RCAN: A SOFTWARE FOR CHANCE AND NECESSITY MODELLING

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ABSTRACT. Uncertainty is a key challenge in modelling marine systems and a source of misunderstandings between scientists and other approach. Recently, a Chance and Necessity approach has been proposed to address this issue in trophic network modelling. Instead of seeking for a precise description of the system functioning and trajectory, CaN approach (a) focuses on the few certain physical and physiological laws and (b) samples all trajectories that can satisfy these laws, while being compatible with observations that have been collected about the system. This type of approach is thought to facilitate discussion among actors since it is based on information shared by most actors, it does not presume any knowledge of modelling practices and avoids knockout arguments based on scientific authority.

However, to be a good discussion support, user-friendly software are required to easily implement such models. In this paper, we present a software allowing to quickly develop this approach about a marine ecosystem that has been observed for several years. RCaN is a library of R commands. It implements efficient algorithms allowing to sample polytopes in spaces with a very large number of dimensions. RCaNconstructor is a graphical interface to RCaN.

We recall the main principles of CaN modelling, we present the software that has been developed and we give all the details of its use to the analyze of the trophic marine system of the Barents sea.

1. Introduction

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Modelling complex ecological systems is often a trade-off between the accurate representation of the many components and interactions within an ecosystem and the reduction of ecosystem processes to few and important elements. Rather than attempting to model multiple ecological processes in details, CaN modelling focuses on exploring possible ecological dynamics given a set of constraints. The principles of CaN modelling and the corresponding mathematical formulation have been outlined in [1]. The general idea is that it is easier for various actors (managers, scientists, stakeholders) to agree about ecological constraints, which separate what is possible from what isn't, than to agree on the mechanistic formulation of detailed ecological processes. This is particularly true when modelling complex ecological systems for which available information/observations are limited. This approach is called "Chance and Necessity" modelling (CaN): chance refer to the indeterminacy in ecological processes while necessity reflects the constraints that delineate what is possible from what isn't. While the CaN principles can be applied to a wide range of ecological problems, 19 the first application was specifically designed to explore the temporal dynamics of marine systems [1]. This has been motivated by the shift from conventional singlespecies fisheries management towards ecosytem-based fishery management (EBFM, see for example [2, 3]). This shift implies upscaling of the traditional population scale management into a complex set of biotic (e.g. trophic food interactions) and abiotic sets of interactions (e.g. interactions with physical habitats). This has led to the development of complex ecological models, but which ability to help management is questioned by many actors who may have limited trust in such models [4].

In this context, there is a call for transparency in the science that supports man-

e agement, and participatory modelling and assessment have been proposed a a way

to rebuild mutual trust. CaN is proposed as one tool to support transparency and

participatory modelling by providing a simplified food-web modelling framework, in

which the ideas of uncertainty and ecological limits are central. Assumptions about

knowns and unknowns and about possible and impossible processes are presented

explicitly and all model constituents can be described in plain language (little or

no modelling jargon).

By contributing to the transfer of biomass, energy and polluants in ecosystems,

trophic interactions play a major role in ecosystem functioning. Trophic food web

models have proved to be key tools for the quantification of these fluxes, they

39 provide a holistic view of ecosystem functioning, and are increasingly used to assess

40 ecosystem ecological status and to explore the effect of anthropogenic pressures

such as fisheries [5]. Food web models, mostly Ecopath with Ecosim (EwE) [6, 7],

have played an important role in the implementation of the EBFM. CaN modelling

further contributes to this effort by providing a modelling framework for marine

44 food-webs that primarily relies on ecological constraints which can be agreed upon

by diverse actors.

The principles of CaN modelling have been outlined in [1]. The main technical

difficulty: sampling a polytope in a highly dimensional space have been tackled

inside the R framework [8]. Practical results have been obtained [1].

49 Until now, there existed no software to easily perform CaN modelling. The first

50 models were constructed in an *ad hoc* fashion by assembling and structuring relevant

at data and developing tailor-made programs in Mathematica or R to run the model.

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the access of the model to non-modellers. Making CaN models. It also restrained the access of the model to non-modellers. Making CaN modelling transparent, replicable, and performant in a participatory modelling framework requires that model construction, sampling and output visualisation be easily accessible by modellers and non-modellers alike, and that the structure of CaN models be standardised. A graphical user interface (GUI), which provides an easy entry level for users is also a highly desirable feature for a modelling approach targeting non-modellers. In this contribution, we present a software for the implementation of CaN modelling in R, called RCaN, and an associated GUI in Java, called RCaNconstructor. RCaN and RCaNconstructor can be used jointly or separately. Their combined use allow users to easily construct, document, sample and interprete the results of CaN food-web models. The relationship between RCaN and RCaNconstructor is shown in figure 1. The main features of RCaN and RCaNconstructor include:

- (1) a user-friendly software that can handle the complex numerical and mathematical parts of the modelling. In such way, users can then focus on the discussion about their knowledge of the ecological system and how to best structure a model that fits their needs,
 - (2) a file and data management system that ensures consistency between the different elements of a CaN model. For example, it must be guaranteed that each link connects existing components or that each constraint points to components, links or data series that are adequately specified in the model,
 - (3) a standardised file format to fully specify a CaN model,

- 74 (4) Importation of observation data-files often result in the repetition of many 75 procedures: selecting an external file, selecting year range and observations 76 in the file, etc., with the the risk of incoherencies, forgettings, etc.
 - (5) a set of R functions that allow experimented programmers to construct, manipulate and visualise the outputs of CaN models in a flexible manner,

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- (6) standardised graphical outputs of the model results, which promote discussions among modellers and other actors and ease the interpretation of model results,
- (7) a system for registering meta-information about the model, such as model version, authors, data sources, assumptions, and so on. This ensures transparency and reproducibility of modelling experiments.

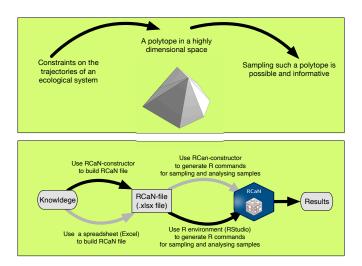


FIGURE 1. Top: Principles of CaN modelling. Bottom: RCaN and RCaNconstructor. The usual ways of using RCAN, with a common element, a RCaN-file.

In section 2 we summarise the elements of the CaN modelling approach. In section 3, we present the format of an RCaN file. In section 4 we present the R library RCaN which is designed to construct, sample and produce graphical outputs

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2. Principles of the Can approach

In CaN, food-web dynamics is defined by time-trajectories of biomass and fluxes between trophic groups. The biomass of all trophic groups and the fluxes between them can usually not be precisely observed. Therefore, the food-web dynamics is indeterminate, and a range of dynamics is possible. However, not everything is possible because some ecological or physiological constraints are known to bound the temporal evolution of ecological system, and/or because some observations can inform about the past dynamics of some components of the food-web. These eco-100 physiological constraints and observations can be translated into mathematical con-101 straints that need to be satisfied before a food-web trajectory can be considered 102 possible. The ensemble of these mathematical constraints constitutes the "neces-103 sity" in a CaN model. It is by focusing on constraints that can be easily expressed 104 and communicated between actors and by explicitly acknowledging indeterminacy 105 in natural systems that CaN modelling facilitate exchanges among actors to support 106 resource management. 107

2.1. **Network structure.** In CaN modelling, the food-web is defined as a network. In this network, each vertex/node is called a component; it corresponds to a species, or more generally a trophospecies, i.e. a group or sub-group of species that share common prey and predators. Components may be within the model domain;

then their biomass trajectories are explicitly considered. They also may be outside
the model domain, then we have not knowledge of their biomass trajectories. An
edge/link corresponds to a flux of biomass from/to comp. Most fluxes are trophic:
from a prey to a predator. Some fluxes are non-trophic: they correspond to import/export of biomass from adjacent regions or to removal of biomass through
fishing.

2.2. Components characteristics. Component inside the system are character-118 ized by the following biological properties. Satiation reflects the maximum con-119 sumption rate per unit biomass of the predator. Inertia expresses that variations 120 in biomass from one year to the next are bounded between a maximum growth 121 rate and a maximum mortality rate. Digestibility is a correction factor that ac-122 counts for variations in energy content between prey. Assimilation efficiency 123 expresses the proportion of the biomass ingested by a predator that is effectively 124 assimilated; the product of the potential assimilation efficiency by the digestibility 125 correction factor is the absorption efficiency (the proportion of prey biomass di-126 gested and absorbed). Refuge biomass is the absolute minimum biomass that a species group can reach. Other losses is a mortality coefficient that account for losses, i.e. metabolic losses and other mortality, not explicitly accounted for in the 129 model. 130

131 Components outside the model domain do not require input parameter except
132 when they constitute a prey, in which case digestibility should be provided.

2.3. **Observations.** The CaN modelling approach emphasizes the past observations of the dynamics of the food-web. Observations can be: catch or landings data, biological samples of specific populations, stomach samples or other sources of diet information, survey abundance estimates, outputs from stock assessment

models, estimated ranges of biomass, and so on.

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2.4. Constraints. Constraints that limit the dynamics of the food-web are at the

139 heart of CaN modelling and they are the way by which most of the knowledge and

data enter a CaN model. Some constraints are implicitly incorporated into CaN

while others can be explicitly formulated.

A few implicit constraints are standard for all CaN models. They are related to

the above components characteristics. Constraints are as follows: (a) there is con-

servation of energy during trophic processes; it relates trophic flux and biomasses:

for a given compartment, assimilated inflows must compensate outflows and main-

tenance losses that are proportional to biomass; resulting biomass of compartments

147 are positive and above refuge biomass, (b) trophic fluxes between compartments

are positive, (c) the sum of fluxes into a compartment is limited according to its

biomass (satiation), (d) the proportional changes in biomass of a compartment are

bounded (inertia).

Additional explicit constraints can be provided. These are written in the form of

inequalities or equalities. The left side of the (in)equality must contains a reference

to one or several compartments or fluxes. The right side of the (in)equality can

contain fixed values, compartments, fluxes, data time series.

Roughly speaking, there are two kinds of additional explicit constraints. Some

constraints are the expression of a knowledge about system functioning and relate

the biomass of a components to its incoming or outgoing fluxes. Some other con-

158 straints relate the possible values of a biomass or a flux to observations. These last

constraints constitute the way to deal with uncertainties in CaN modelling.

2.5. Trajectories. A food-web trajectory is defined by the ensemble of biomass fluxes at each time-step and by the initial food-web configuration, i.e. the initial 161 biomass in each component. Each trajectory can be expressed as a single point in a 162 multi-dimensional space of dimension $P = nF \times nt + nB_0$, with nF the number of 163 fluxes, nt the number of time steps and nB_0 the number of initial biomasses. This 164 dimension can be very high: a simple ecosystem has about 10 components and 20 165 types of fluxes; following it during 15 time steps results in $P = 20 \times 15 + 10 = 310$. 166 All constraints are linear equalities or inequalities. The can be expressed as bear-167 ing on food-web trajectories. As constraints are linear, the set of the trajectories 168 that satisfy all constraints has the shape of a convex polytope in a high dimensional 169 space. 170

2.6. Sampling trajectories. The main tool of a CaN modelling approach is the sampling of possible trajectories given (1) the food-web structure, (2) the species biological properties, (3) available observations and (4) constraints. The collection of sampled trajectories expresses the indeterminacy in the system.

Sampling food-web trajectories is achieved by sampling this high-dimension poly-

3. RCAN FILE

tope using dedicated sampling algorithms.

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In RCaN, all input information is provided in a simple excel spreadsheet. In sheet **Components**, first column corresponds to the name of a component. The second column indicates whether the component is inside our outside the trophic network. Other columns correspond to components characteristics that have been presented above.

In sheet **Trophic fluxes**, each flux is characterized by an Id (first column) and links a source component (column From) to a sink component (column To) and by its type, trophic or non trophic (last column); in a trophic flux, digestibility and assimilation should be applied to the flux.

In sheet **Observations**, first column gives the identifier of time steps (most of the time years). Other columns correspond to the extracted time series of observations that can be used to constrain the system (see 2.3).

In sheet **Constraints**, rows correspond to the constraints on biomasses, fluxes and time series. Each constraint has an Id (first column), a formula defining the linear constraints involving fluxes, time series and biomass in components (second column), a time period of validity (third column) and a flag indicating whether the constraint should be used or not (fourth column).

What is important to notice is that the contents of these sheets are interrelated and that this results in some coherency rules.

197 4. RCAN

4.1. Introduction. RCaN is an R package aiming at building and running CaN 198 trophic food web model. As explained in previous parts, the mathematical struc-199 ture to analyse is a set of analytical linear equalities and inequalities. A complete 200 mathematical exposition is given in [1]. 201 The rationale is that: (a) constraints related to elementary biological processes or 202 to past observations result in linear equalities or inequalities involving the dynamics 203 of the system, that is its trajectories, (b) these constraints define a set in a highly 204 dimensional space, this set has the structure of a polytope, (c) a lot can learnt 205 about the system by sampling this polytope. 206

Implementing the whole process implies (a) to specify entities of the system, (b)
to express constraints involving entities and their trajectories, (c) transform set of
constraints in a polytope of trajectories, (d) analyse elementary properties of the
polytope (non-emptiness, bounds), (e) sampling the polytope, (f) analyse sample.

Next paragraphs are about technical features of the implementation of these
different steps in the R language.

4.2. The different steps to use RCaN.

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4.2.1. Build a polytope from RCaN-file. Once the RCaN-file has been built, a first 214 step is to organize all the information and to build the polytope describing the 215 considered model. More precisely, the mass conservation of biomasses and con-216 straints can be summarized in matrix notation, and all these matrices should be 217 automatically generated whatever are the constraints and parameters used by the 218 modeller. Constraints can be summarized in a matrix form as $A \cdot x \ll b$ (inequality 220 constraints) and $C \cdot x = v$ (equality constraints) with x a solution (e.g. a trajectory 221 defined by initial biomasses per component and fluxes at each time step), A and 222 C two matrices with as many columns as parameters in the model (fluxes per time 223 step and initial biomass per component) and a row per constraint, and vector v224 and b the bounds of the inequalities. 225 Using the constraints formula and the symbolic links among variables, RCaN 226 automatically build matrices C and A and vectors b and v for each active constraint. 227 This is done by a simple call to the function **build CaNmod** which reads all 228

the information from the RCaN-file and returns a single object that represents all

the trophic network representation and especially, all the corresponding polytope

matrices. For example, in the Barents Sea case study (section 6), the function automatically constructs the matrix A which has 2593 rows and 775 columns, and the matrix C which has 54 rows (and by definition, the same number of columns). 4.2.2. Checking polytope characteristics. At first try, the specification of model of-234 ten leads to empty polytope (i.e. a model with no solution that satisfy all the 235 constraints) or unbounded polytope (i.e. a model in which the specified constraints 236 are not sufficient to bound a given parameter that can vary subsequently to in-237 finty). Before running the model, it is wise to check the status of the polytope (the 238 model won't run with an empty polytope while results are generally not relevant 239 with unbounded polytope). The package provides different functions to check the 240 properties of the polytope, of which the two most important are checkPolytopeS-241 tatusCaNmod, which checks whether the polytope is closed and non empty, and 242 getAllBoundsParamCaNmod, which estimates the bounds for all parameters. 243 If the model is empty, the package provides a function findingIncompatibleCon-244 strCaNmod, which indicates to the user which constraints raise problems. 245

4.2.3. Sampling polytope. Once all the previous steps are completed, the aim of this step is to achieve a uniform sampling within the convex polytope (if it is not empty). 247 Achieving a uniform sampling is not straightfoward since the a CaN polytope has 248 a very high number of dimensions: the number of time steps times the number 249 of internal components (corresponding to initial biomasses), plus the number of 250 fluxes. This is the role of the function fitmyCaNmod, which carry out a uniform 251 sampling within the polytope and returns results in the standard coda format of 252 a mcmc.list [9]. Based on a Monte-Carlo sampler, the functions allows running 253 several chains in parallel. 254

4.2.4. Diagnostics about sampling. One sampling is done, it is necessary to check whether the uniform sampling was successful. Since the result of **fitCaNmod** is a mcmc.list object, we can use all the diagnostics tools provided in the package coda, such **traceplot**, **summary** or **gelman.diag** and rubin tests or autocorrelograms.

4.2.5. Graphical analysis of sampling. Each iteration of the MCMC sampling pro-259 vides a possible set of time series of biomasses and fluxes. RCaN provides several 260 function to explore these results. Among others, ggResult and ggViolin can be 261 used to plot the temporal distributions of any biomass and/or flux. It is also possible 262 to explore the diet of the species using the function ggDiet, to look at the rela-263 tionships among species with functions ggPairsBiomass or ggTrophicRelation, 264 or to focus on the biomass variations of specific species with functions ggGrowth 265 and **ggSatiation**. 266

4.3. Technical considerations. The development of the packages raises several challenges. The first challenge was to improve computation performance. For this 268 purpose, RCaN is interfaced with C++ using two R packages Rcpp [10] and 269 **ReppEigen** [11]. The second challenge was check the characteristics of the poly-270 tope. This was achieved by using standard linear programming library: RCaN uses 271 lp solve through the R package lpSolveAPI [12]). A challenge was also to trans-272 late the content of a RCaN-file into matrices, and especially to allow user to specify 273 constraints in a simple language. This was made possible by using the symengine 274 R package [13], an interface to the symengine, a fast symbolic manipulation library 275 (the constraint syntax is presented in Supplementary Material). 276

Finally, the most challenging issue was to achieve the uniform sampling within 277 the polytope given the dimensions of the polytope. To address this problem, we im-278 plement two algorithms. Hit-and-run sampling have been proposed for a long-time 279 to achieve uniform sampling of high-dimensional convex space [14][15]. Basically, 280 hit-and-run sampling starts from a point in the polytope. Then at each iteration, 281 a direction of the high dimensional space is randomly drawn and a new point is 282 uniformly sampled between the two extreme bounds defined by the intersection 283 with the envelop of the polytope. As such, at each iteration, the point is only 284 moved in a random, but single direction, and consequently, when the sampler is 285 "trapped" in a narrow zone of the polytope, it may take many simulation to pick 286 the appropriate direction to exit the narrow zone resulting in autocorrelation. A 287 variation of the hit-and-run sampler is referred as the Gibbs sampler or Coordinate 288 Hit-and-Run [15][16]: instead of picking a direction and updating all coordinates 289 in this direction, the Gibbs sampling picks randomly a dimension (i.e. a parameter 290 of the model) and generate a new parameter value that satisfies the constraints. 291 By doing so, it guarantees an efficient convergence [16]. By default, RCaN uses a 292 Gibbs sample (but hit-and-run can be used), and its tuning is transparent for the 293 294 user.

5. RCanconstructor

Main goal of the RCaN constructor is to help the user to manage the RCaN-file.

It insures the coherency of the RCaN-file (changing the characteristics of an object somewhere triggers the necessary changes elsewhere).

- 299 It allows to run RCaN commands. RCaNconstructor allows to keep a trace of
- the meta information related to the scientific project of which the modelling is part
- and of the data files that have provides the observation that constrain the model.
- 302 RCaNconstructor is a Java program using Javafx for building the graphical in-
- 303 terface and allowing the code to be imported and run on external computers; it
- uses a Java library named RCaller for interfacing R and Java.
- 5.1. Meta information. RCaNconstructor allows to mobilize meta-information
- 306 about the model. In which context, for which purpose it is being carried out;
- 307 by whom? What is the provenance of datasets? All that information, of which
- the recollection is often neglected, reveal themselves crucial, when it is the time to
- 309 communicate and justify results.
- 5.2. Views. RCaNconstructor allows the user to define the objets that are used
- as inputs of the models. This is done with some dedicated views on the system,
- 312 its network structure, its components, observations and constraints. According to
- the principles of RCaN modelling, views on the system are about: (a) the network
- 314 structure of the trophic system, (b) its components, (c) its fluxes, (d) observations
- that have been selected on the system, (e) constraints that have been identified
- 316 about its dynamics.
- From these different points of views, the user can add, edit or remove objects:
- components, fluxes, observations, constraints. They are saved in a file which fulfill
- the requirements of a RCaN-file.
- 5.3. R interface. The RCaNconstructor is interfaced to R with the RCaller library
- 321 [17]. From the RCaNconstructor menu, the user can interactively: (a) start a R
- session and load RCaN library, (b) Build polytope (corresponds to the RCaNMod

command of RCaN), (c) sample polytope (corresponds to the fitMyMod command of RCaN), (d) get sampling diagnostics, (e) analyze sample.

6. Example: the Barents Sea food-web

To illustrate CaN modelling using RCaN and RCaNconstructor, we use a simplified food-web of the Barents Sea as an example.

In what we present below, we have chosen to build the RCaN-file using RCaNconstructor and then to run RCaN commands to construct the polytope, sample it, and analyse the properties of the sample.

- 331 6.1. Monitoring of the Barents Sea. Monitoring of the Barents Ecosystem has 332 been conducted for several decades and a collection of data series are reported 333 regularly and compiled by the ICES working group on the integrated assessment 334 of the Barents Sea (WGIBAR, [18]). These time series cover the period 1988-2019 335 and include data on:
- (1) landings for pelagic and demersal fish, krill, shrimps and marine mammals,
- (2) survey-based biomass estimates of zooplankton, pelagic and demersal fish,
- 338 (3) satellite based estimate of Net Primary Production (NPP, from 1998),
- (4) consumption estimates by Atlantic cod (*Gadus morhua*) of krill, shrimps,

 capelin (*Mallotus villosus*), herring (*Clupea harengus*), polar cod (*Bore-ogadus saida*) and Atlantic cod.
- In addition, there are estimates of the minimum and maximum plausible biomasses of benthos, marine mammals and birds which are used as limits for the whole time-period in the model ([19]).

- 6.2. Meta Information. Information about the model version, authors, funding
 sources, data sources and pre-processing, assumptions and uncertainties are pro-
- $\,$ vided via the menu Meta-information/model description.
- 348 6.3. Food-web Structure. The model of the Barents Sea food web is composed of
- 349 11 components. Four of them are external (two plankton standing stocks from the
- adjacent Norwegian Sea, primary producers and Fisheries), and seven are within the
- model domain, and include plankton (Hzoo: herbivorous zooplankton, Ozoo: om-
- nivorous zooplankton), benthos (bent), fishes (PelF: pelagic fishes, DemF: demersal
- fishes) and top predators (MM: marine mammals, birds). These 11 components are
- connected via 24 biomass fluxes among which 18 correspond to trophic relationships
- and 6 to imports (plankton) or export (fisheries catches) of biomass.
- With RCaNconstructor the food-web structure is specified by drawing the com-
- ponents and fluxes (menu View/Network). Using this graphical interface (fig. 2,
- top-left) it is possible interactively add, delete and edit components and fluxes.
- 359 The graphical positioning of the components of the network can also be modified
- to ease the visual interpretation of the food-web structure.
- 361 6.4. Input parameters. The input parameters for individual components of the
- 362 Barents Sea food web (menu View/Components) are taken from [19]. These were
- derived from the Metabolic Theory of Ecology, Life-history theory or previous mod-
- elling exercises using for example Ecopath [20]. These are summarised in Table 1,
- 365 in the supplementary material.
- 6.5. Observations. Observations data can be see as a table (Menu Views.
- 367 Submenu Observations). A button Button add an observation allows to create a
- new observation, i. e., a new column in this table. This observation is coming

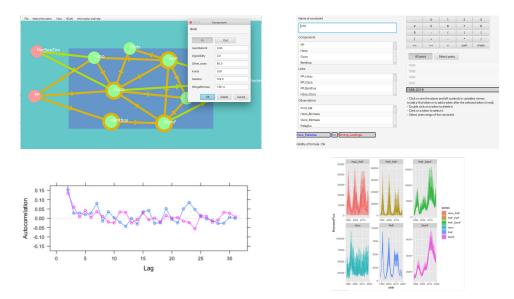


FIGURE 2. A selection of input/output windows from the RCaN-constructor applied to the Barents Sea food-web model. Top left: RCaNconstructor graphical interface to draw and specify the trophic network. Top right: the graphical interface used to specify the model constraints. Bottom left: sample diagnostic plot showing the autocorrelation of two chains of one flux. Bottom right: sampled trajectories (time-series) of selected fluxes and components.

from a file (a CSV file with a simple structure; first line: observations names; first column: years) that has to be specified in the interface and to and to a column that has to be selected in this file. For the Barents sea, we have used the following data sets: ...

6.6. Constraints. A RCaN model contains the following implicit constraints: satiation, inertia, positive fluxes and refuge biomass. These are specified in the input
parameters. Additional constraints can be added (Menu Views/Constraints/Add a
constraint, fig. 2, top, right.). These explicit constraints reflect knowledge about
the ecological system and can be used to link the model to available observations.
In the Barents Sea case study, the additional constraints are defined as follows:

- (1) The consumption of primary production by zooplankton and benthos is constrained by net primary production estimates (\pm 30%) for the period when these estimates are available (1998 to 2019). For other years, this sum is bounded by estimates of absolute maximum and minimum primary production that are set to 1/2 million and 2 million tonnes respectively.
- (2) Time-series of landings provide accurate information about the fluxes from
 herbivorous and omnivorous zooplankton, pelagic and demersal fish, and
 marine mammals to corresponding fisheries. Therefore, these fluxes can be
 set to the values of the estimated landings.
- 388 (3) The annual estimates of biomass for herbivorous and omnivorous zooplank-389 ton, and pelagic and demersal fish, derived from research surveys, can be 390 used to constrain the biomass of these groups.
 - (4) The estimates of minimum and maximum plausible biomasses for benthos, marine mammals and birds can be used as limits for these groups for whole time-period in the model.

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- (5) The food consumption by demersal fish can be bounded based on consumption estimates by cod in the Barents Sea. These bounds are as follows:
 - (a) the consumption of demersal fish by demersal fish is greater than the consumption of cod by cod,
 - (b) the consumption of pelagic fish by demersal fish is greater than the consumption of capelin, herring and polar cod by cod;
 - (c) the consumption of omnivorous zooplankton by demersal fish is greater than the consumption of krill and shrimp by cod

(d) the total consumption by demersal fish is not greater than twice the the total consumption estimates by cod.

6.7. Polytope building. Once the components, input parameters, fluxes, obser-404 vations and constraints are provided, the model is fully specified. This information 405 is gathered in the corresponding RCaN file. The polytope can be constructed by 406 running R commands of the RCaN library. This can be achieved within the RCaN-407 constructor environment or directly within the R environment. Both ways have 408 their advantages and limitations. Using RcaNconstructor is intuitive and does not 409 require prior knowledge of the R language. Using R provides a greater flexibility 410 for users who are familiar with the R language. We provide below the commands 411 in the R language. 412

We build the polytope with following R command:

```
4141 library(RCaN)

4152 CanMod <- buildCan("BarentsSeaReconstructions_20210227.xlsx")</pre>
```

In the Barents Sea case, the polytope has 847 dimensions (7 initial values - one 416 for each componentwithin the model domain - and 24 fluxes times 35 years). There 417 are 2811 constraints (both implicit and explicit). Constructing this polytope on 418 a laptop computer takes 80s (MacBook Pro Retina, 13-inch, Early 2015, 3.1 GHz 419 Dual-Core Intel Core i7). 420 It is possible to check the status of the polytope (bounded, empty or unbounded) 421 and to compute the bounds of the polytope in every of its 847 dimensions using 422 the following commands (the time taken to obtain the results is indicated in round brackets):

```
4251 checkPolytopeStatus(CaNMod) \\ (16s)
```

```
4262 CaNBounds <- getAllBoundsParam(CaNMod) \\ (2900s)
```

6.8. Polytope sampling. When the polytope is built, and if it is properly shaped
(i.e. not empty or unbounded), it is then possible to sample it. Each sample
corresponds to the trajectory of the food web and contains the initial biomass
values for each component inside the model domain and the values of the fluxes
at each time step. That is 847 values in the exemple of the Barents Sea model.
Sampling the polytope is achieved with one RCaN command:

```
CanSample <- sampleCaN(CanMod, N=100, thin=100, nchain=2, ncore=2, method

= "gibbs") \\ (520s)
```

This command returns an R list object which contains the original model structure and two chains of 100 samples (i.e. 100 food-web trajectories). In total 10,000 samples were explored in each chain, but only every 100th sample was retained. The polytope sampling algorithm used is the Gibbs sampler.

6.9. Sample diagnostics. An example of sampling diagnostics is shown in Figure
1, bottom left. This shows the autocorrelation functions for the two chains, for the
flux from primary production to benthos (PP_Benthos) in the year 2011. This is
obtained with the following command:

```
4431 acfplot(CaNSample$mcmc[,"PP_Benthos[2011]"],lag.max=30) \\ (<1s)
```

6.10. Sample Graphical outputs. An example of time-series outputs for 3 fluxes and 3 components is provided in Figure 1, bottom right. This is obtained with the following command:

```
4471 library(ggplot2) \\
4482 ggSeries(CaNSample,c("Hzoo_PelF","PelF_PelF","PelF_DemF","Hzoo","PelF"
449 ,"DemF")) \\ (<1s)</pre>
```

In addition to the R function ggSeries, a collection of pre-defined plots are provided. These can be used to quickly visualise the main model results. These include violin plots of biomass and fluxes (ggViolin), the diet fractions of the food-web components (ggDiet), the relationships between growth and biomass (ggGrowth), the correlations between components' biomass (ggPairsBiomass), the trophic functional relationships (ggTrophicRelation) or the relationships between ingestion and predator biomass (ggSatiation).

6.11. **Concluding.** Review initial objectives (RCaNmod, menu Meta Information). Communicate in terms of uncertainty.

7. Discussion

The RCaN modelling approach has first been an attempt to directly address the 460 issues of uncertainty and lack of knowledge in the modelling of exploited marine sys-461 tem. It has given several modelling experiments during which algorithms have been 462 defined and improved. The R libraries for Bayesian modelling have revealed to be 463 a powerful environment. On an other hand, the RCaN modelling approach implies 464 different modelling protocols. The main issue is an adequate selection of constraints: 465 practically, they must result in a non empty and bounded polytope. Contradiction 466 between constraints allows to reconsider the scientific knowledge about a marine 467 system. This is the goal of the RCaN constructor to make data management and 468

computing easier allowing then the necessary focus on the nature of scientific knowledge about marine systems. Next step will consist in improving algorithms and in 470 deepening the specific methodology for RCaN.

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