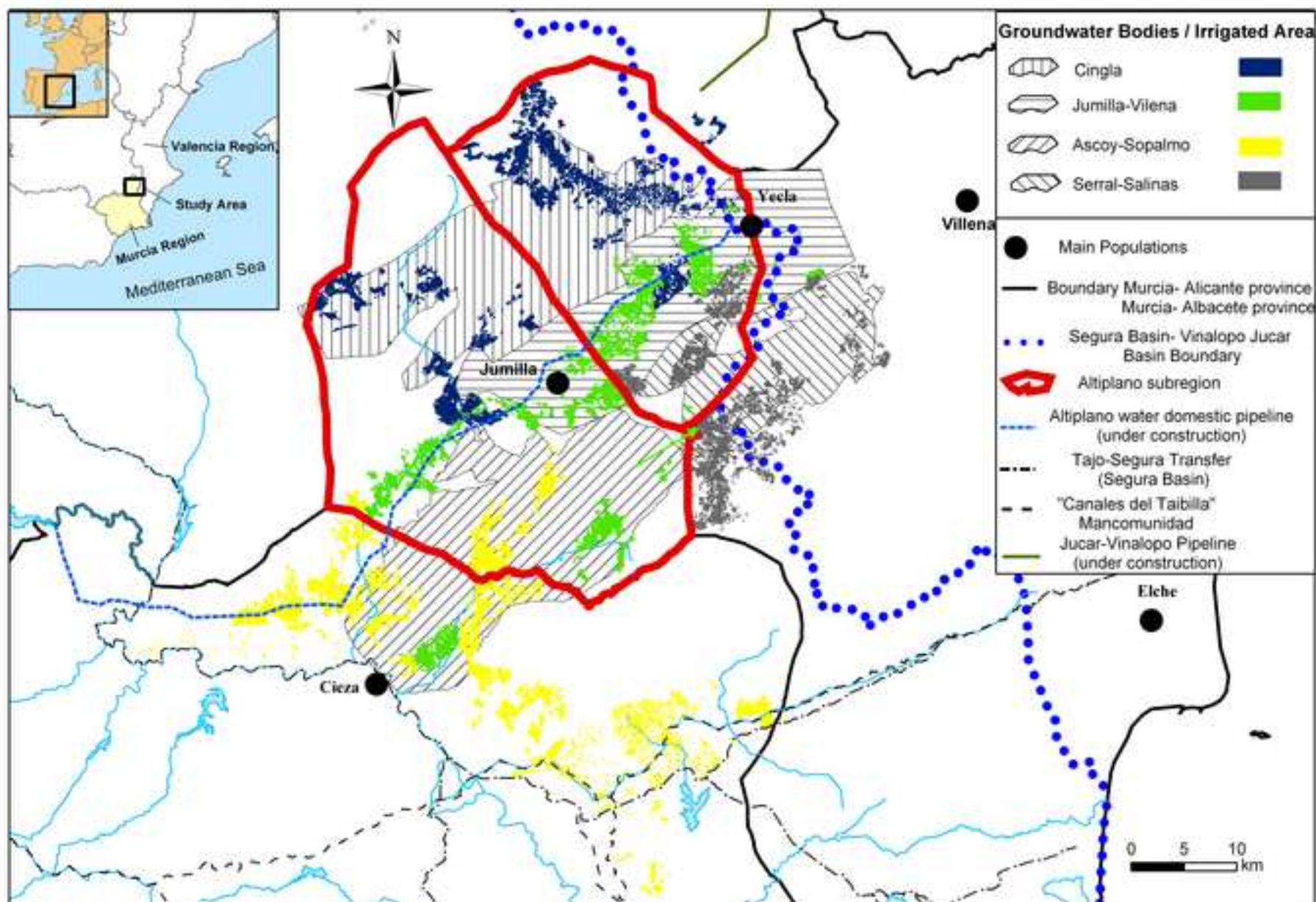


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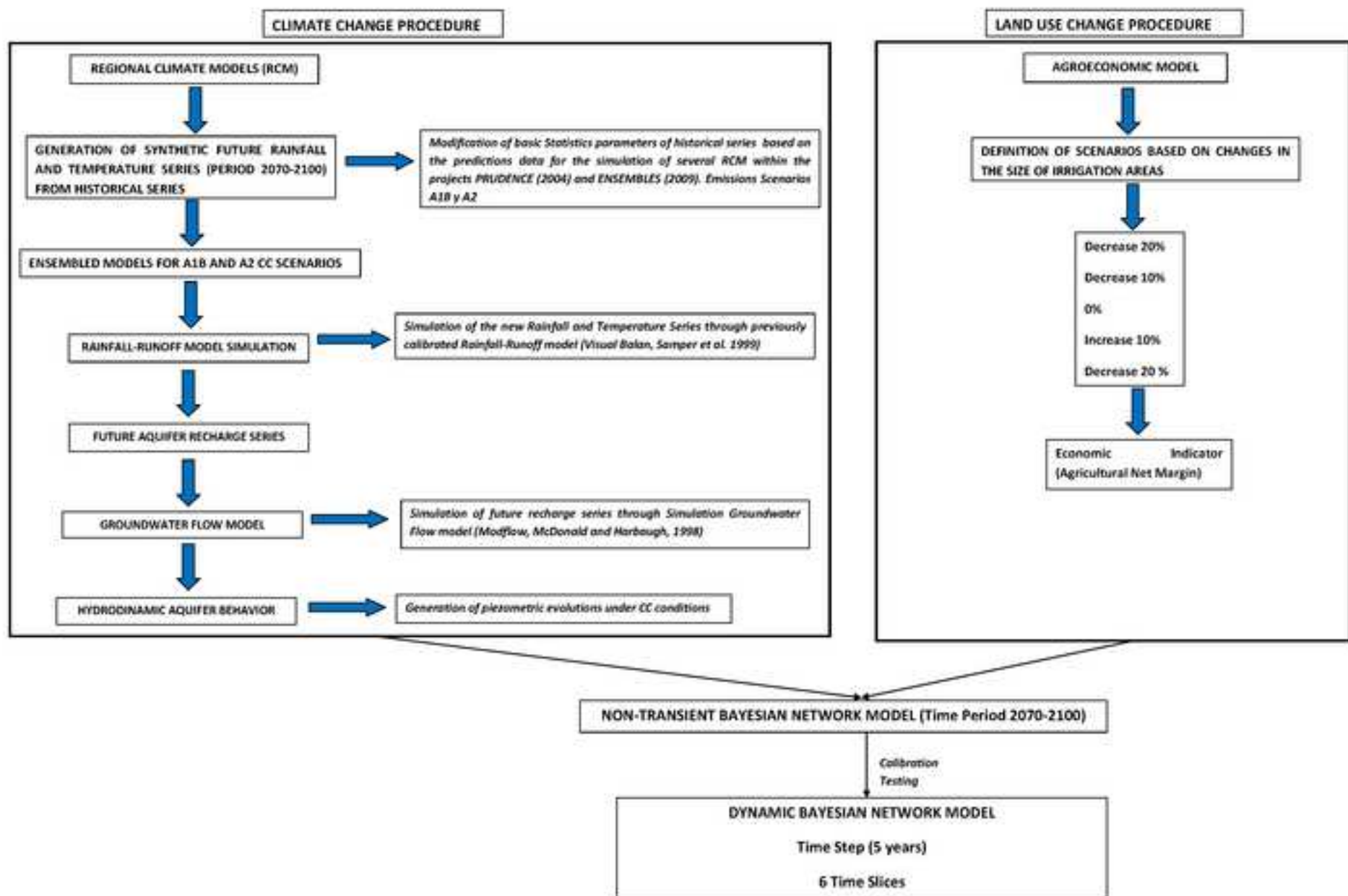


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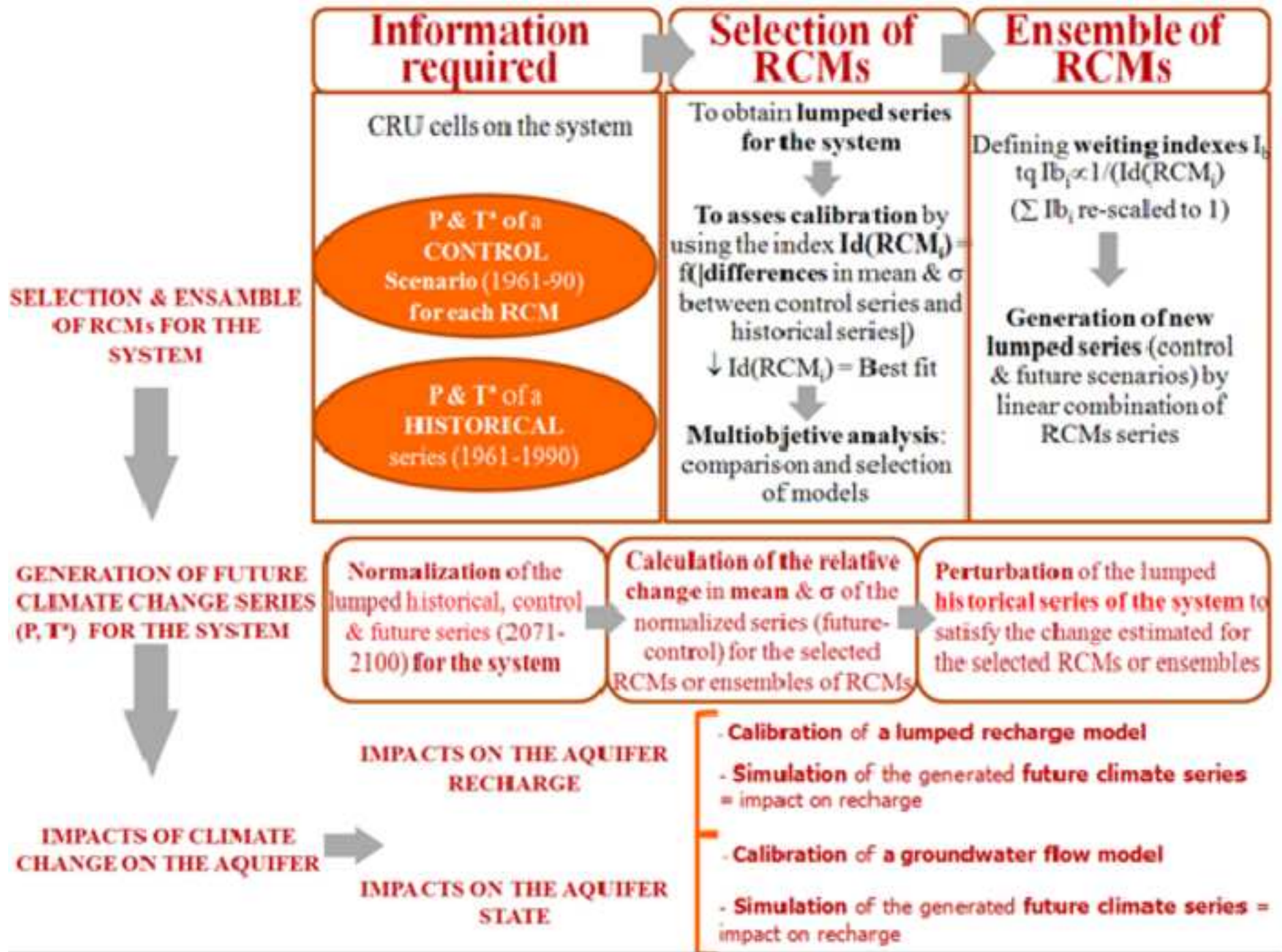


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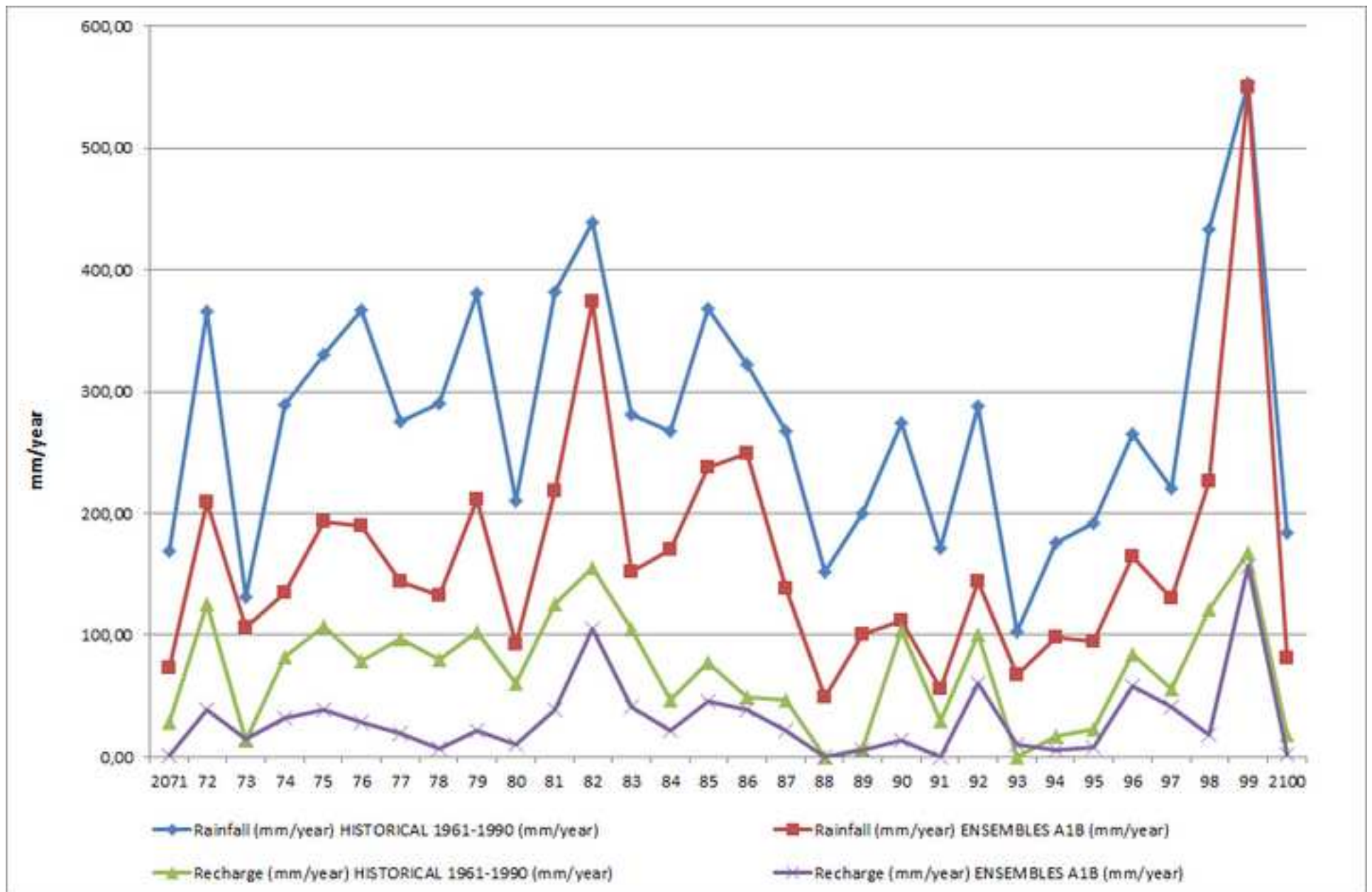


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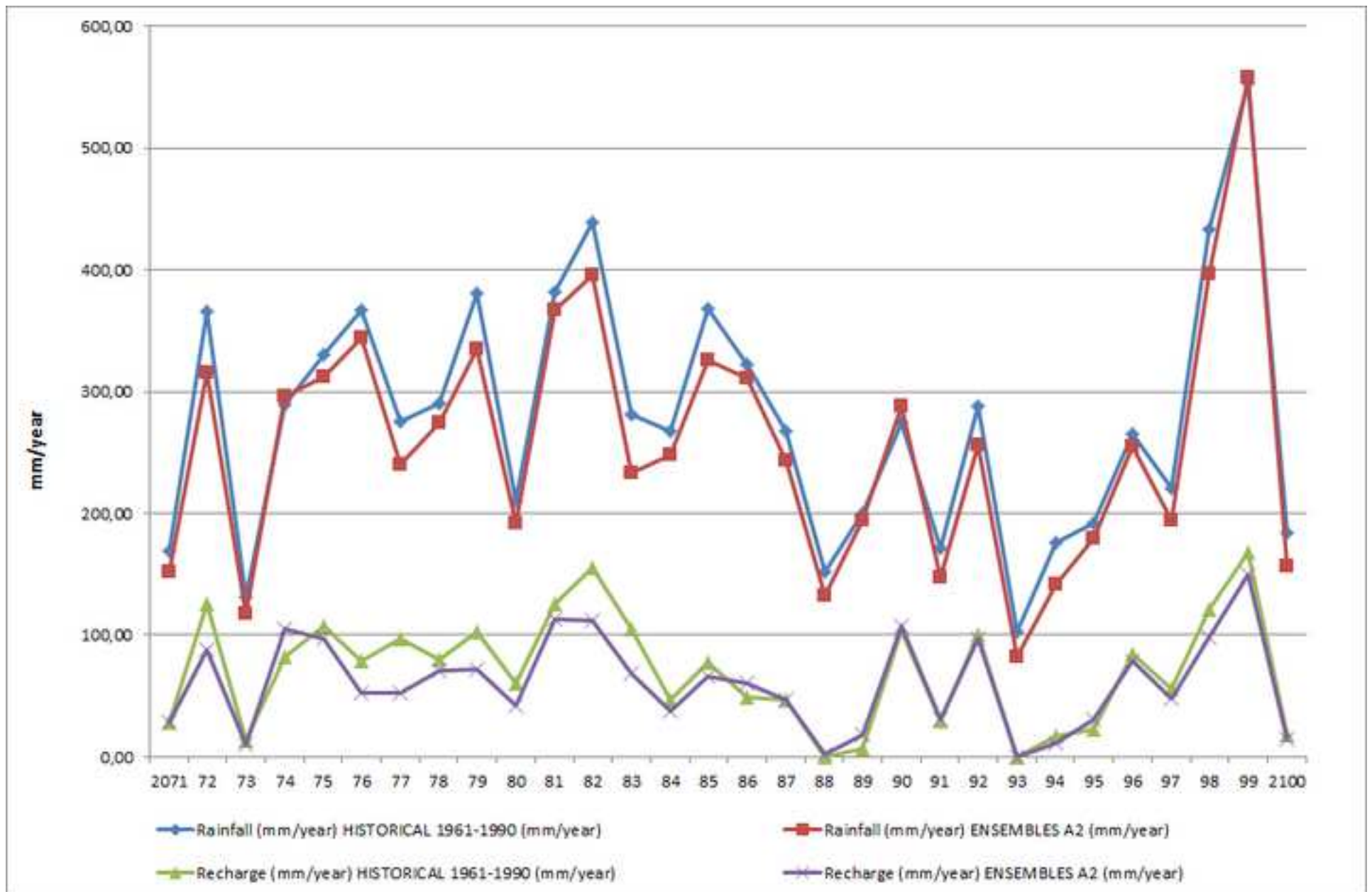


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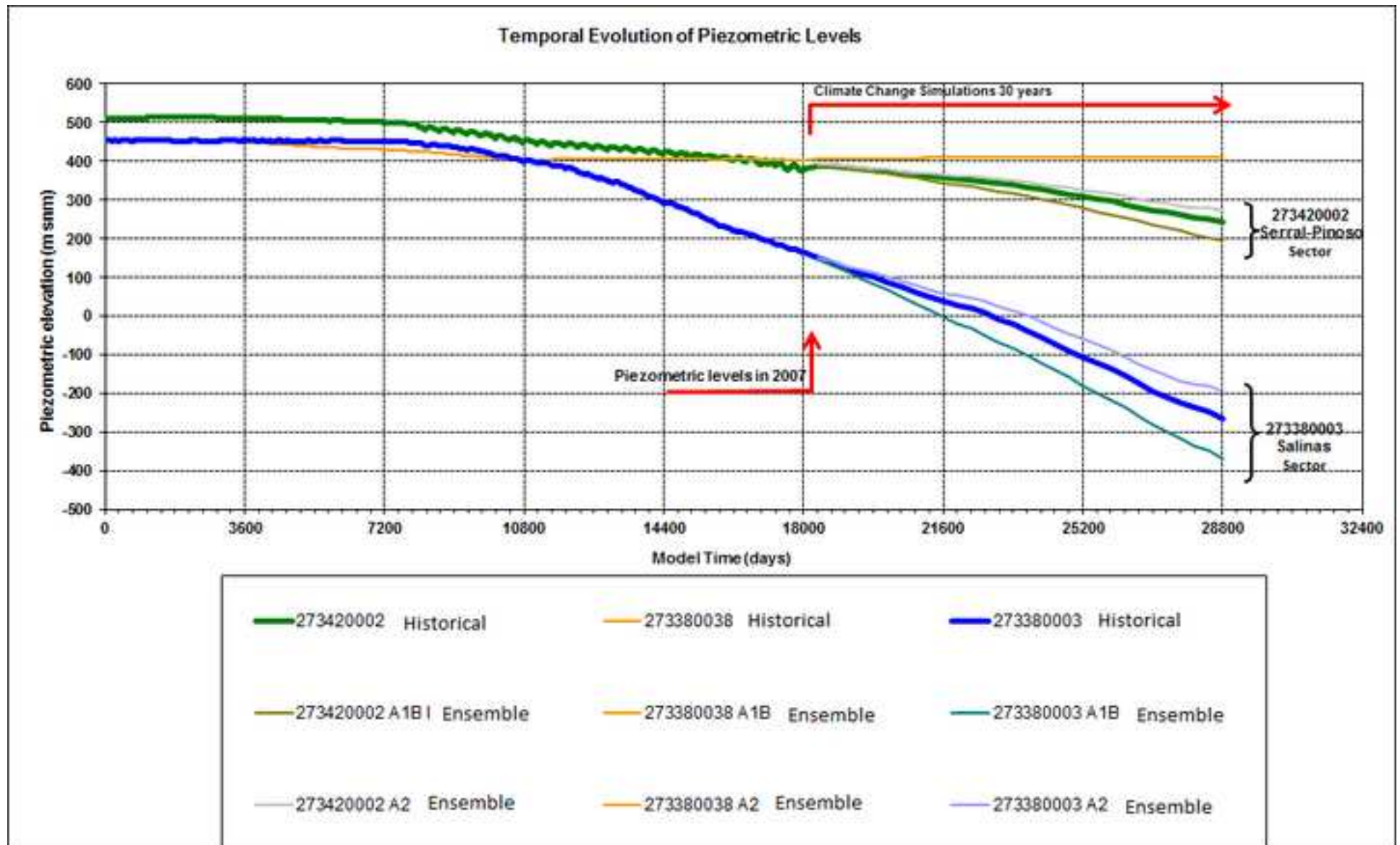


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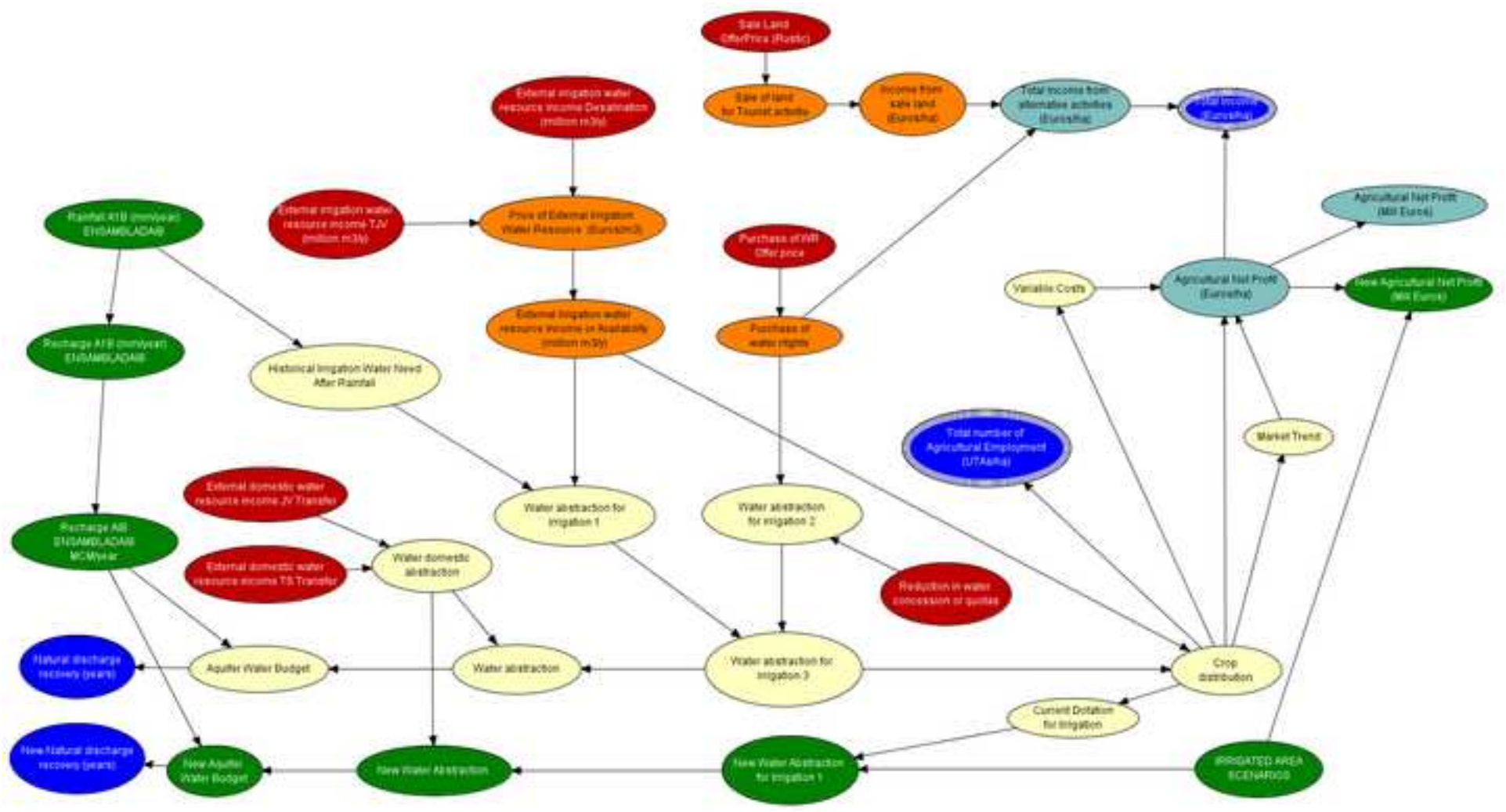


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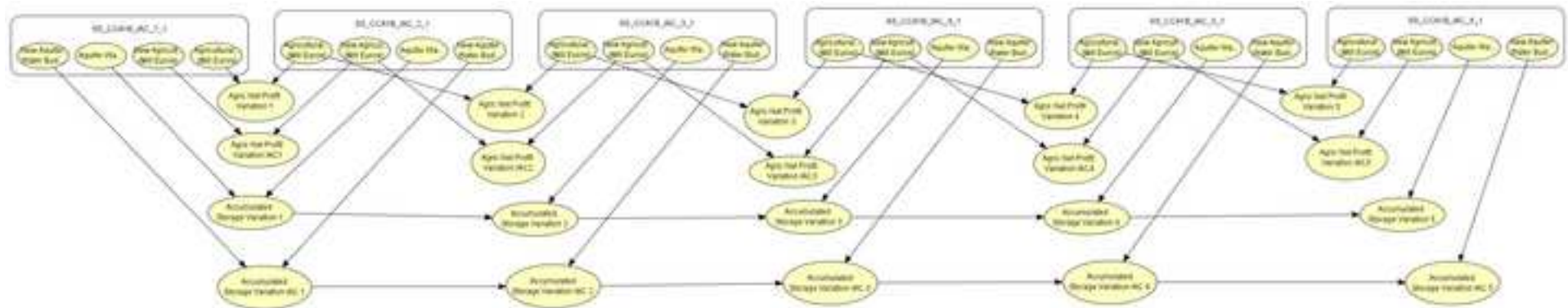


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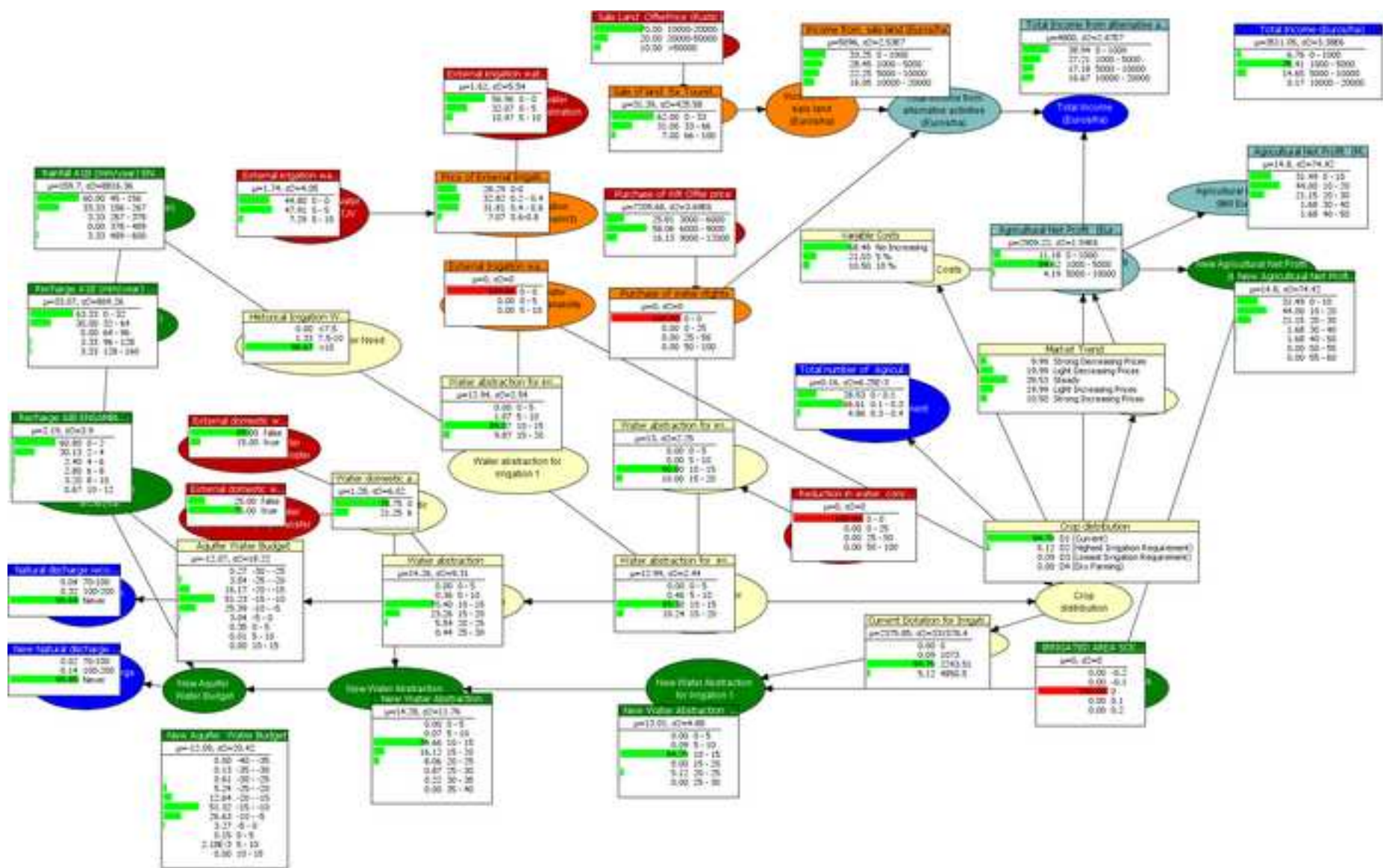


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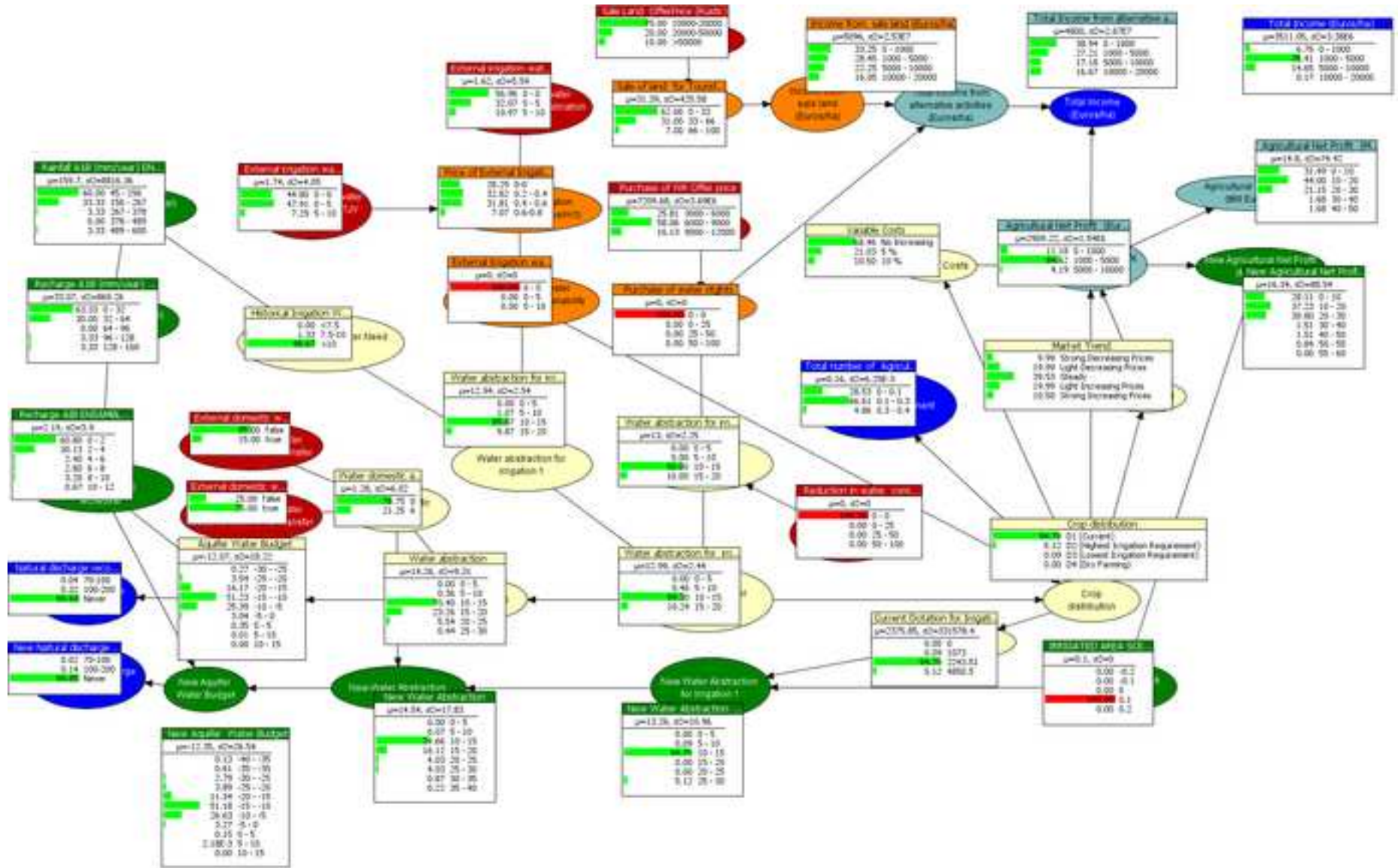


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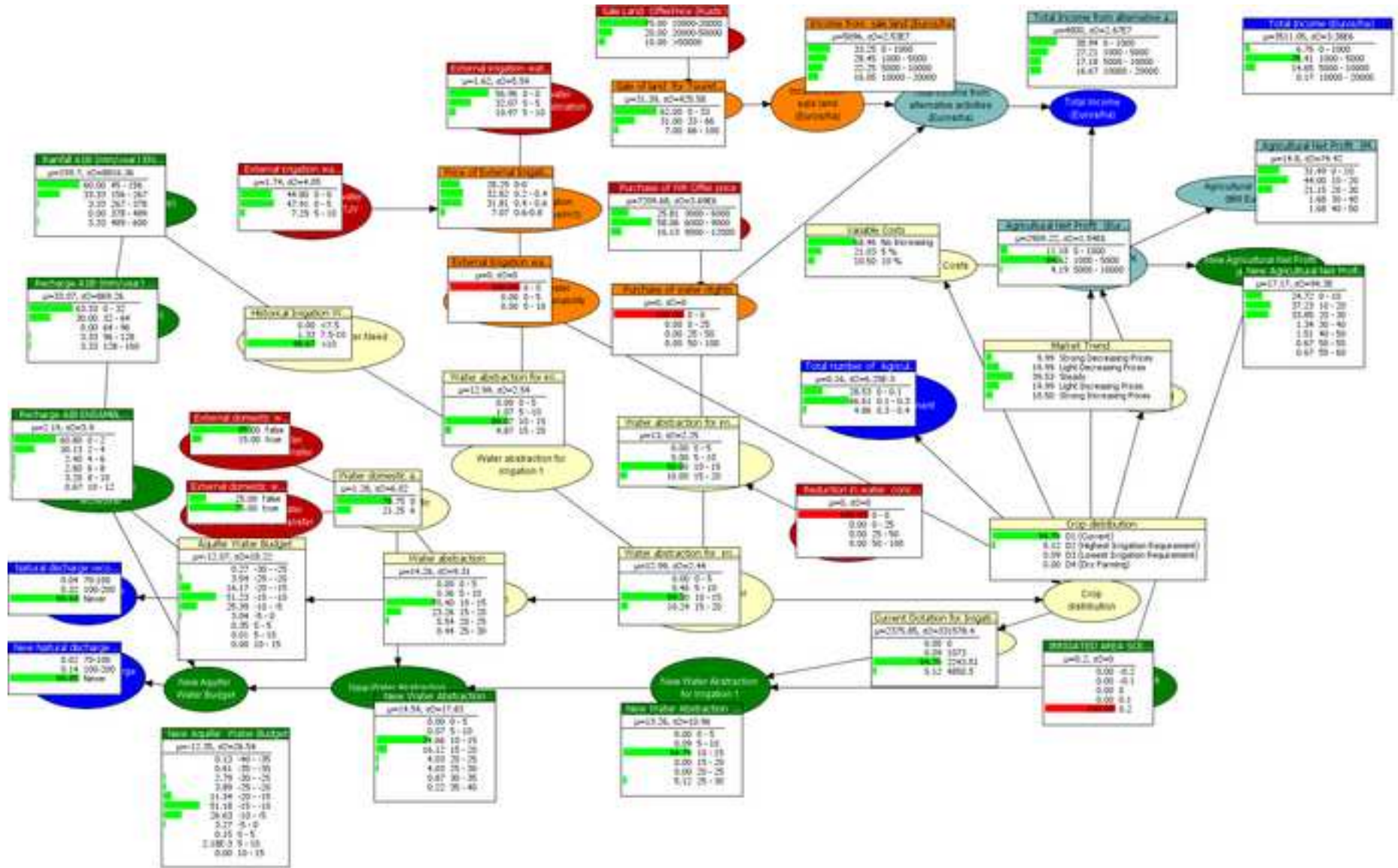


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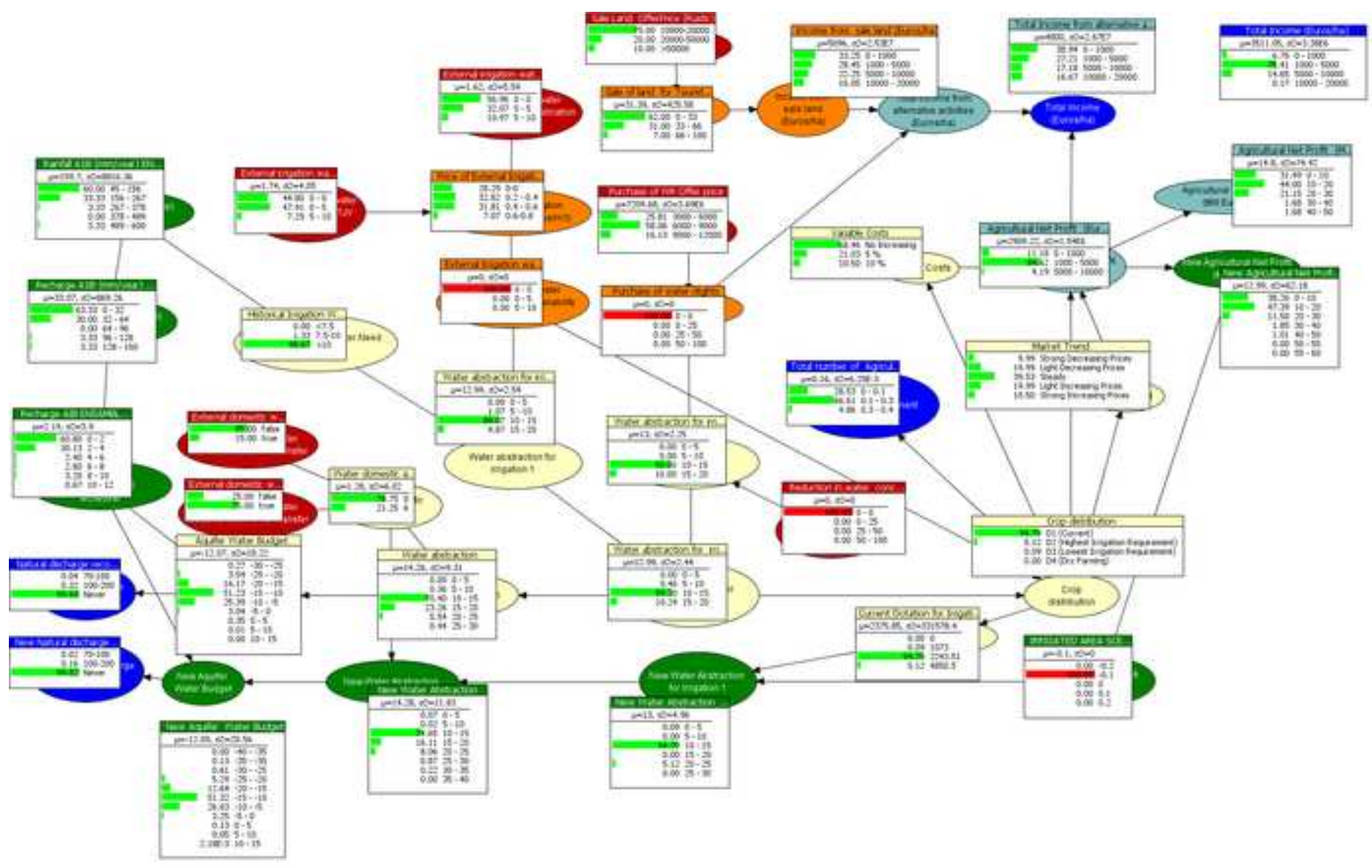


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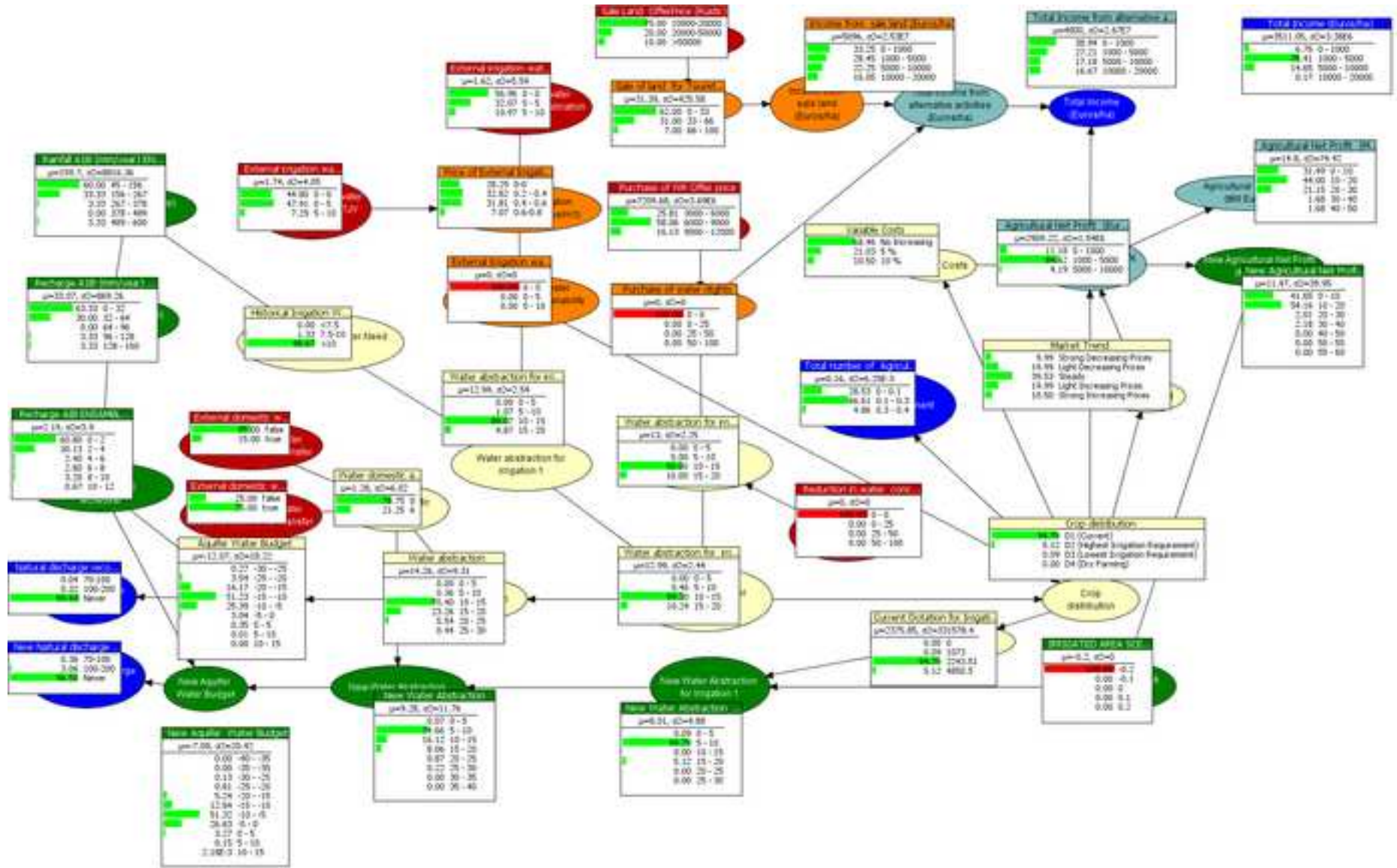


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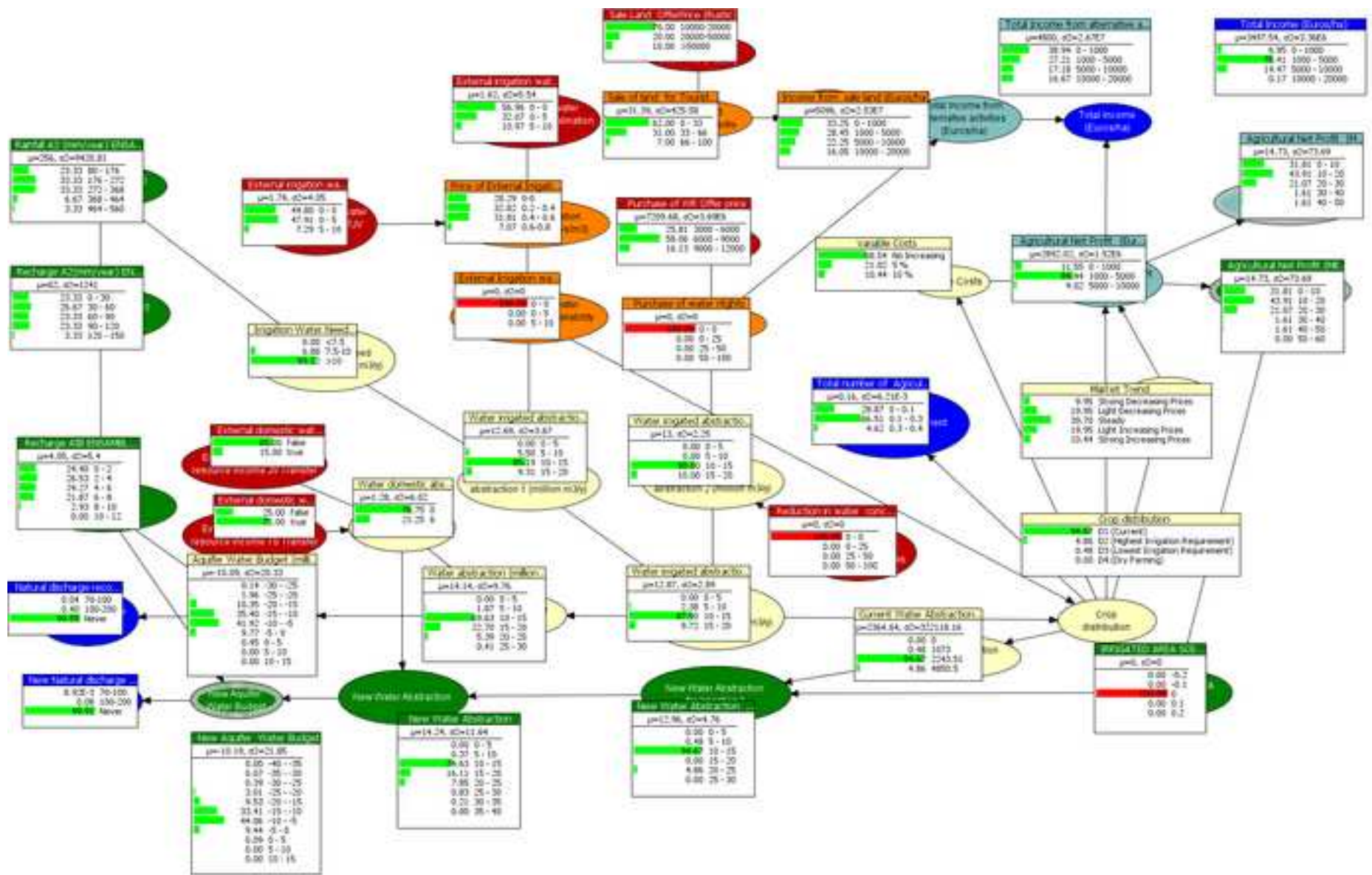


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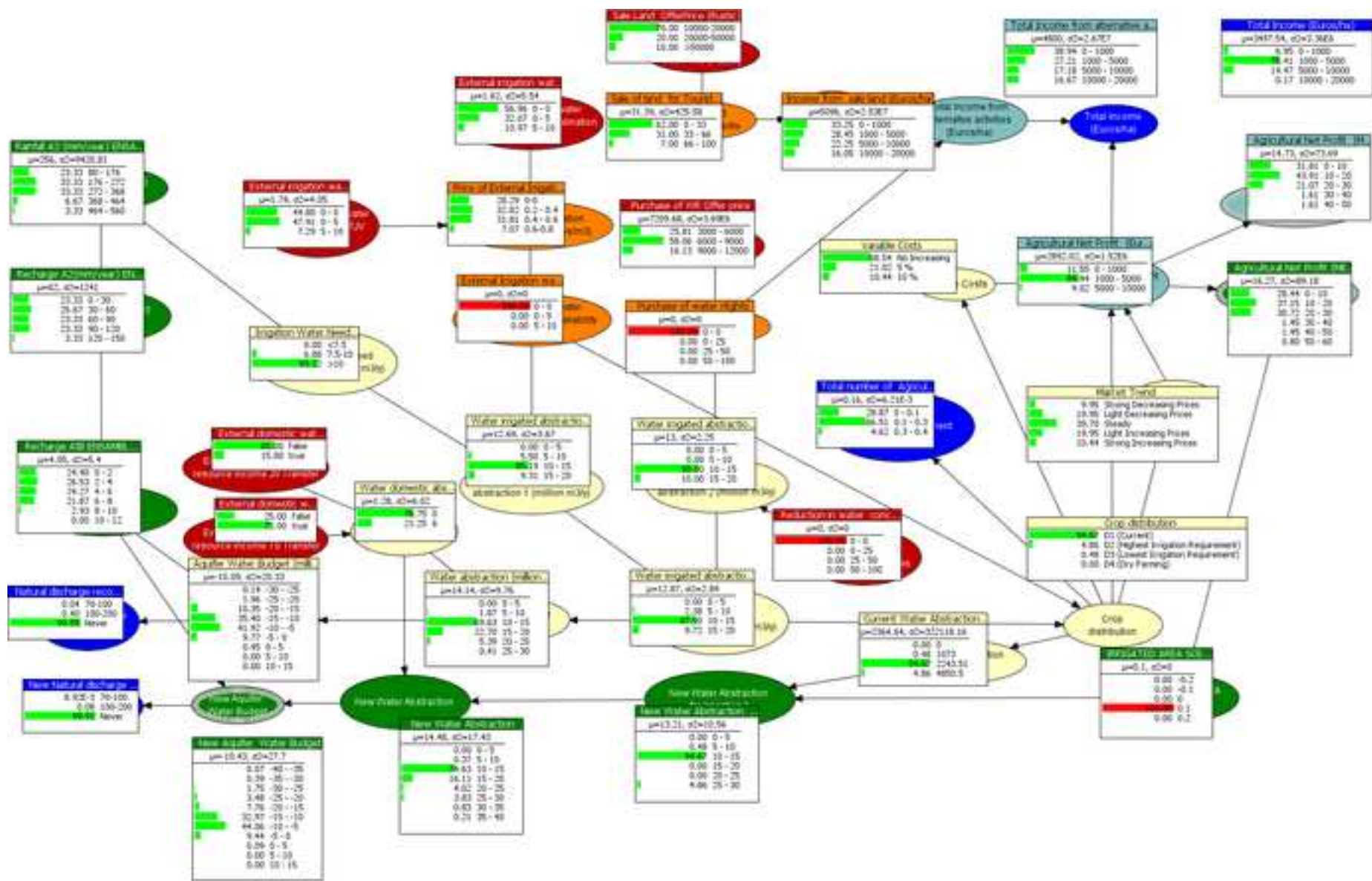


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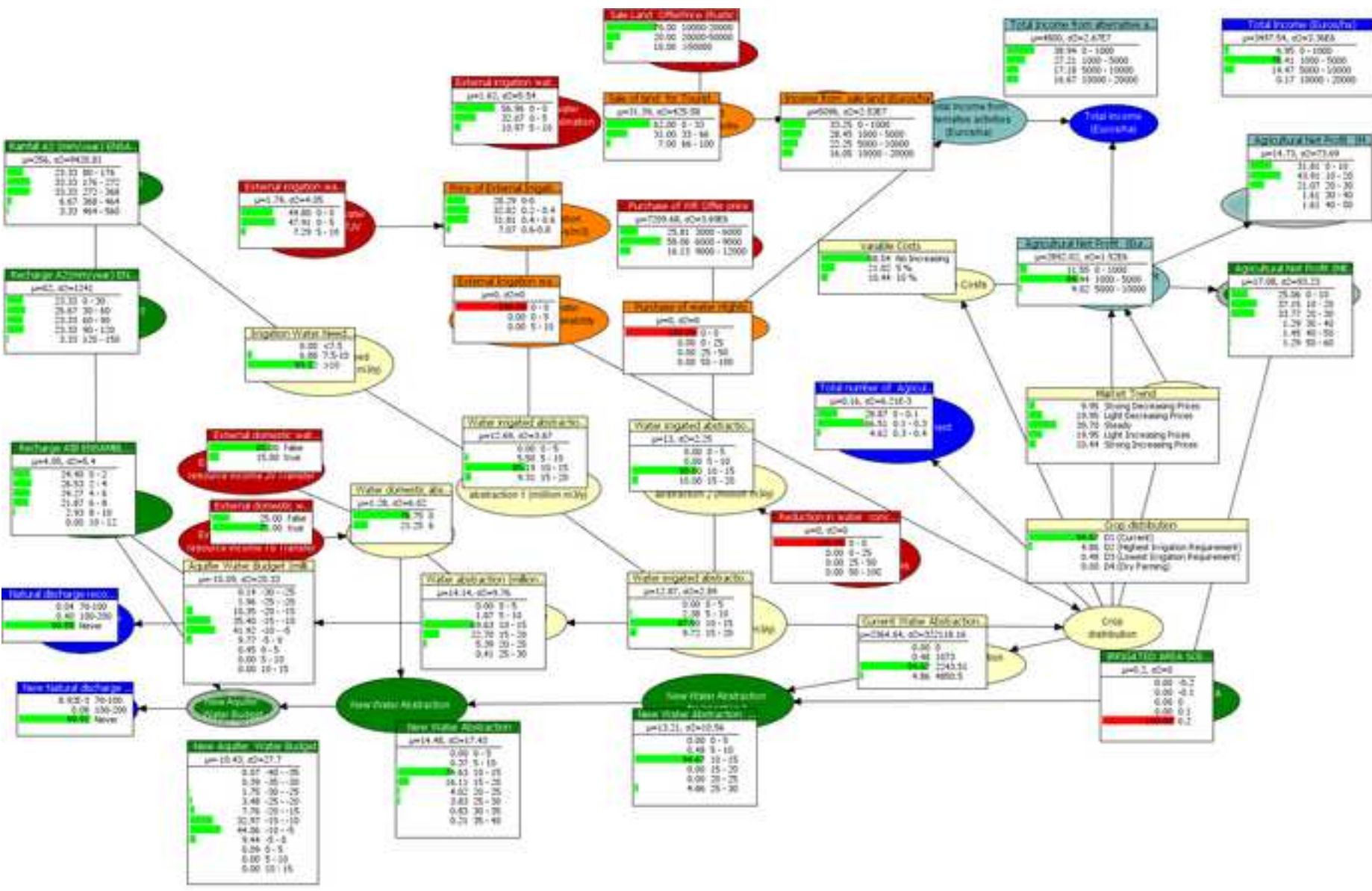


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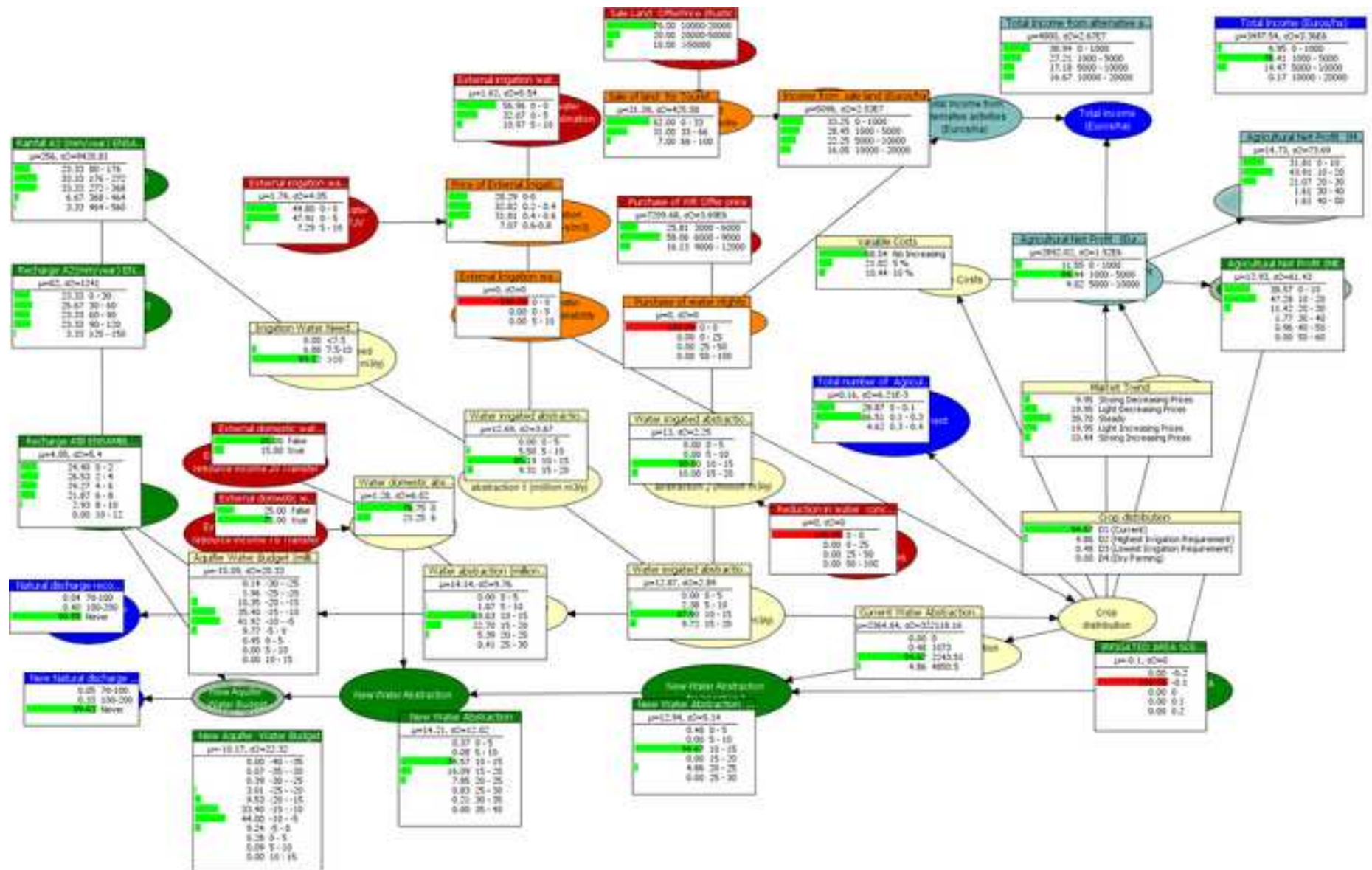


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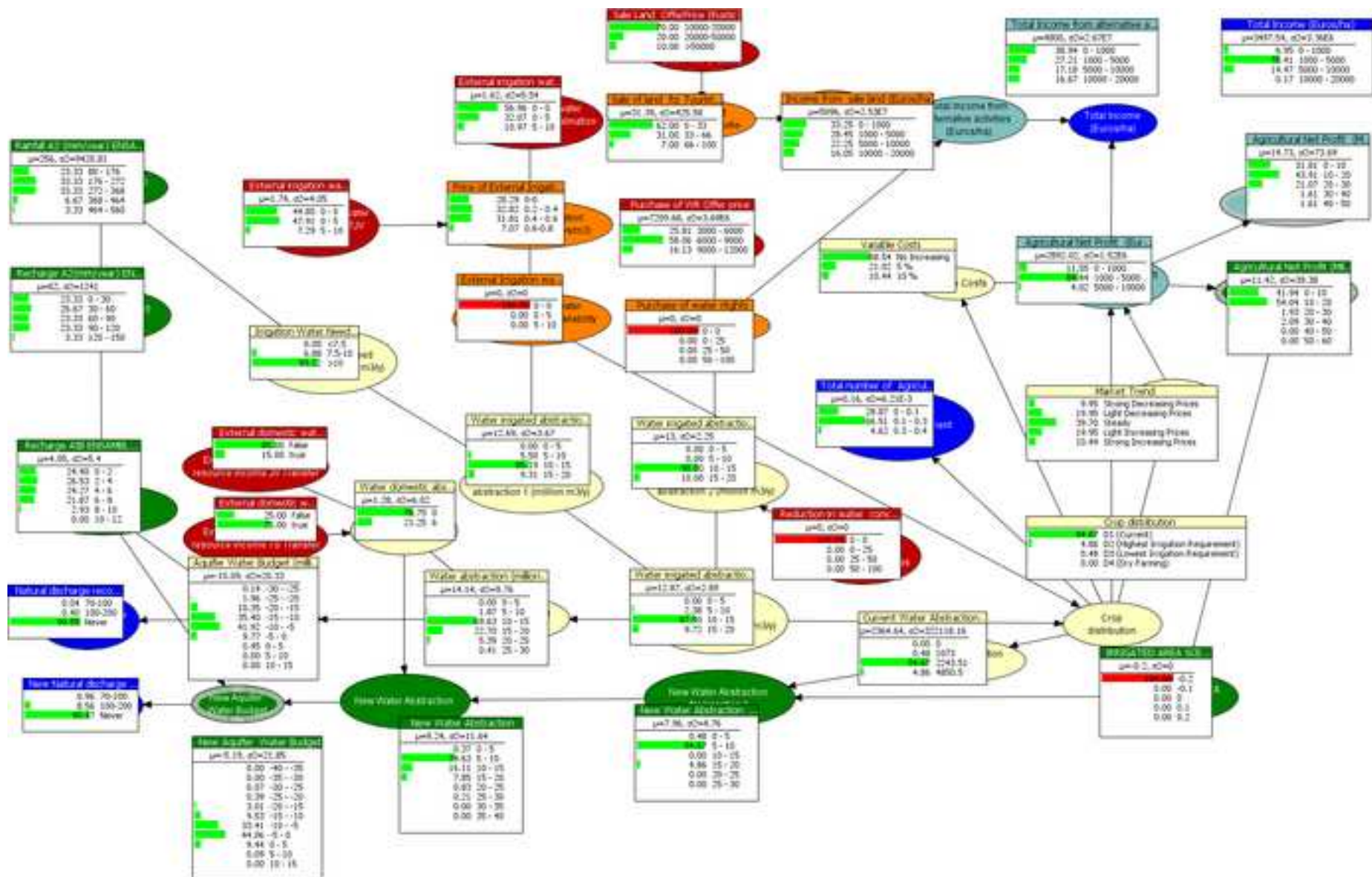


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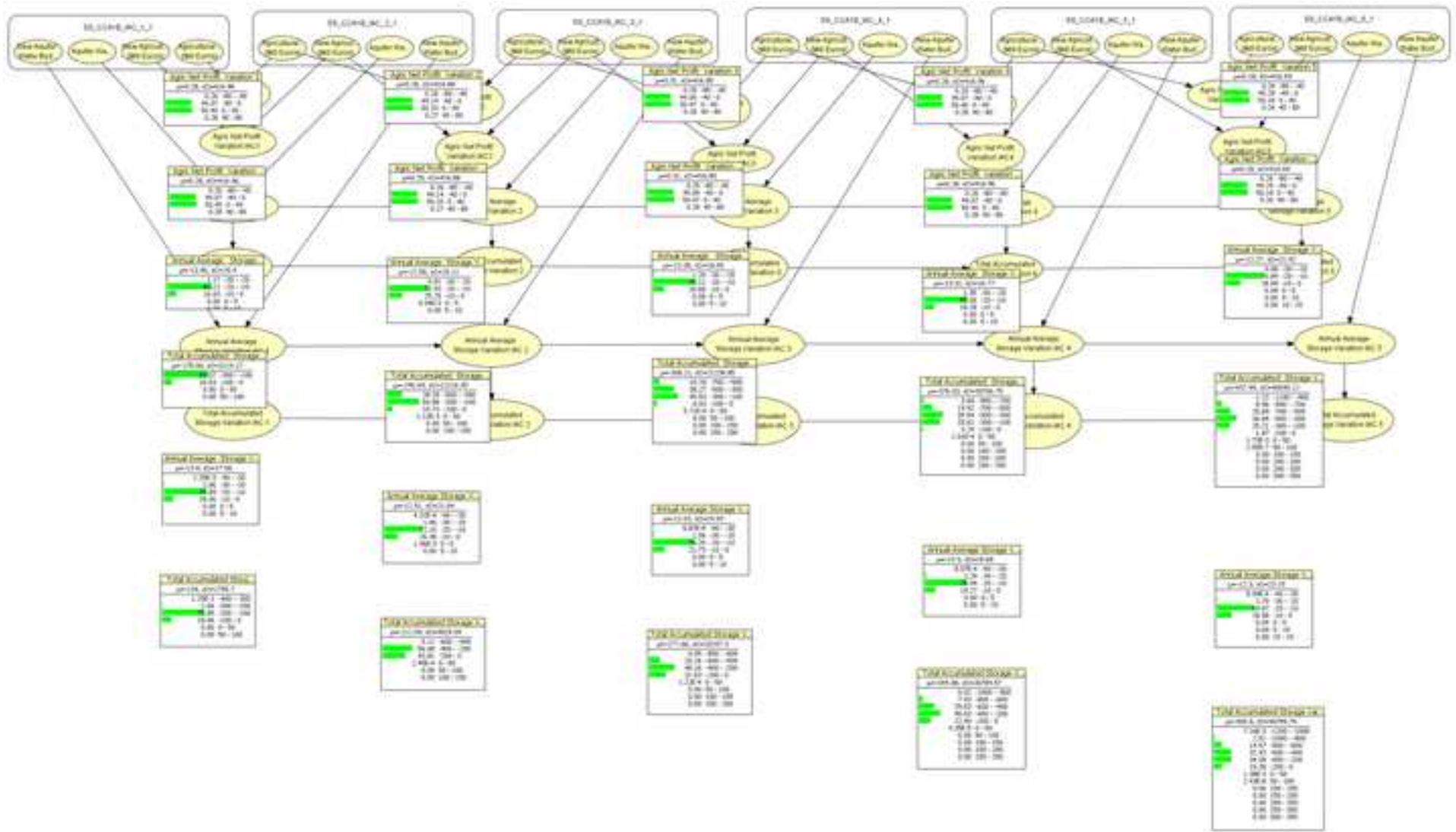


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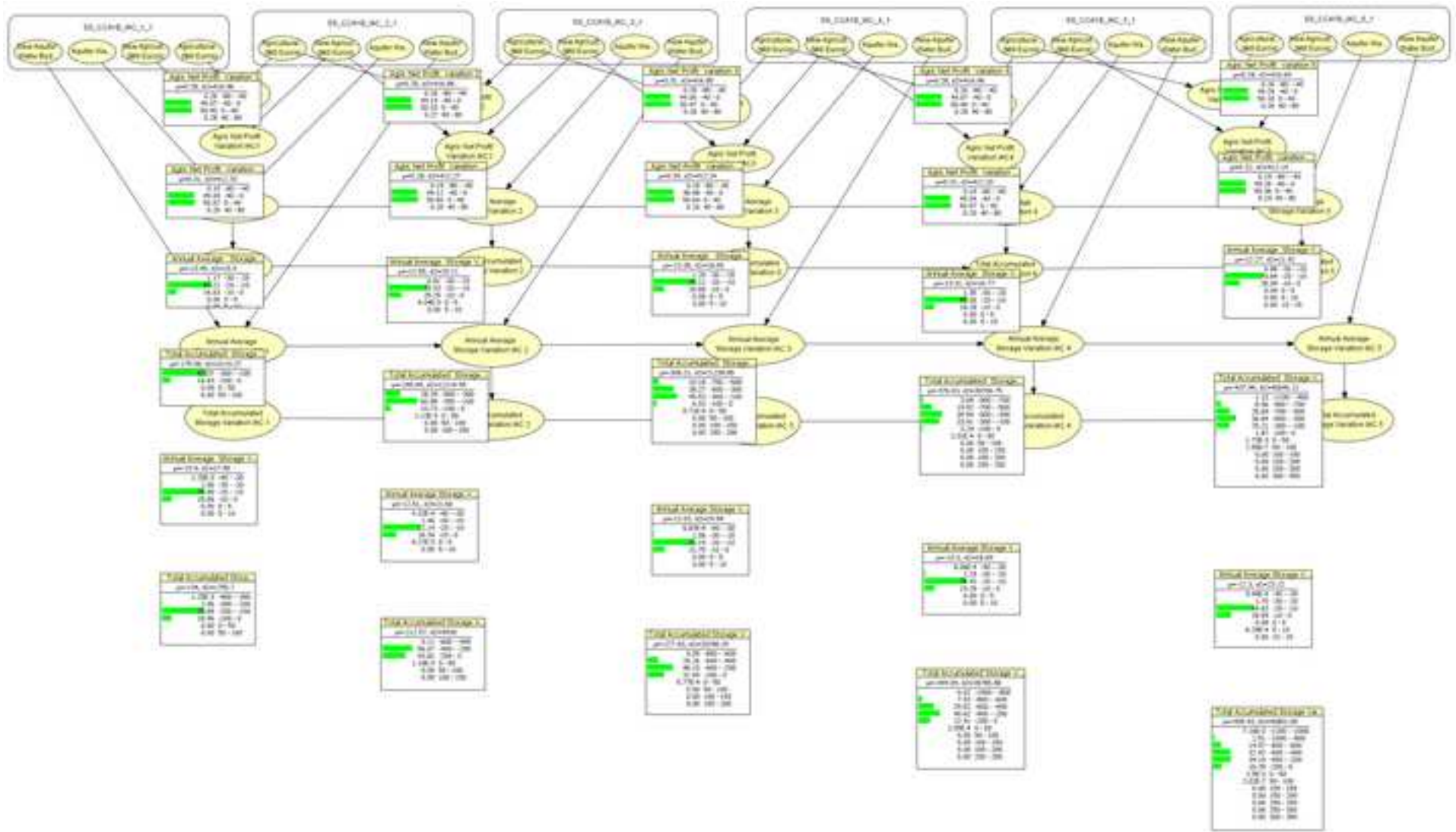


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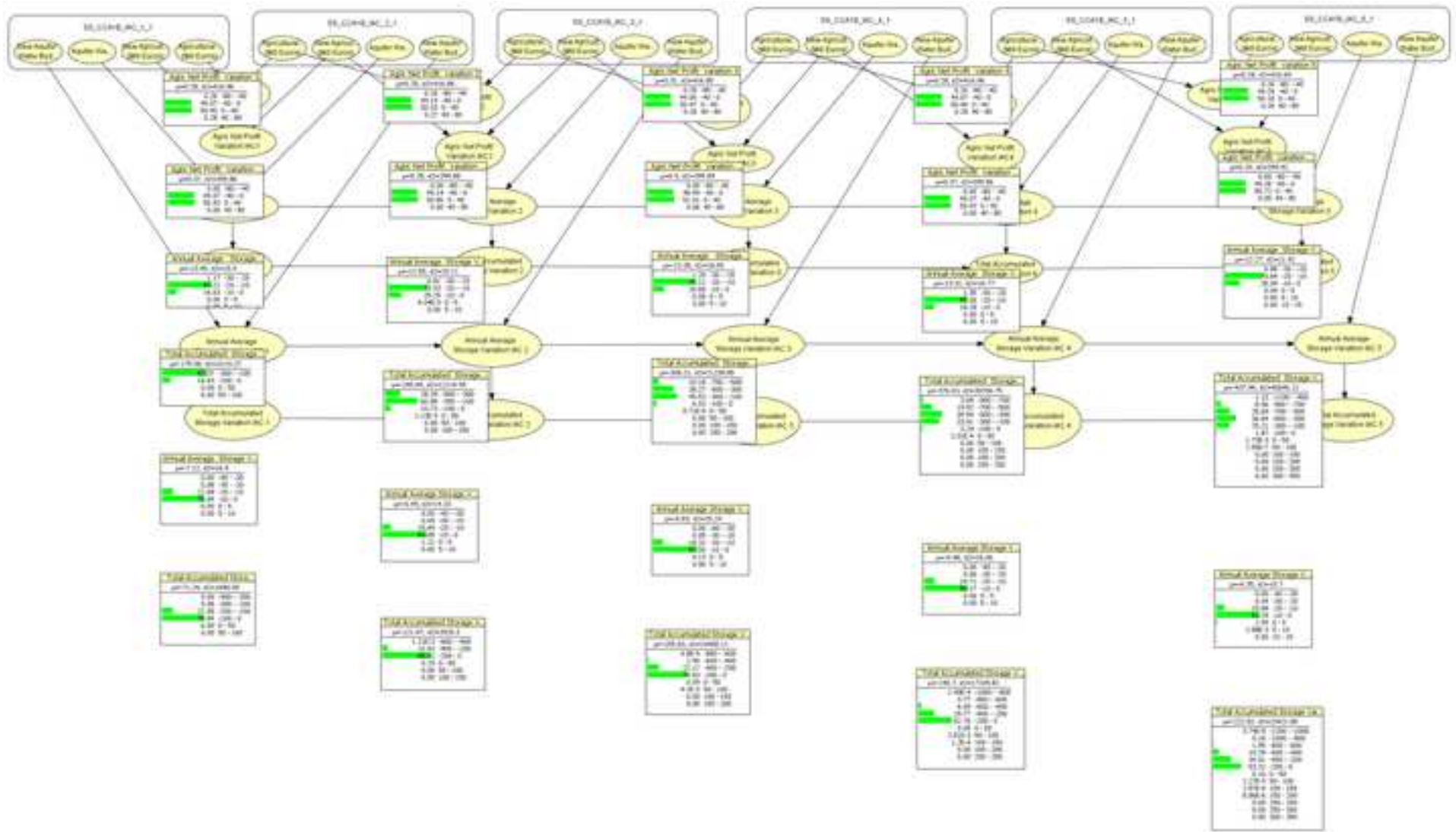


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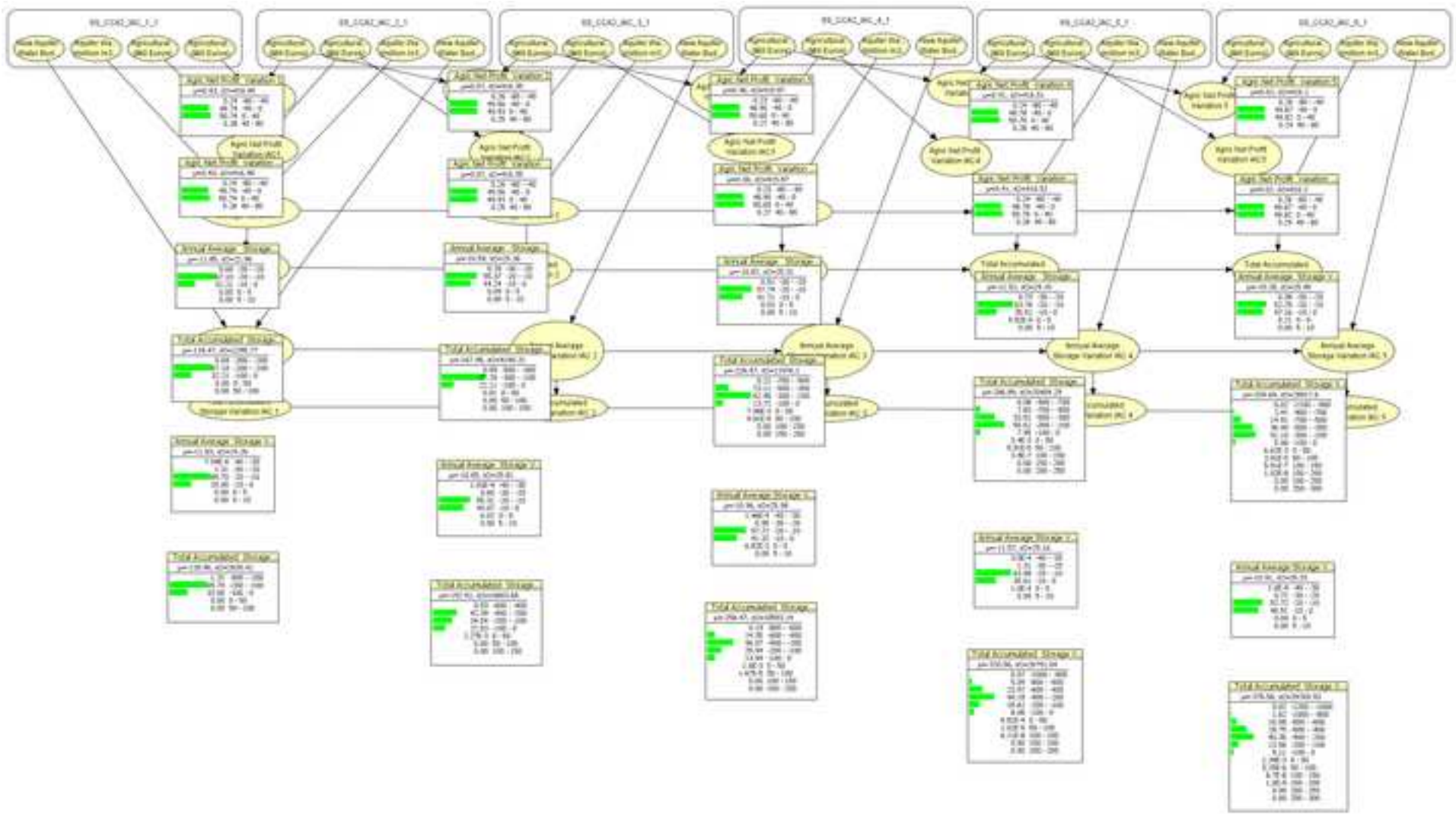


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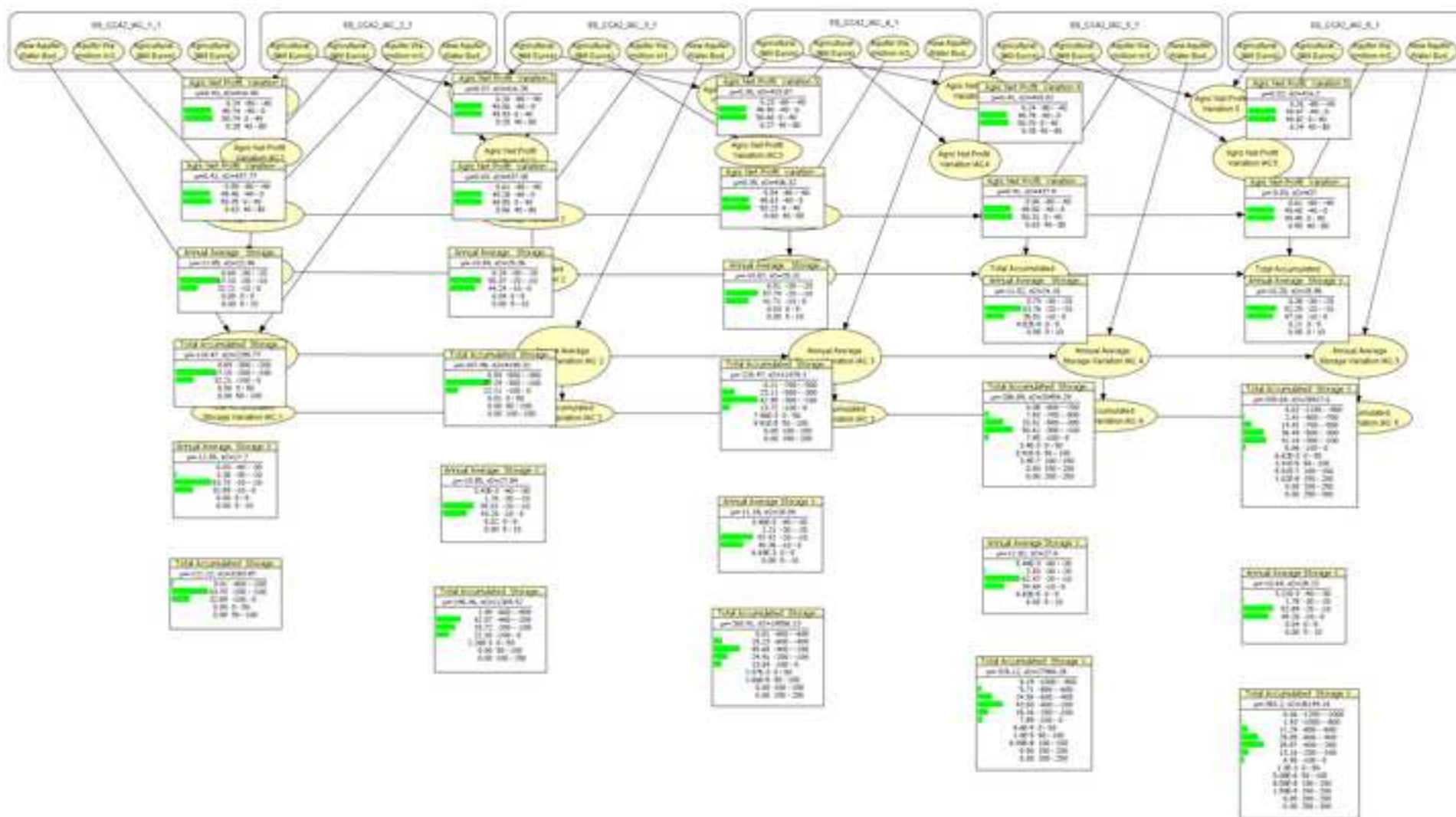


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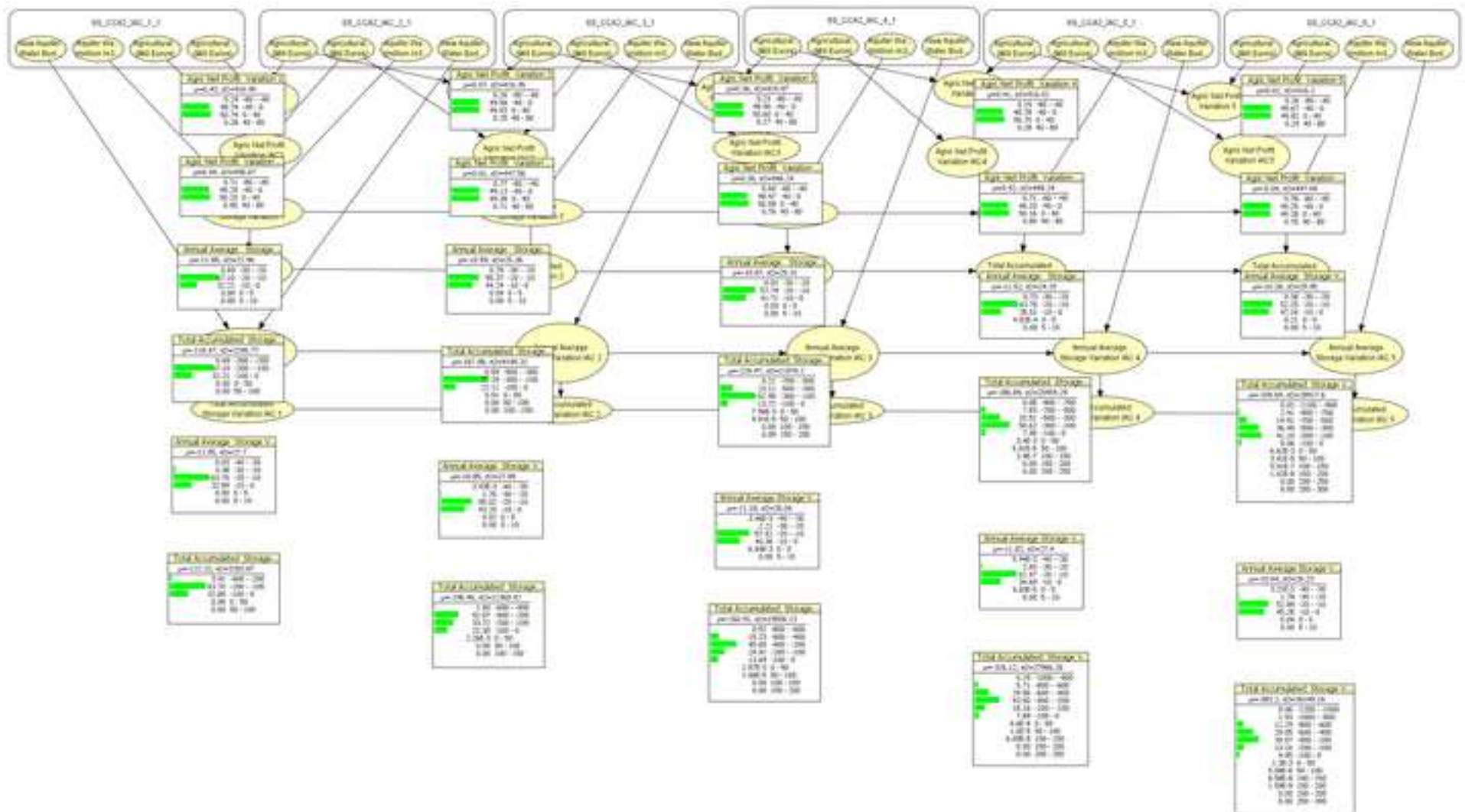


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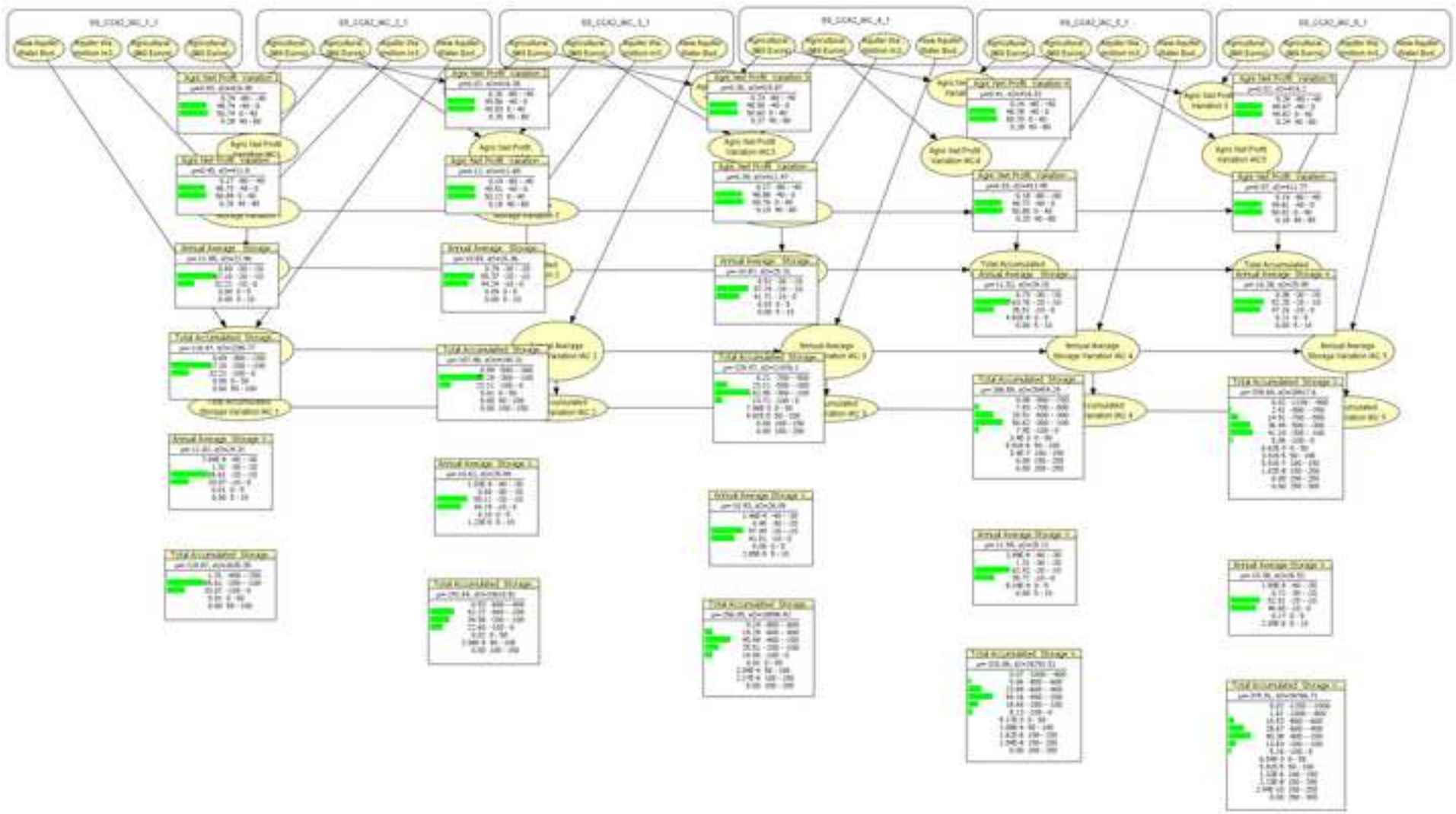
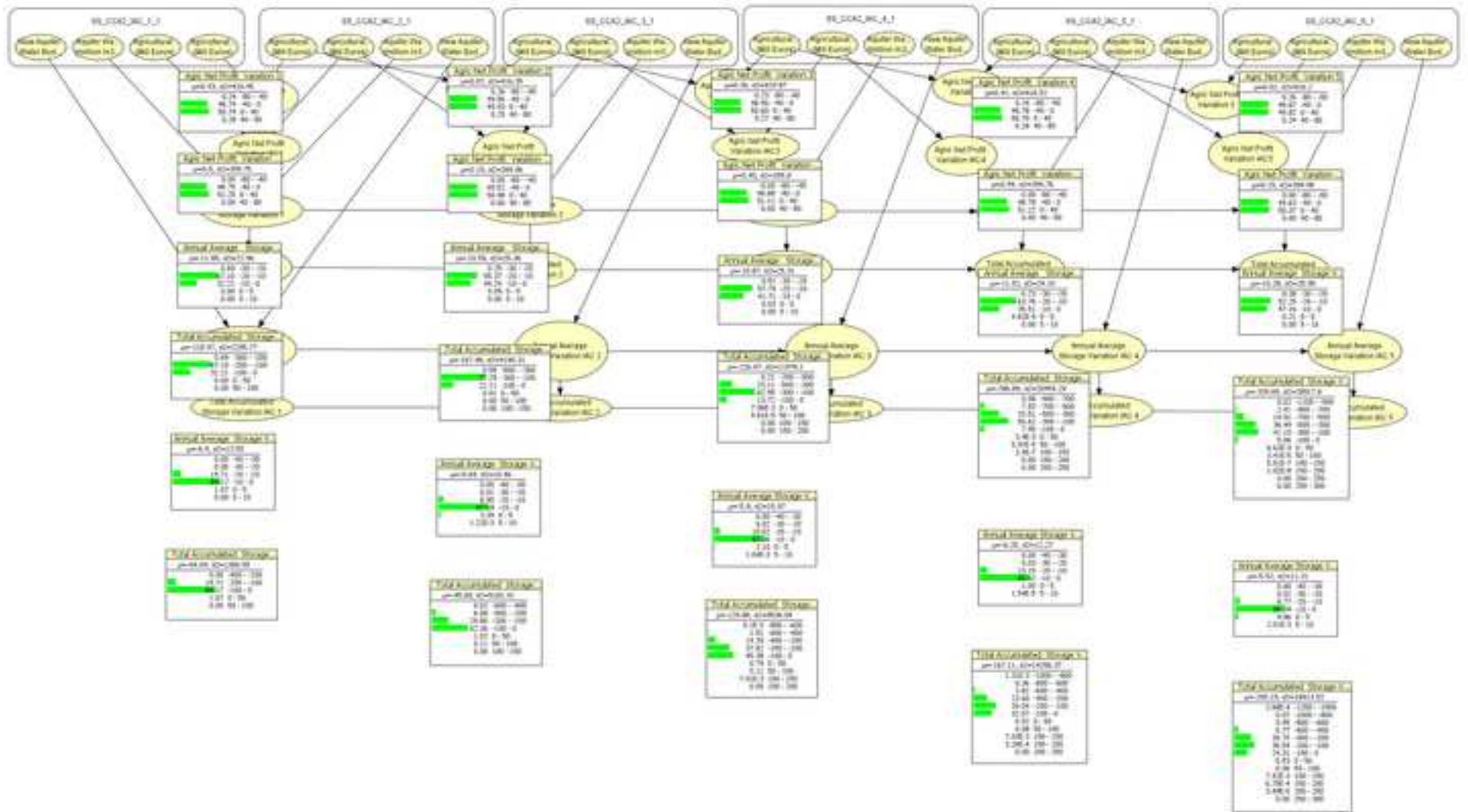


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HIGHLIGHTS for the manuscript “*Dynamic Bayesian Networks as a Decision Support Tool for assessing Climate Change impacts and adaptation of groundwater systems*”

- DBNs are used to assess impacts generated by different Climate Change (CC) scenarios.
- We quantify hydrological and socioeconomic impacts generated by Climate and Land Use changes.
- These applications allow establishing adaptation strategies for aquifer systems as the CC comes into effect.
- Uncertainty, by means of probability, is incorporated in the assessment.
- DBNs are an extension of traditional non-transient nature BNs, for modeling dynamic systems.