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1 **An Integrated Bayesian Network Approach to**
2 ***Lyngbya majuscula* Bloom Initiation**

3

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14

15 **Abstract**

16 Blooms of the cyanobacteria *Lyngbya majuscula* have occurred for decades
17 around the world. However, with the increase in size and frequency of these
18 blooms, coupled with the toxicity of such algae and their increased biomass,
19 they have become substantial environmental and health issues. It is therefore
20 imperative to develop a better understanding of the scientific and
21 management factors impacting on *Lyngbya* bloom initiation. This paper
22 suggests an Integrated Bayesian Network (IBN) approach that facilitates the
23 merger of the research being conducted by various parties on *Lyngbya*.
24 Pivotal to this approach are two Bayesian networks modelling the

25 management and scientific factors of bloom initiation. The research found that
26 Bayesian networks (BN) and specifically Object Oriented BNs (OOBN) and
27 Dynamic OOBNs facilitate an integrated approach to modelling ecological
28 issues of concern. The merger of multiple models which explore different
29 aspects of the problem through an IBN approach can apply to many multi-
30 faceted environmental problems.

31 **Keywords:** Bayesian network, cyanobacteria, DOOBN, dynamic, IBN,
32 *Lyngbya majuscula*, object oriented, OOBN.

33

34 1 Introduction

35 *Lyngbya majuscula* is a cyanobacterium (blue-green algae) occurring
36 naturally in tropical and subtropical coastal areas worldwide (Osborne *et al.*,
37 2001; Arquitt and Johnstone, 2004; Dennison *et al.*, 1999), including Moreton
38 Bay in Queensland, Australia. *Lyngbya* grows on the sediment or over the
39 seagrass, algae or coral (Dennison and Abal, 1999; Watkinson *et al.*, 2005)
40 and when the conditions are favourable, the algae goes through a rapid
41 growth phase, resulting in a substantial increase in biomass, commonly
42 referred to as a bloom (Ahern *et al.*, 2007; Hamilton *et al.*, 2007c). *Lyngbya*
43 blooms appear to be increasing in both frequency and extent (Dennison and
44 Abal, 1999; Albert *et al.*, 2005; Ahern *et al.*, 2007), which can have major
45 ecological (Stielow and Ballantine, 2003; Paul *et al.*, 2005; Watkinson *et al.*,
46 2005), health (Osborne *et al.*, 2001; Osborne *et al.*, 2007) and economic
47 consequences (Dennison and Abal, 1999). It is therefore imperative to better

48 understand the scientific and management factors that drive the initiation of *L.*
49 *majuscula* blooms.

50

51 Deception Bay, located in Northern Moreton Bay in Queensland, Australia,
52 has a history of *Lyngbya* blooms (Watkinson *et al.*, 2005; Ahern *et al.*, 2007)
53 and forms a case study for this investigation. With its proximity to Brisbane,
54 Australia's third largest city with an estimated population in 2004 of 1.78
55 million (ABS, 2004), it is a popular tourist destination. The many waterways
56 feeding from intensive and rural agricultural activities into the Bay and its use
57 for commercial and recreational fishing, put pressure on the marine
58 environment and compound the issues resulting from a nuisance algal bloom
59 (Dennison and Abal, 1999).

60

61 A modelling approach was required to identify the high priority research that
62 needed to be undertaken into the poorly known features of *Lyngbya* initiation.
63 Therefore it was necessary to capture and represent all the available data and
64 expert knowledge about the initiation of *Lyngbya* blooms in Deception Bay.
65 This approach had to engage stakeholders, represent the available
66 information at different spatial and temporal scales, identify scientific and
67 management factors affecting *Lyngbya* initiation and quantify the factors and
68 their inter-dependencies. Moreover, the stakeholders were particularly diverse
69 comprising ecologists and scientists familiar with *Lyngbya* and the factors that
70 affect its bloom, state and local government representatives, committee
71 members of local organisations, as well as individuals with an active interest

72 in *Lyngbya*, including a third generation local fisherman with decades of
73 accumulated knowledge of *Lyngbya* blooms in the Bay.

74

75 There are several modelling approaches that could be considered for such a
76 problem, including decision trees, stochastic petri nets and Bayesian
77 networks. A decision tree has a “top-down approach”. The first factor (root
78 node) at the top of the tree is split according to the decision taken. Each
79 subsequent node is then split in a similar way (Janssens *et al.*, 2006). This
80 approach lacked the ability to represent the many interactions between the
81 factors which would be needed to model the initiation of a *Lyngbya* bloom. A
82 stochastic petri net (SPN), also known as a place/transition net is used to
83 model concurrent systems (Angeli *et al.*, 2007). Implementing a SPN is not
84 trivial, even with the use of bespoke software. It mandates some statistical
85 knowledge as well as some familiarity with stochastic process theory and
86 Monte Carlo simulation techniques (Goss and Peccoud, 1998). A Bayesian
87 Network (BN) provides a graphical representation of key factors, which are
88 represented as nodes in the diagram and their causal relationships with each
89 other and with the outcome of interest (Borsuk *et al.*, 2006; McCann *et al.*,
90 2006; Jensen and Nielsen, 2007; Uusitalo, 2007) are depicted as directed
91 links or arrows connecting a ‘parent node’ to a ‘child node’, resulting in a
92 directed acyclic graph (DAG) (Saddo *et al.*, 2005; Jensen and Nielsen, 2007;
93 Uusitalo, 2007; Park and Stenstrom, 2008). BNs are better able to portray the
94 complexity of the decision process and the many inter-dependencies between
95 the factors of the decision process (Janssens *et al.*, 2006). Moreover, they are
96 visually appealing, easy to use, comprehend and interact with. For more

97 detailed information about the advantages and disadvantages of BNs and
98 comparisons with alternative statistical methods, we refer the reader to
99 (Wilson *et al.*, 2006; Uusitalo, 2007; Ahmed *et al.*, 2009).

100

101 Bayesian networks have been used successfully to better understand and
102 model many complex environmental problems (Bromley *et al.*, 2005). They
103 facilitate the representation of different management decisions and scenarios
104 that may impact on the environmental issue being modelled and the
105 consequences of these situations and actions (McCann *et al.*, 2006; Uusitalo,
106 2007). However, the focus of many networks is often on a single aspect of the
107 outcome, and multi-faceted inferential needs are most commonly addressed
108 through multiple independent networks. This paper describes an approach to
109 integrating diverse knowledge about *Lyngbya* bloom initiation in the Deception
110 Bay area, by developing an Integrated Bayesian Network (IBN). The IBN
111 comprises a series of BNs designed to conceptualize and quantify the major
112 factors and their pathways contributing to the initiation of *Lyngbya*, from both
113 scientific and management perspectives. In Figure 1 a unified modelling
114 language (UML) use case diagram illustrates the conceptual processes of the
115 *Lyngbya* IBN. To our knowledge an IBN approach has not previously been
116 applied to *Lyngbya* bloom initiation.

117

118

(Place figure 1 here)

119

120 In Section 2 we describe the characteristics of a traditional BN, an object
121 oriented BN (OOBN) and the natural progression to a dynamic OOBN

122 (DOOBN). We then introduce the integrated BN approach (IBN) which
123 consolidates the information held in various networks and models. We present
124 the results of this approach in Section 3 by applying it to the initiation of
125 *Lyngbya* blooms.

126

127 **2 Methods**

128 **2.1 Bayesian Network (BN)**

129 As described in Section 1, a BN visualizes knowledge about an ecological
130 issue of interest with the important factors depicted as nodes in the network.
131 These nodes may be at different temporal and spatial scales and the data
132 represented in the BN may originate from diverse sources such as empirical
133 data, expert opinion and simulation outputs (Saddo *et al.*, 2005; Borsuk *et al.*,
134 2006; McCann *et al.*, 2006; Jensen and Nielsen, 2007; Pollino *et al.*, 2007;
135 Park and Stenstrom, 2008). In the case of the *Lyngbya* network, the outcome
136 of interest is the initiation of a *Lyngbya* bloom. Each node of the network is
137 described by a set of states (for example high/medium/low,
138 adequate/inadequate) and quantified by associating a probability table with
139 each node. The probability table is determined by these states and the states
140 of the nodes that influence it. An example is the conditional probability table
141 (CPT) for the *Bottom Current Climate* node, shown in Table 1, which has two
142 states (*Low* and *High*) and has three parent nodes that influence it (*Wind*
143 *Direction*, *Wind Speed* and *Tide*) (Saddo *et al.*, 2005; Pollino *et al.*, 2007; Park
144 and Stenstrom, 2008).

145

146 (Place Table 1 here)

147

148 Two important characteristics of a BN which also simplify probability
149 calculations are directional separation (d-separation) and the assumption of
150 the Markov property (Jensen and Nielsen, 2007). The criterion for d-
151 separation was first proposed by (Pearl, 1988) and an alternative criterion was
152 specified by Lauritzen *et al.*, (1990). If nodes are d-separated then they are
153 conditionally independent (Kjaerulff, 1995, Taroni *et al.*, 2006). The Markov
154 property means that the probability distribution of a variable depends only on
155 its parents. Consequently from the multiplication law of elementary probability
156 theory, the conditional independence (d-separation) and the Markov property
157 enable the probability distribution of a BN with n nodes (X_1, \dots, X_n) to be
158 factorized as follows:

159
$$P(X_1, \dots, X_n) = \prod_{i=1}^n P(X_i / Pa(X_i))$$
 where $Pa(X_i)$ is the set of parents of node X_i

160 This greatly simplifies calculations of the joint probability distribution and
161 allows us to focus on each node in turn to combine the expertise and data
162 available for that node and its parents. The BNs described in this paper were
163 developed as part of a larger study of the major factors and their pathways
164 contributing to the initiation of *Lyngbya* blooms. They were constructed in
165 close collaboration with a *Lyngbya* Science Working Group (LSWG) drawn
166 from a range of disciplines and a *Lyngbya* Management Working Group
167 (LMWG) drawn from local and state government and private organisations
168 (Abal *et al.*, 2005).

169

170 The Science Network focused on nutrient and physical factors that were
171 agreed by the LSWG to be the most influential contributors to the initiation of
172 *Lyngbya*. To construct the Science Network, numerous meetings were
173 convened to determine the most important factors that were believed to have
174 an impact on the ecosystem surrounding Deception Bay. Once the initial
175 structure was agreed upon, the factors were then clearly defined. This was
176 necessary to ensure throughout the process all involved could refer to these
177 definitions to agree that this was indeed the focus of that particular aspect.
178 The initial *Lyngbya* Science BN was then colour coded into six logical groups
179 of coherent nodes. The groups are *Water* (containing nodes *Rain-present*, *No*
180 *prev dry days*, *Groundwater Amount* and *Land Run-off Load*), *Sea Water*
181 (containing *Tide*, *Turbidity* and *Bottom Current Climate*), *Air* (containing nodes
182 *Wind* and *Wind Speed*), *Light* (containing nodes *Light Quantity*, *Light Quality*
183 and *Light Climate*), *Nutrients* (containing nodes *Dissolved Fe Concentration*,
184 *Dissolved Organics*, *Dissolved N Concentration*, *Dissolved P Concentration*,
185 *Particulates (Nutrients)*, *Sediments Nutrient Climate*, *Point Sources* and
186 *Available Nutrient Pool*), and *Lyngbya Algae* (containing only the target node
187 *Bloom Initiation*).

188

189 Thereafter the network was quantified by populating a conditional probability
190 table for each node, based on the factors affecting that node. For example,
191 the probability of low or high *Bottom Current Climate* was determined for
192 different states of its parent nodes, *Wind Direction* (north, south-east or other),
193 *Wind Speed* (low or high) and *Tide* (spring or neap), as shown in Table 1. The
194 CPTs were populated in this way using data obtained from expert elicitation,

195 output from simulation models and statistical models and data obtained from
196 monitoring sites and government agencies. The datasets spanned different
197 time periods ranging from one season to several years, depending on
198 availability and applicability. Meta-data on these datasets were compiled as a
199 key component of the project. The meta-database, comprising the source,
200 ownership, type of data and dates collected, is summarised in a Healthy
201 Waterways report (Fielding *et al.*, 2007), and is available on the organisation's
202 website.

203

204 Validation of the BN was assessed in three ways: through sensitivity analysis,
205 outcomes comparison and scenario testing. Sensitivity analysis is a popular
206 technique in mathematical modelling and the field of decision theory to
207 investigate uncertainty in a model's parameters and their effect on the model
208 output (Hamby, 1994; Coupe *et al.*, 2000). For BNs this means studying the
209 changes in the probabilities of the target node as a result of changes in the
210 network's CPT values (Coupe *et al.*, 2000). In the Science BN the
211 probabilities of one node was varied, while keeping the others fixed, and then
212 observing the changes in the probability of a *Lyngbya* bloom initiation.
213 Sensitivity analysis is considered crucial to model validation and for targeting
214 further research (Hamby, 1994). It is performed on the BN model to reduce
215 uncertainty in the target node and to identify those nodes that have the largest
216 impact on the target node (Hamby, 1994; Coupe *et al.*, 2000). Additional
217 research effort can then be directed to the quantification of those nodes
218 (Bednarski *et al.*, 2004).

219

220 Outcomes comparison involves comparison between external data and model
221 predictions. In the case of the *Lyngbya* Science BN, no such external data
222 were available since all known available data had been used to populate
223 aspects of the BN. Moreover, for any observed *Lyngbya* outbreak, data were
224 not available for the complete set of nodes in the BN model. As a result, a
225 more limited outcomes comparison was undertaken through scenario testing,
226 in which selected scenarios reflected known conditions associated with
227 documented initiation or lack of initiation of *Lyngbya* outbreaks in the last 30
228 years.

229

230 Scenario testing is important to investigate model behaviour for different
231 expert defined scenarios, assessing whether the model behaves as expected
232 in light of past experience and in accordance with current credible research
233 (Laskey, 1995; Bednarski *et al.*, 2004). The expert team therefore nominated
234 scenarios of interest and evidence was entered into the BN to represent these
235 scenarios. The relevant nodes were updated to reflect the proposed scenario
236 and this evidence was propagated through the BN to update the probability of
237 a *Lyngbya* bloom initiation under those conditions (Laskey, 1995; Bednarski *et*
238 *al.*, 2004). For example, evidence of 'best practice' was entered into the BN
239 by setting the *Point sources* node to low. Further sensitivity analysis was then
240 performed on the other nodes in the BN to observe the sensitivity of the target
241 node to changes in node probabilities for that scenario.

242

243 The Management Network focused on management inputs that potentially
244 influence the delivery of nutrients to the Bay and was constructed through a

245 series of meetings with the LMWG. The potential nutrient sources that were
246 identified by the LMWG were split into point sources (coming from a relatively
247 concentrated area e.g. waste water treatment plants) and diffuse sources
248 (nutrients being contributed to the water catchment from a larger geographical
249 area e.g. grazing land). The management model has evolved into a graphical
250 representation of the catchment area showing the waterways and identifying
251 the location of the sources within the catchment as well as their nutrient
252 contributions. Participants of the LMWG identified the existing, committed and
253 best practice management options for each source. The network was then
254 quantified by assigning probabilities to each node to reflect the probability of
255 low or high nutrient discharge for each source under each management
256 option.

257 **2.2 Object Oriented Bayesian Network (OOBN)**

258 The basic building block in an Object Oriented Bayesian Network (OOBN) is
259 an object, which can be a physical or an abstract entity, or a relationship
260 between two entities. Typically, an entity comprises one or more nodes in a
261 BN that are related in a physical, functional or abstract sense. From a
262 probabilistic point of view, the attributes (nodes and links) are encapsulated in
263 an object and therefore d-separated from the rest of the network.

264

265 The definition of classes of objects in OOBNS enables a more generic,
266 reusable network to be described, which can then be used in different
267 contexts. A class is a generic network fragment and when this class is
268 instantiated it is called an object. A class may be instantiated many times
269 (Jensen and Nielsen, 2007). It is not uncommon for several classes to share

270 common substructures. These subclasses can inherit many attributes and
271 behaviours from the parent class, which they can then modify and enhance.
272 The parent class can be viewed as being more abstract than its subclasses
273 with only the important details being retained, whereas subclasses define
274 more specific attributes and behaviours. The ability to create subclasses that
275 inherit properties from another class is a well known and very useful
276 characteristic of object oriented modelling (Koller and Pfeffer, 1997).

277

278 Applying this object oriented approach to BN modelling, an OOBN can be
279 instantiated within another OOBN. An instantiated OOBN is called an *instance*
280 *node* and represents an instance of another network, which in turn could
281 contain instance nodes. Connectivity between these OOBNs is achieved
282 through interface nodes (*input* nodes and/or *output* nodes) (Hugin, 2007;
283 Jensen and Nielsen, 2007). It is clear that OOBNs enable a more structured,
284 hierarchical approach to modelling and consequently the construction of
285 complex and dynamic models (Koller and Pfeffer, 1997; Hepler and Weir,
286 2008).

287

288 The groups of nodes defined in Section 2.1 for the Science Network formed
289 the basis for the creation of OOBN sub-networks, for example the 'Dissolved
290 Elements subnet' and 'Light subnet', respectively. Thereafter the interface
291 nodes were identified and added to the sub-networks to facilitate the transfer
292 of information and evidence into and out of the sub-nets. The OOBN sub-
293 networks were then linked via the interface nodes to recreate the *Lyngbya*
294 Science network. The new structure now facilitated the independent parallel

295 development and interrogation of the sub-networks so that they could be
296 reintegrated into the parent network when they were deemed to be complete.

297 **2.3 Dynamic Object Oriented Bayesian Network (DOOBN)**

298 The temporal behaviour of a network can be represented by time slices, one
299 for each period of interest. The resulting network, consisting of several OOBN
300 time slices, is referred to as a dynamic OOBN (DOOBN) (Kjaerulff, 1995;
301 Weber and Jouffe, 2006). *Lyngbya* blooms in Moreton Bay occur more
302 frequently during the summer months when conditions are more favourable
303 for bloom initiation (Watkinson *et al.*, 2005). Additional statistical modelling
304 was conducted by Hamilton *et al.* (2007a) on the effects of temperature,
305 rainfall and light on *L. majuscula* blooms and the importance of groundwater
306 in stimulating *Lyngbya* blooms has been studied by (Ahern *et al.*, 2006) and
307 was nominated by LSWG as a key node that may exhibit temporal behaviour.
308 It was thus considered that the DOOBN would be better able to predict the
309 probability of *Lyngbya* bloom initiation. A UML use case diagram illustrating
310 the processes involved in creating this DOOBN, is shown in figure 2.

311

312 (Place Figure 2 here)

313

314 The initial static Science BN model used annual averages for rainfall and
315 temperature, but captured some temporal behaviour by introducing a node to
316 represent the previous number of dry days. As directed by the LSWG the
317 *Lyngbya* Science BN was extended to incorporate the temporal nature of *L.*
318 *majuscula* to create a DOOBN with five time slices (one for each of the
319 months of November to March). The DOOBN is therefore able to predict the

320 probability of a *Lyngbya* bloom initiation by incorporating specific monthly data
321 while also taking into account the influence of the previous month.

322

323 Using Bayesian statistical modelling (Hamilton *et al.*, 2007b) investigated the
324 response of *Lyngbya* bloom initiation to temporal factors such as average
325 minimum and maximum monthly temperature, monthly rainfall, average
326 monthly solar exposure and average monthly clear sky (the inverse of cloud
327 cover). One month time lags and interaction terms were also included for rain
328 and minimum temperature. From a total of 890 models evaluated, the single
329 term average minimum monthly temperature model (with an intercept term)
330 had the best predictive behaviour. Rainfall at a lag of one month was the only
331 other variable that appeared in the top five identified models.

332

333 **2.4 Integrated Bayesian Network (IBN)**

334 We describe here the IBN for the probability of initiation of a *Lyngbya* bloom.
335 This network comprises two primary BNs, the Management Network and the
336 Science Network described in Section 2.1, integrated with a Water Catchment
337 simulation model, which was concurrently developed under the *Lyngbya*
338 Programme. The IBN is conceived as a series of steps, in which the
339 Management Network informs about nutrient discharge into the Deception
340 Bay catchment, the Catchment model simulates the movement of these
341 nutrients to the *Lyngbya* site in the Bay, and the Science model then
342 integrates this nutrient information with other factors to determine the
343 probability of initiation of a *Lyngbya* bloom.

344

345 Figure 3 is a UML activity diagram detailing the processes of the IBN for
346 *Lyngbya* bloom initiation. In addition to providing a rich, cohesive model of
347 *Lyngbya* bloom initiation from both a science and management perspectives,
348 an important use of the IBN was for scenario modelling. A set of exemplar
349 scenarios that could impact on nutrient delivery to the *Lyngbya* site was
350 proposed. This included: upgrading point sources from existing to best
351 practice (e.g. eliminating potassium output from sewage treatment plants
352 across the catchment), describing a climate event (e.g. a severe summer
353 storm), and conditions least favourable for bloom initiation (e.g. low
354 temperature and nutrients).

355

356 For each proposed scenario the changes in the level of nutrients or to the
357 factors affecting the initiation of *Lyngbya* in the Science network were
358 assessed. If nutrient loads were changed, the impact on nutrient
359 concentrations across the catchment arising from a management scenario
360 could then be simulated through the Water Catchment model by the
361 application of filters. The E2 software package (eWater CRC, 2007) used to
362 create the Water Catchment model contains several pre-defined filters
363 capable of simulating various complex management actions and adjusting the
364 catchment load output accordingly. For example filters such as percentage
365 removal of a nutrient and nutrient trapping may be chosen. Thereafter the
366 Science Network was updated to reflect the modified nutrient loads and other
367 changes related to the proposed scenario. This evidence was then
368 propagated through the network to yield the probability of initiation of a
369 *Lyngbya* bloom under the specific scenario.

370

371

(Place Figure 3 here)

372

373 The networks in the IBN were developed using a variety of software modelling
374 tools. The conceptual Management Network was visually represented using
375 the BN package Netica® (Norsys, 2007) and then interfaced with the
376 hydrological flow and nutrient load model created in the whole of catchment
377 simulation software package, E2 (eWater CRC, 2007), in order to identify
378 nutrient loads reaching the *Lyngbya* site. The Science Network was
379 developed entirely in Netica® and later in Hugin® (Hugin, 2007) where the
380 network was transformed into a DOOBN by creating time slices (Kjaerulff,
381 1995; Weber and Jouffe, 2006; Jensen and Nielsen, 2007). In summary, the
382 novelty factor here is that although a static BN is unable to ‘communicate’ with
383 another BN, we can transform it to an OOBN to facilitate information flow and
384 linkage to other OOBNs of interest. Thus we can exploit the purpose for which
385 each model was designed to build a more comprehensive model of the
386 environmental issue of concern.

387

388 **3 Results**

389 The static Science BN for initiation of *Lyngbya* is depicted in figure 4 with the
390 nodes representing the factors identified by the LSWG as important in the
391 initiation of a *Lyngbya* bloom.

392

393

(Place Figure 4 here)

394

395 Sensitivity analysis of this BN revealed that the seven most influential factors
396 in the Science Network were (in decreasing order of influence): available
397 nutrient pool (dissolved), bottom current climate, sediment nutrients, dissolved
398 iron (Fe), dissolved phosphorous (P), light and temperature. Furthermore
399 scenario modelling consistently identified available nutrient pool as the factor
400 which most heavily influences the probability of initiation of a bloom. Point and
401 diffuse sources deliver nutrients to the bay and this nutrient delivery is
402 affected by management actions at the sources.

403

404 The Science BN was also interrogated using management and climatic
405 scenarios and analysing the effect on the probability of bloom initiation to
406 changes in the various factors. The predicted changes in the probability of a
407 *Lyngbya* bloom initiation as a result of each of the seven most influential
408 factors in isolation, is shown in Table 2. In a 'typical' year, as defined by the
409 LMWG, the probability of a bloom initiation was reported as 28%; this
410 increased significantly during a severe summer storm event to 42%, when
411 *light climate* was optimal and *rain-present* was high. Bloom initiation was a
412 predicted as a certainty (100%) when the *available nutrient pool (dissolved)*
413 was enough, *temperature* was high and *light climate* was optimal. However,
414 when only the *available nutrient pool (dissolved)* was set to 'not enough', the
415 probability of a bloom initiation dropped to 3%, but jumped to 80% when it
416 was changed to 'enough'. Although *bottom current climate* was a key
417 influential factor, changing only this factor caused the probability of bloom
418 initiation to drop to 15% when the *bottom current climate* was 'high' and to
419 increase to 43% when it was 'low'. This is a variation of 28% in the probability

420 of a bloom initiation and although large, is clearly overshadowed by the 77%
421 variation caused by changes in nutrient availability. Changing iron availability
422 alone increased the probability of a bloom initiation from 21% to 37%.
423 Changing organics availability alone increased the probability of a bloom
424 initiation from 25% to 31%.

425

426 (Place Table 2 here)

427

428 Next the Science OOBN sub-network (figure 5) was created from the static
429 *Lyngbya* Science BN as outlined in Section 2.2, retaining all the key factors
430 (with the exception of the *No of prev dry days*) and their CPTs from the static
431 BN. As is characteristic of Object Oriented networks, the Science OOBN sub-
432 network includes instances of other sub-networks, shown in figure 5 as
433 rectangles with rounded edges, such as the *Wind subnet* and the *Turbidity*
434 *subnet*. Input nodes were added to the Science OOBN sub-network as
435 placeholders for the real nodes, *Temperature*, *Rain- present*, *Land Run-off*
436 *Load* and *Ground Water Amount*. The sub-networks were based on the
437 groups created in the static Science BN to yield standalone networks capable
438 of linking to other networks via the interface nodes (input and output nodes),
439 or being instantiated in other networks. Importantly, providing the interface
440 remains intact, these OOBN sub-networks can be further expanded without
441 affecting the structure of any other networks linking to it. As a consequence
442 we have a powerful concept of parallel development by independent expert
443 teams while retaining the overall cohesive model.

444

445 (Place Figure 5 here)

446

447 In collaboration with the LSWG and based on the findings of (Hamilton *et al.*,
448 2007a) as described in Section 2.3, the static *Lyngbya* Science network was
449 adapted in the following manner to incorporate monthly rainfall and
450 temperature data and the lag effect of rainfall on the amount of groundwater
451 and land run-off. First, the lag effect of rainfall on groundwater amount and
452 land run-off was replicated by creating a Rainwater OOBN sub-network as
453 shown in figure 6. In this OOBN, the *Prev Groundwater* and the *Prev Land*
454 *Run-off* are input nodes (double edged eclipse with a broken outer line), which
455 enable connectivity to the previous time slice's *Ground Water Amount* and
456 *Land Run-off* nodes, respectively. The *Rain – present* input node enables the
457 instances of the Rainwater OOBN to be bound to the rainfall relating to that
458 instance, e.g. the November Rainwater OOBN instance will have November's
459 rainfall bound to the *Rain – present* input node. The *Ground Water Amount*
460 and *Land Run-off Load* output nodes (double edged eclipse with a solid outer
461 line) make them visible to other networks and therefore allow them to be
462 bound to input nodes in other networks.

463

464 (Place Figure 6 here)

465

466 Finally the DOOBN was created with five time slices (figure 7), one time slice
467 for each of the summer months (December to February), one for the end of
468 spring (November) and one for the start of autumn (March) . Every time slice
469 has an instance of the Rainwater and Science sub-networks as well as the

470 temperature and rainfall nodes for that month. Data from the Bureau of
471 Meteorology was used to quantify the DOOBN, as well as the information
472 contained in the initial static BN.

473

474 (Place Figure 7 here)

475

476 As can be seen in figure 8, the rainfall information for a particular month is
477 bound to the *Rain present* input node in the Rainwater and Science model
478 sub-network instances for that month and the *Groundwater Amount* and *Land*
479 *Run-off* output nodes from one month bind to the *Prev Groundwater* and *Prev*
480 *Land Run-off* input nodes of the following month, respectively.

481

482 (Place Figure 8 here)

483

484 The point and diffuse nutrient sources contributing to the Management
485 Network for *Lyngbya* initiation included: aquaculture, composting, onsite
486 sewage, poultry, waste disposal, waste water treatment plant, agriculture,
487 artificial development, development and clearing, extractive industries,
488 forestry, grazing, natural vegetation and stormwater. The sources and
489 nutrients identified by the management committee are shown in Table 3.

490

491 An extract of the Management Network, which identifies and locates point and
492 diffuse sources of nutrients for the Mellum Creek Sub-catchment, visually
493 represented in Netica®, is shown in figure 9.

494

495 (Place Figure 9 here)

496

497 Scenario modelling predicted higher probabilities of *Lyngbya* bloom initiation
498 during the summer months and confirmed the temporal nature of *Lyngbya*
499 bloom initiation. Incorporating this behaviour resulted in the DOOBN for
500 *Lyngbya* bloom initiation (figure 7) being developed as outlined above with
501 one month lag effects included for groundwater amount and land run-off.

502

503 As shown in figure 10 below, the BN predicts a sharp increase in the
504 probability of initiation of a *Lyngbya* bloom from the end of spring (November)
505 to the first month of summer (December). The increased probability continued
506 during the next two summer months, with a slight fall in autumn (March).
507 Although these predicted probabilities for *Lyngbya* bloom initiation are low, the
508 increased trend in bloom initiation is clearly visible. When evidence of summer
509 rainfall was added to these time slices we observed a more dramatic
510 increase. For example, the probability of a bloom initiation was predicted as
511 52% when evidence of a summer rainfall event was entered into the
512 December time slice. This compares to 42% in the original static annual BN
513 model.

514

515 (Place Figure 10 here)

516

517 **4 Discussion**

518 This paper describes an Integrated Bayesian Network approach applied to the
519 initiation of *Lyngbya* blooms. The aim was to present the exposition of BN

520 methodology to a complex ecological problem such as *Lyngbya* bloom
521 initiation and illustrate how it can be used to integrate models for different
522 aspects of the same issue. We have illustrated the process that could be
523 followed to integrate two static BNs and another type of model (such as the
524 E2 model of the Whole of Catchment) to achieve an integrated BN. The IBN
525 approach described here can also be used for investigating other features of
526 this organism, such as growth, biomass and decay, through appropriate
527 changes to the Science Network. These networks are currently being
528 developed. The Integrated Network approach is also conceptually suitable for
529 investigating other outcomes of interest that are impacted by nutrient outputs
530 and water movement in a catchment.

531

532 It is noted that it is beyond the scope of the present paper to provide an actual
533 test of the utility of BNs for predicting cyanobacterial blooms. The paper
534 therefore does not include a comparison of the predictions against classical
535 multivariate techniques; a test of the BNs own output reliability, that is,
536 whether the probabilistic estimate of the likelihood the BNs output is correct
537 for the target data set; a clear presentation of exactly what data are being
538 used; a sufficient amount of data to first build and refine the model on one
539 data set and then test it on a previously unseen set of data. However the
540 Science BN, which has been adopted by Healthy Waterways, will be validated
541 through future data collected as part of the next phase of the *Lyngbya* project.

542

543 More broadly, the general approach proposed in this paper is applicable to
544 environmental or other outcomes involving both scientific and management

545 considerations. Information arising from expert knowledge, data and research
546 can be formally conceptualized and quantified through Science and
547 Management Networks, and combined into an Integrated Network. Such an
548 approach involves definition of the problem or outcome of interest, agreement
549 as to significant contributing factors and their definitions and pathways which
550 impact on this outcome, and identification and integration of information that
551 allow quantification of these factors and impacts. The benefits of such an
552 approach include a much greater specification of the issue at hand or
553 research focus, buy-in from diverse stakeholders, consolidation and
554 formalisation of information, an audit trail for decision-making and future
555 research, and quantitative outcomes in the form of probability statements
556 about the outcome of interest.

557

558 In the static *Lyngbya* BN (figure 4) similar factors were grouped together and
559 colour coded as a visual aid. The nature of the Science BN enabled a simple
560 conversion of the network to an OOBN (figure 6), with a sub-network for each
561 group of factors and interface nodes providing the communication links to
562 other OOBNs (figure 8). In the same way many complex BNs can be
563 simplified by abstracting the network to a higher level to include sub-networks
564 of logically grouped factors, which in turn can include other sub-networks,
565 thereby having several levels of abstraction. An important feature of the
566 OOBN sub-networks is that they can be developed simultaneously by the
567 various expert groups who are responsible for them. When the sub-networks
568 have been quantified, tested and ratified, they are integrated into the master
569 network containing instances of those sub-networks.

570

571 The extension to a DOOBN not only improved prediction but also enhanced
572 interpretability of the network. The inclusion of time-specific dynamics for
573 temperature and water was more consistent with the conceptual framework of
574 *Lyngbya* behaviour held by both science and management stakeholders.
575 Moreover, it is more straightforward to include expert opinion and data of a
576 temporal nature in this expanded model. It is suggested that for other complex
577 ecological systems, the additional complexity of a DOOBN is more than
578 compensated for by the increased flexibility of representation of information
579 and acceptability of the outputs.

580

581 Finally, the creation of an IBN to combine multiple networks which describe
582 different aspects of an outcome of interest is an effective way of providing a
583 cohesive, quantifiable and auditable tool for better understanding and
584 coordination of multi-faceted environmental problems.

585

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594

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732

733 **Legends**

734 **Figure 1:** UML use case diagram of the conceptual processes in the *Lyngbya*
735 bloom initiation Integrated Network

736 **Figure 2:** UML use case diagram of the processes for the *Lyngbya* bloom
737 initiation DOOBN

738 **Figure 3:** UML activity diagram detailing the processes for the *Lyngbya* bloom
739 initiation IBN

740 **Figure 4:** Science Network for *Lyngbya* initiation (Netica®)

741 **Figure 5:** Rainwater OOBN sub-network showing two output nodes,
742 *Groundwater Amount* and *Land Run-off Load*, which are then connected to
743 the input nodes *Prev Groundwater* and *Prev Land Run-off* in the next time
744 slice

745 **Figure 6:** Science OOBN sub-network

746 **Figure 7:** Five time slices forming the DOOBN for *Lyngbya* bloom initiation

747 **Figure 8:** Expanded sub-network instances in Hugin®, showing the interface
748 nodes for each instance. The input and output nodes are represented here as
749 ellipses with broken and solid lines, respectively. Also evident are the directed
750 links between the sub-network instances of the same and the next time slice,
751 so that information from one time slice can flow into the next time slice.

752 **Figure 9:** Extract of the Management Network for Mellum Creek Sub-
753 catchment, a visual representation of the sub-catchment, showing point and
754 diffuse sources of nutrients. The inset shows the complete Management
755 Network

756 **Figure 10:** Probability of *Lyngbya* bloom initiation

757
 758 **Table 1:** Conditional probability table for *Bottom Current Climate* node with
 759 states *Low* and *High* and parent nodes *Wind Direction* (states *North*, *SE* and
 760 *Other*), *Wind Speed* (states *Low* and *High*) and *Tide* (states *Spring* and
 761 *Neap*). These nodes, their states, probabilities and relationships are visible in
 762 the Bayesian network in figure 4

763

Wind Direction	Wind Speed	Tide	Low	High
North	Low	Spring	0.33	0.67
North	Low	Neap	0.61	0.39
North	High	Spring	0.43	0.57
North	High	Neap	0.54	0.46
SE	Low	Spring	0.42	0.58
SE	Low	Neap	0.58	0.42
SE	High	Spring	0.37	0.63
SE	High	Neap	0.59	0.41
Other	Low	Spring	0.39	0.61
Other	Low	Neap	0.59	0.41
Other	High	Spring	0.43	0.57
Other	High	Neap	0.50	0.50

764

765
766 **Table 2:** Changes to the probability of *Lyngbya* bloom initiation for key
767 factors. All possible states for each of the nodes were assessed individually to
768 ascertain the delta effect it had on the probability of a *Lyngbya* bloom
769 initiation.

770

<i>Factor</i>	Change in P(Bloom) (%)
<i>Available Nutrient Pool</i>	77
<i>Bottom Current Climate</i>	28
<i>Sediment Nutrient Climate</i>	17
<i>Dissolved Fe</i>	16
<i>Dissolved P</i>	15
<i>Light Climate</i>	14
<i>Temperature</i>	14

771

772

773

Table 3: Point and diffuse sources contributing nutrients to Deception Bay

774

Source	Point(P) or Diffuse (D)	Nitrogen	Phosphorous	Iron	Organics
Aquaculture	P	X	X		
Composting	P	X	X		
Onsite Sewage	P	X	X		
Poultry	P	X	X	X	
Waste Disposal	P	X	X	X	
Waste Water Treatment Plant	P	X	X		
Agriculture	D	X	X	X	X
Artificial Development	D	X	X		
Developing & Clearing	D	X	X	X	X
Extractive	D	X	X		
Forestry	D	X	X	X	X
Grazing	D	X	X		
Natural Vegetation	D	X	X		X
Stormwater	D	X	X		

775

776

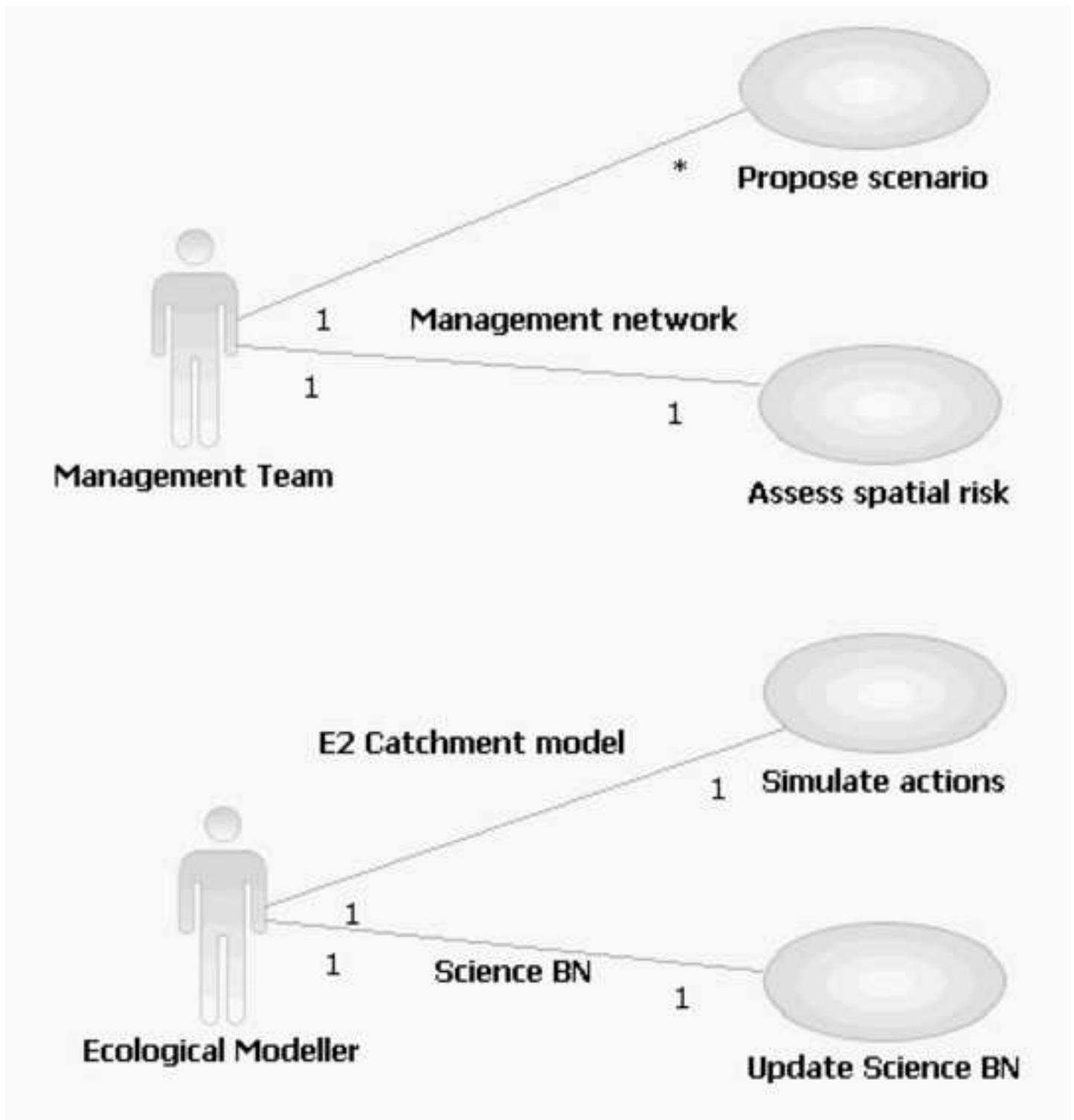


Figure 4

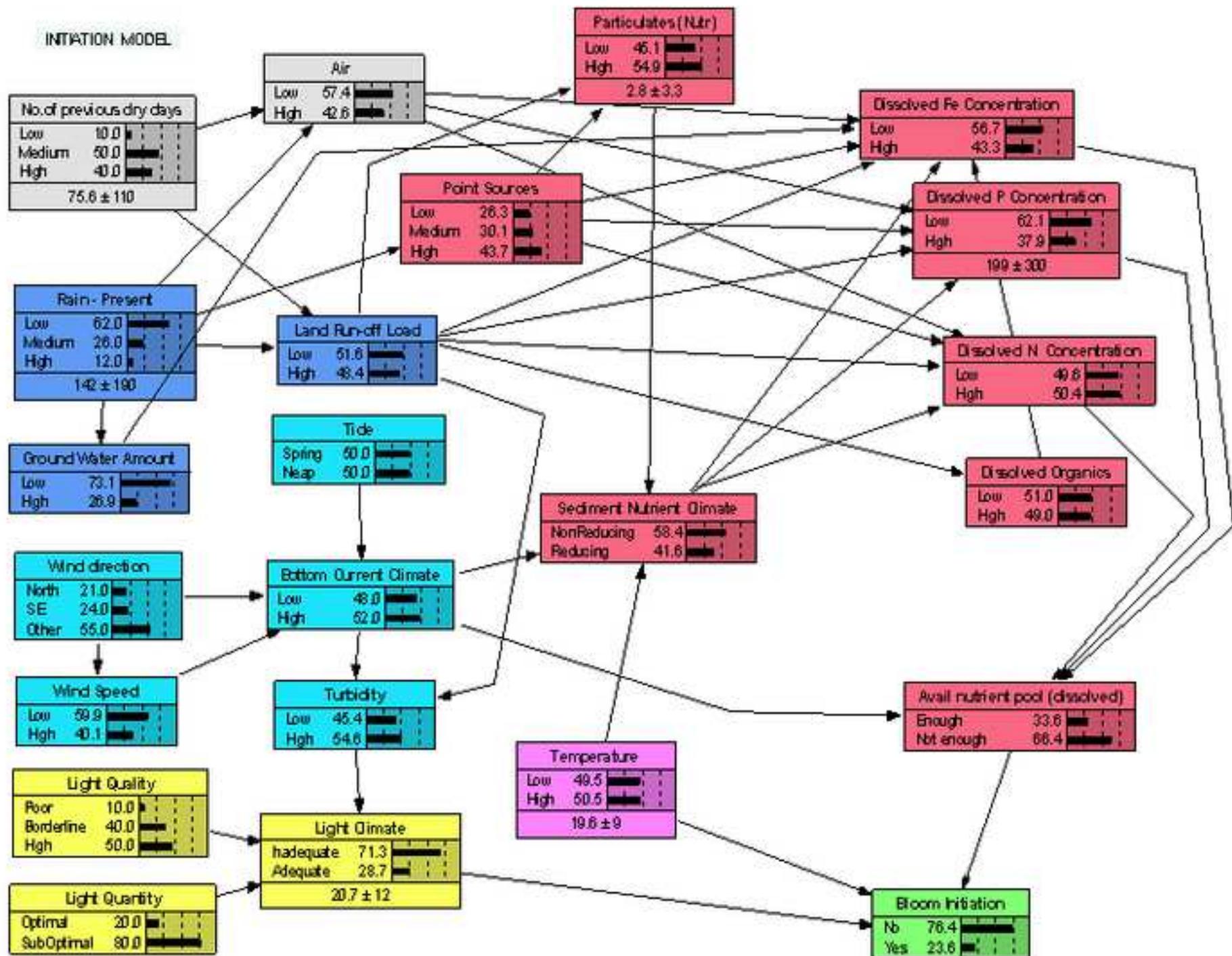


Figure 5

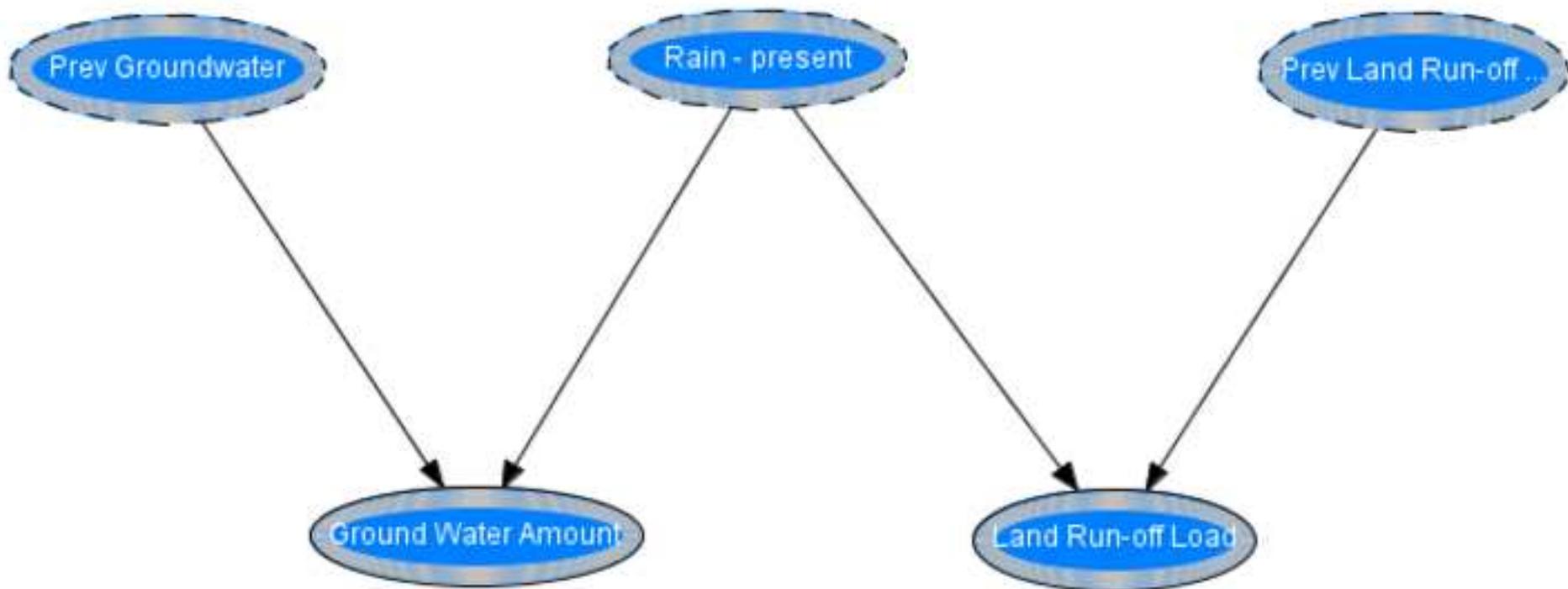


Figure 5

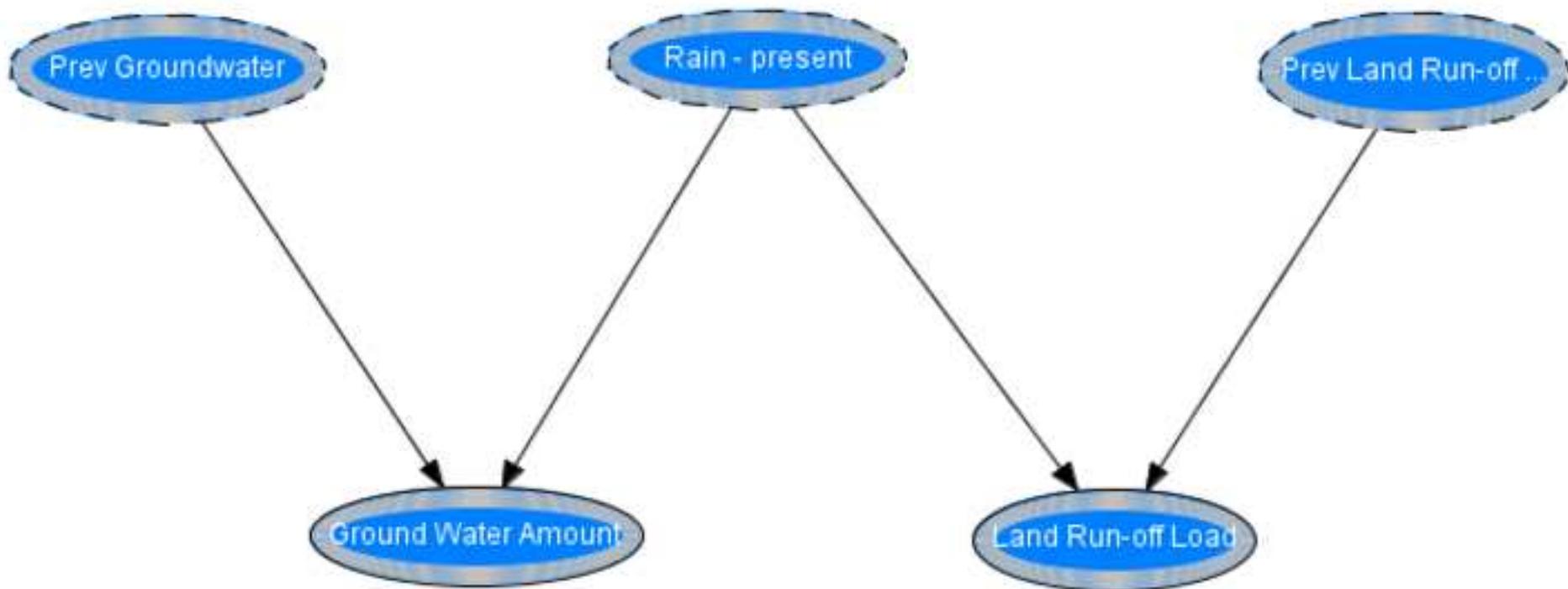


Figure 5

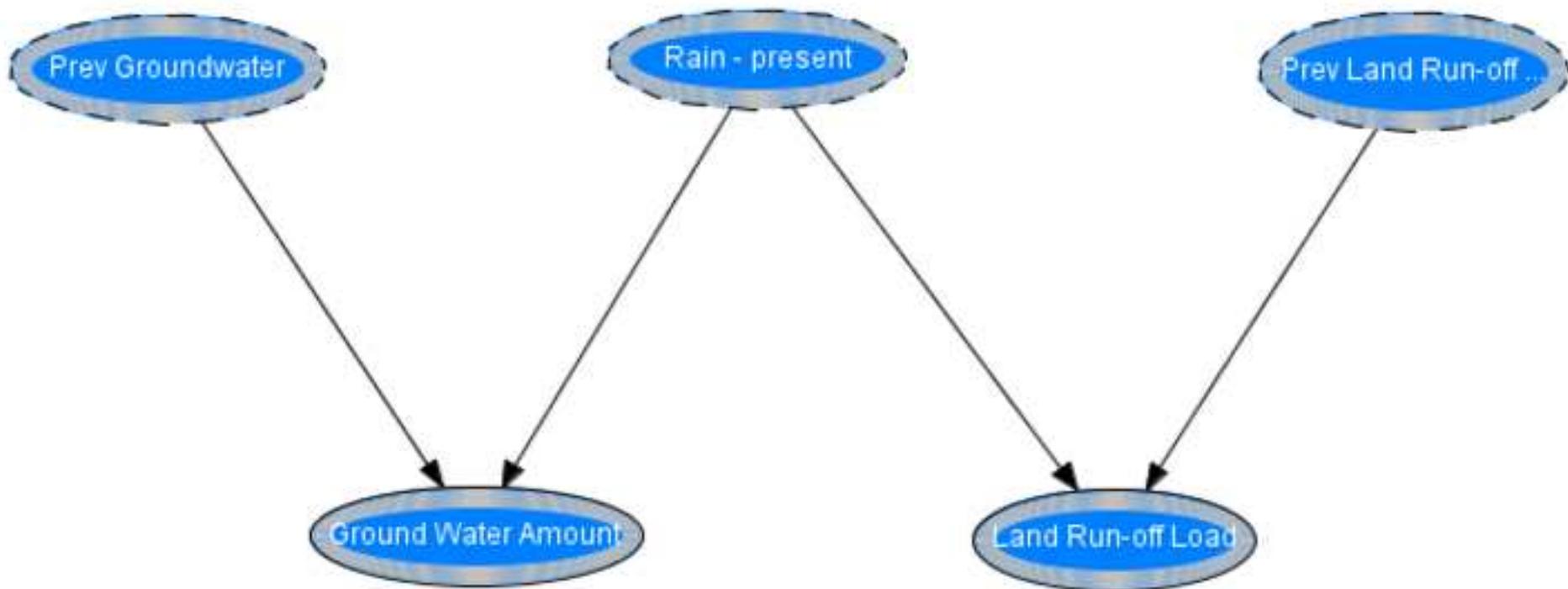


Figure 6

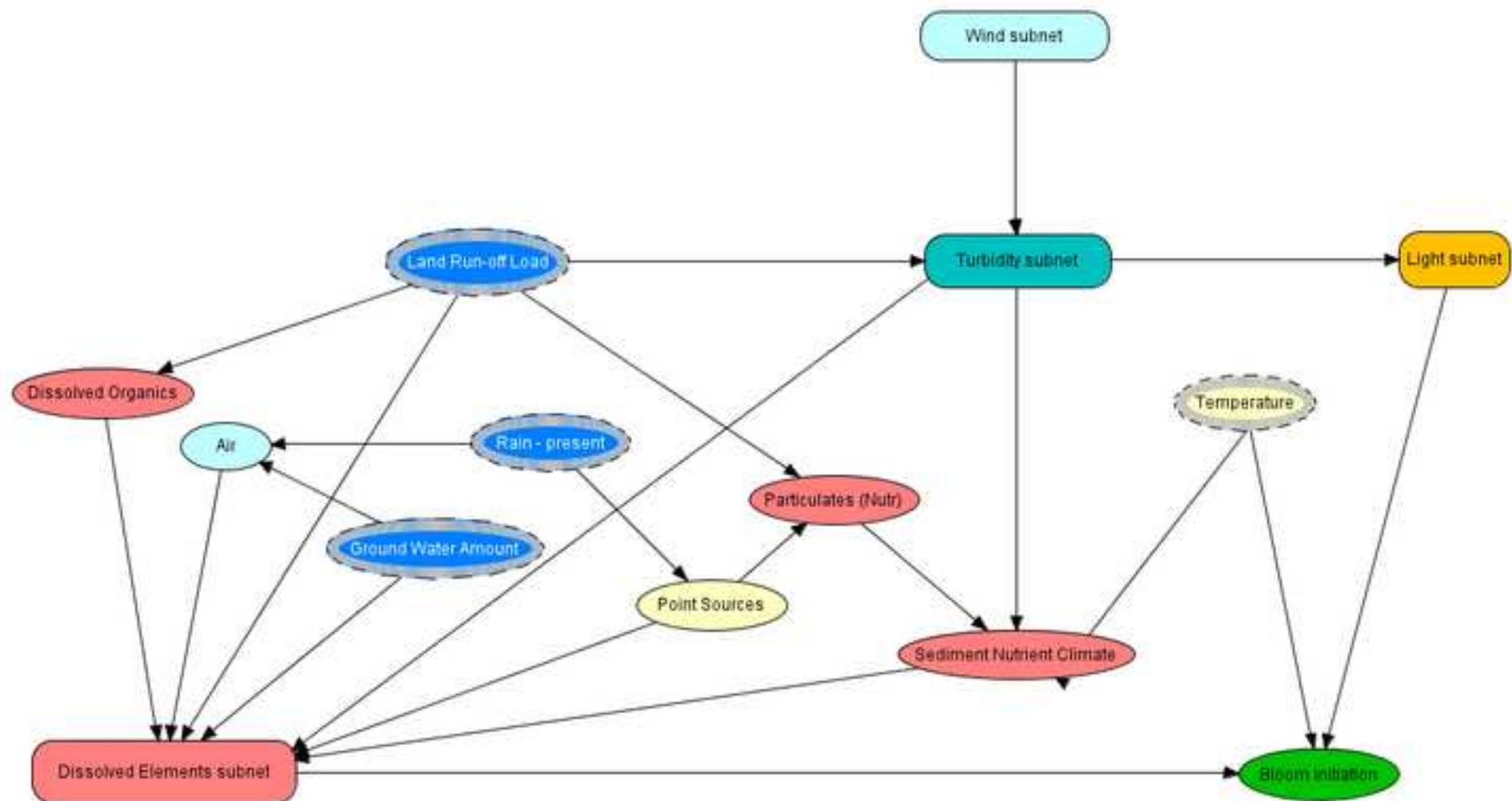


Figure 7

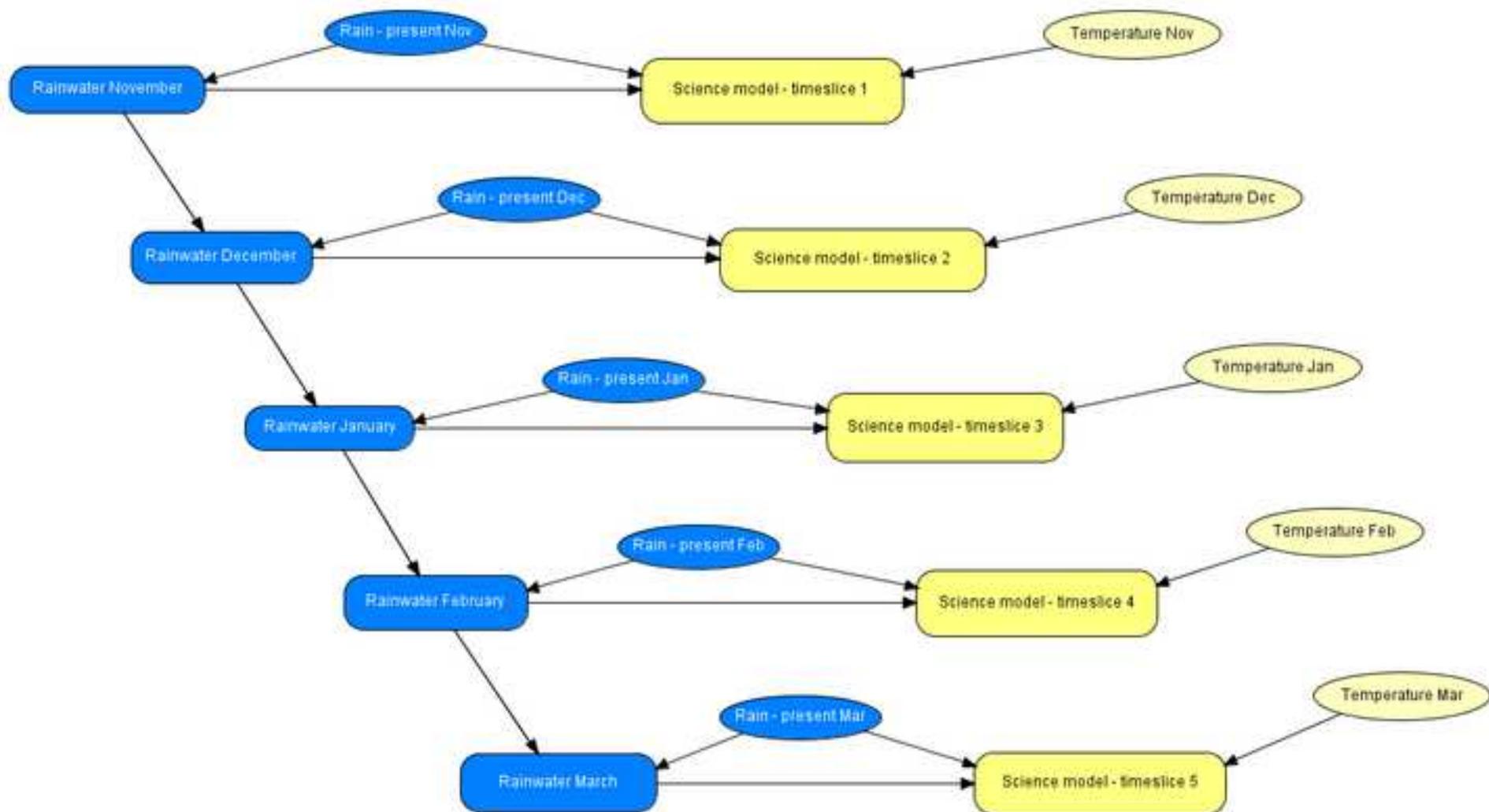


Figure 8

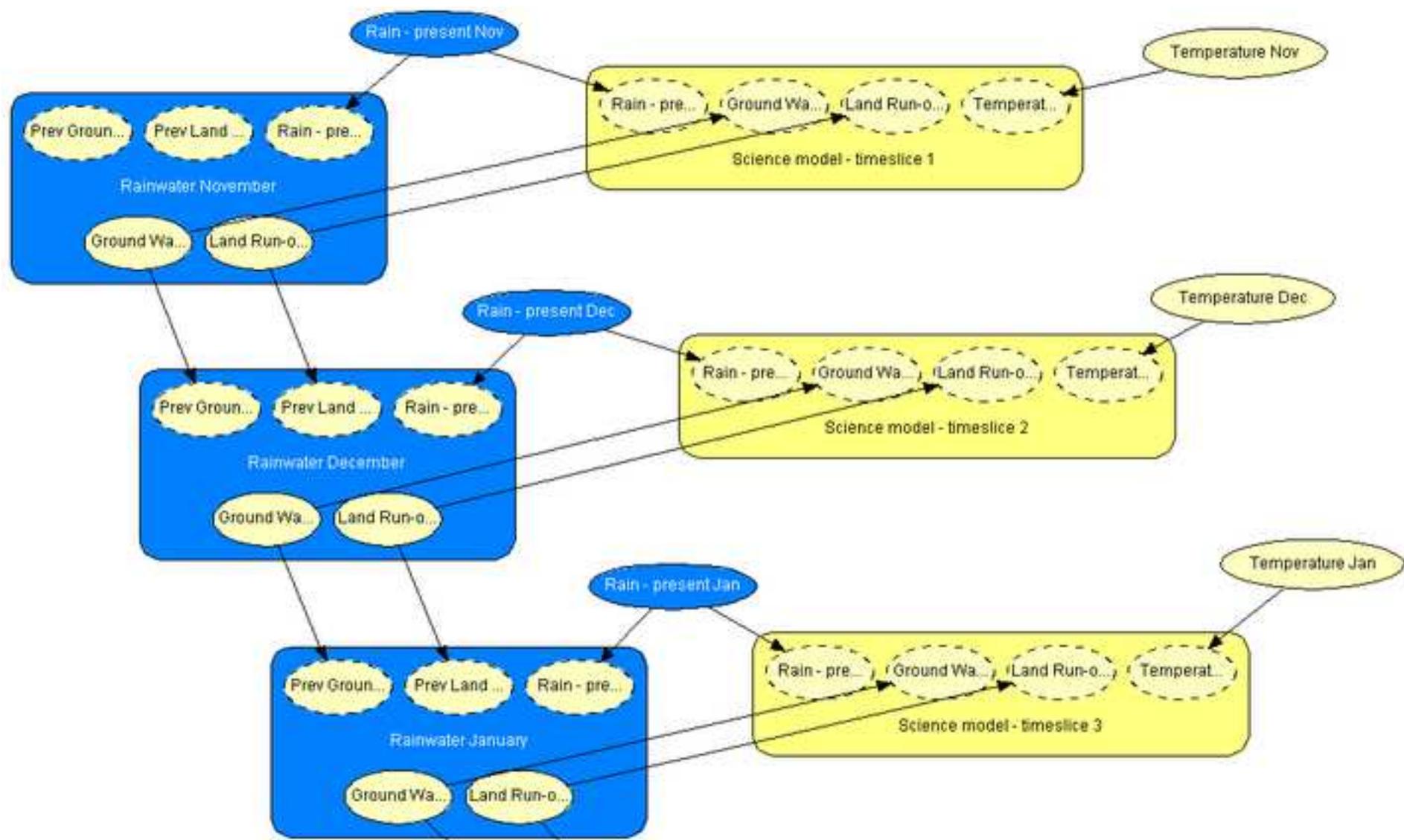


Figure 9

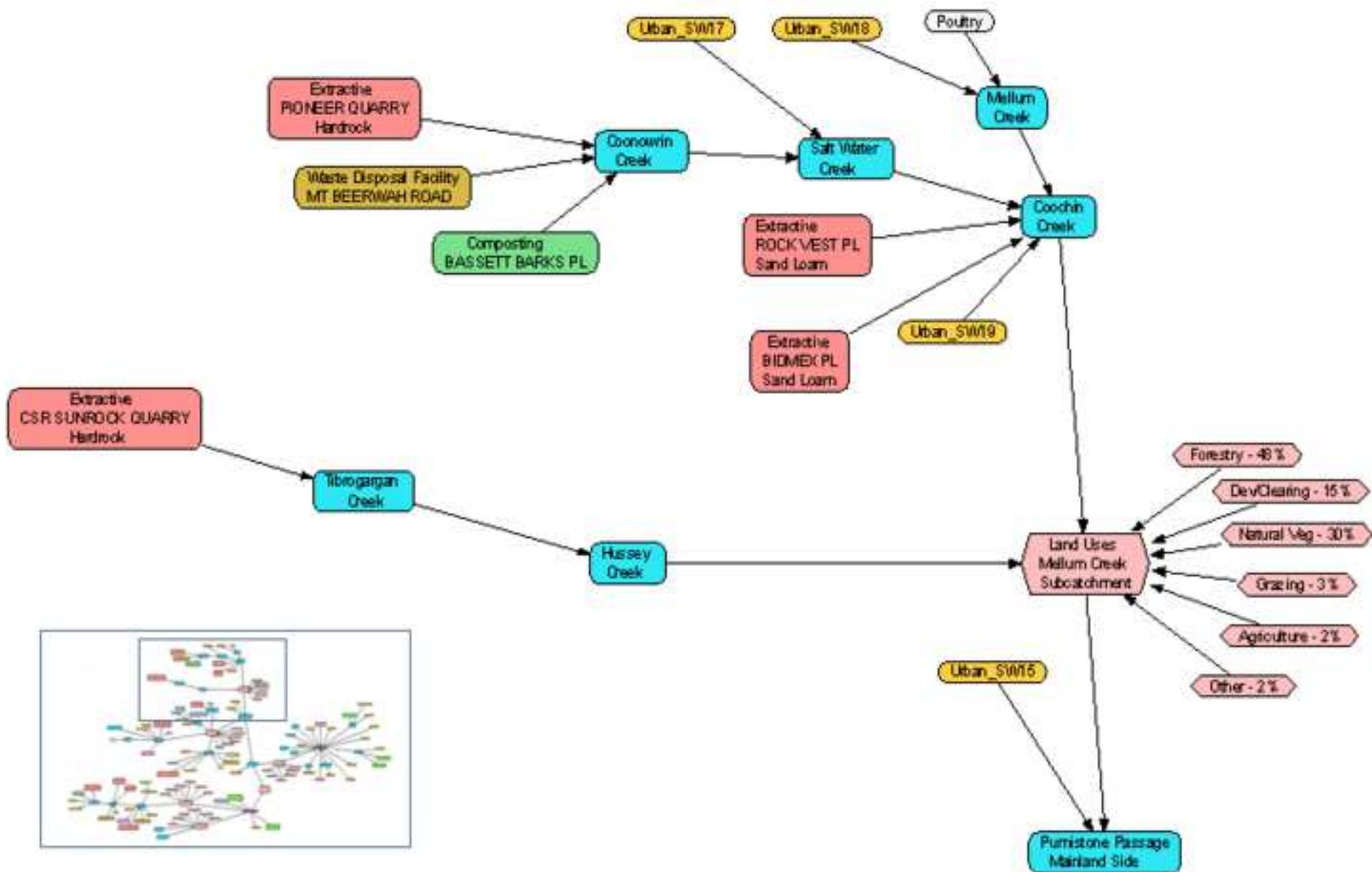


Figure 9

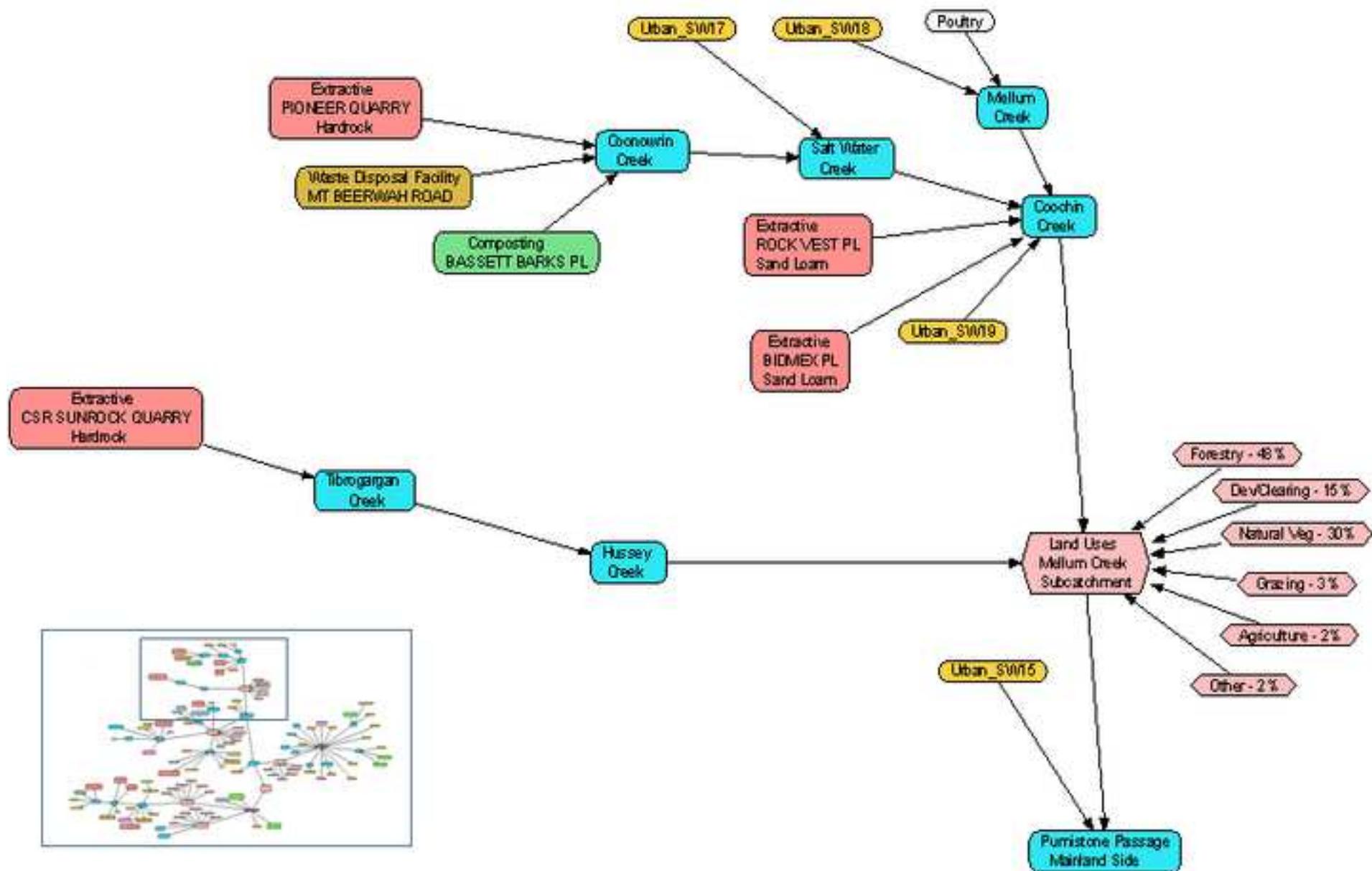
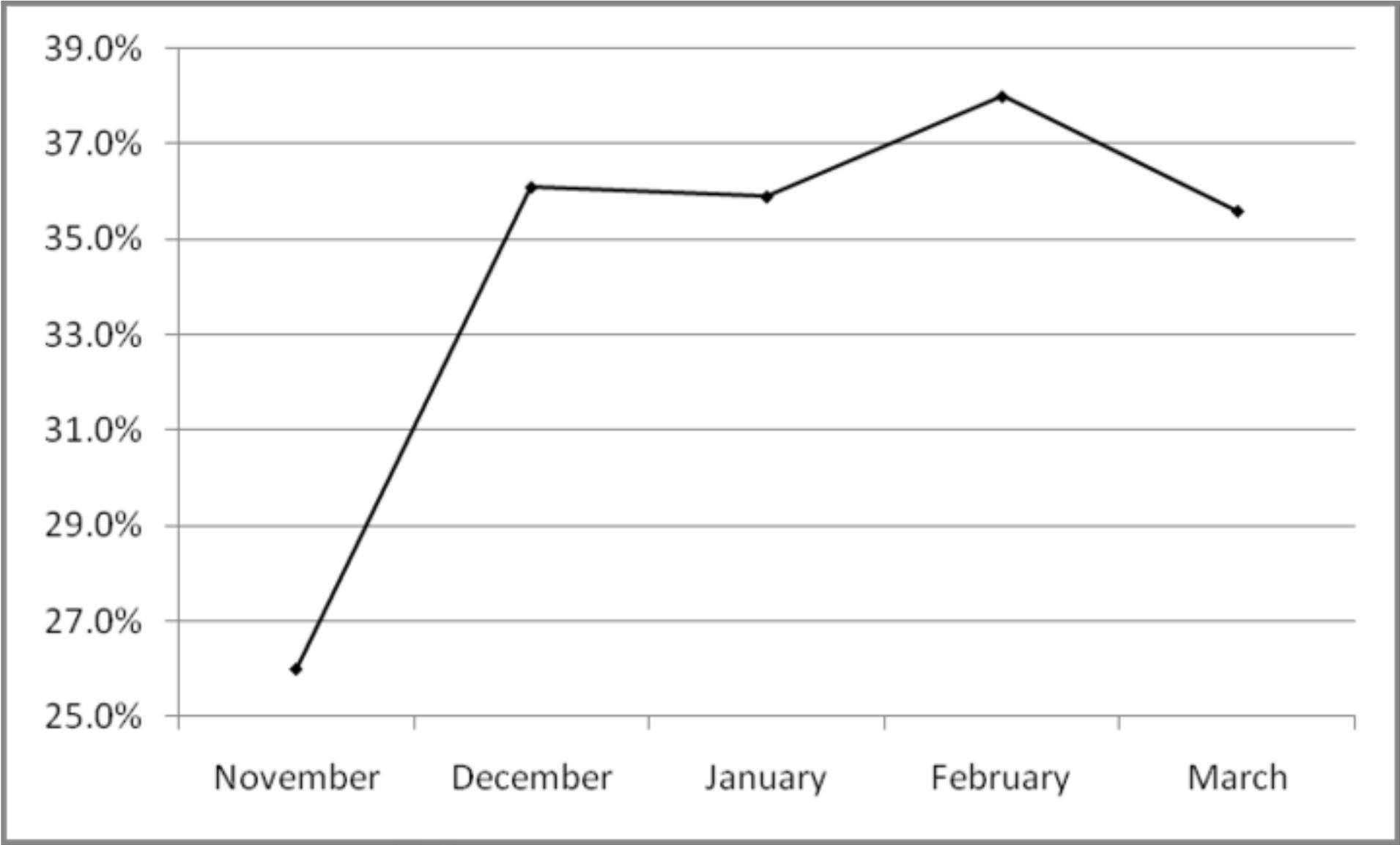
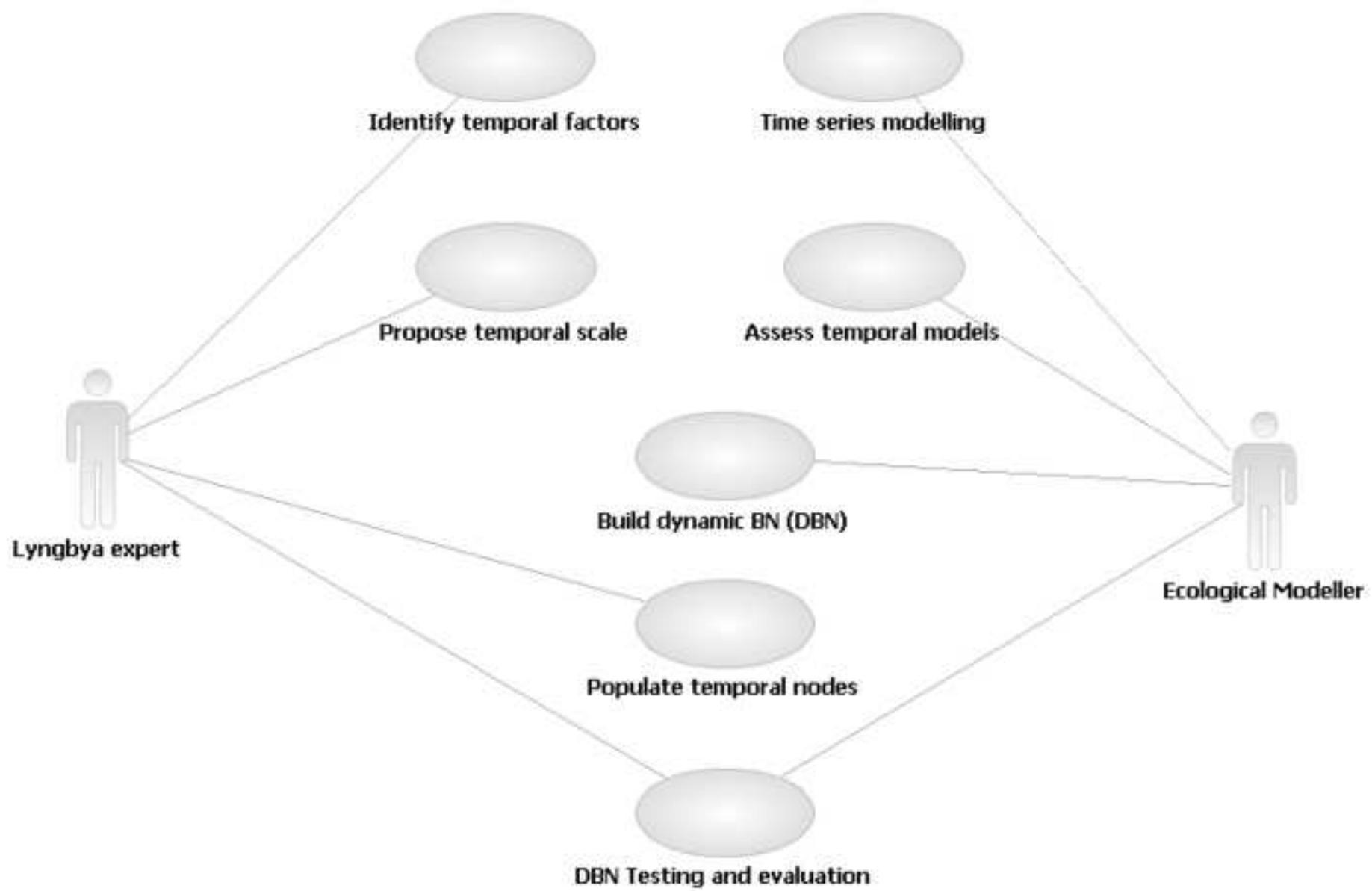


Figure 10



ACCE

Figure 2



ACC

Figure 3

