Exploring the mutual benefits of collaboration between Concept Mapping and System Dynamics – a conceptual argumentation and some puzzles

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Abstract

Concept maps (CM) are a measure to visually structure topics in the form of two dimensional networks. CM initiated in educational research and expanded into educational practice. CM are often used when individuals or groups have to deal with complex subjects from science, economics and management, hence fields where system dynamics (SD) is also present Proponents of both SD and CM have developed rigorous methods to analyze and compare such maps respectively diagrams. We have compared the use, the structure and the analysis methods between CM and SD and identified conceptual compatibility and some methodical complementarities: SD diagrams of mental models of dynamic systems (MMDS) can be interpreted as CM and CM analysis methods for large samples can be brought to MMDS research; also the rigor of SD modeling can become a vehicle for integrative reconciliation of knowledge and thus SD can become a relevant tool for educational researchers. We show these aspects on a conceptual level using a simple illustrative example. We conclude by proposing some relevant research questions.

Keywords: Concept mapping, system dynamics, model comparison, modeling for learning

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1 Introduction

Concept maps (CM) have been used as a strategy to support learning and as a measure to represent knowledge. CM is a recognized area in educational research and applied in subject domains such as science, economic and business problems and sustainability. Specific methods for CM modeling, analysis and assessment have been developed. In more recent times measures have been developed aiming at combining qualitative and quantitative research methods with regard to CM.

Coming from a different background, system dynamics (SD) shares some features with CM: the intention to help resolving complex problems, the focus on learning, the use of diagramming to articulate and to structure a problem, and the interest in model comparison as a help for inquiring learning. At the same time, there are some differences, mainly that SD has a rather specific modeling language, develops very detailed models and is anchored in the recognition that learning about dynamically complex situations requires simulation. Also, SD has not yet diffused inside the educational research field.

In this paper, we want to shed some light on two aspects:

1) Can methods from CM enrich research in SD about how people understand dynamically complex situations?
2) Can SD enrich or complement CM in educational research where it deals with the understanding of complex processes in the economy or in the firm?

We analyze the structure of the diagramming languages and find that a SD diagram can in principle be interpreted as a specific kind of CM; therefore methods for CM analysis and comparison can be applied to SD models and the first question receives an affirmative answer. We also analyze how the specificity and the discipline of simulation make SD an interesting tool for educational researchers using CM, therefore answering the second question with “yes” and arguing that this is an opportunity to increase the influence of SD in the field of educational research.

The paper is organized as follows. Section 2 briefly introduces CM, its use, the structure of CMs and methods for analyzing and comparing them. The following section discusses the possibilities to translate between the different diagram languages; examples of converting from CM to SD diagrams, as well as of the inverse translation, are given. Section 4 discusses the meaning and implications of the similarities and differences and proposes fruitful areas of scientific collaboration.

2 Concept maps

CM are two-dimensional structural representations of a topic consisting of nodes and labeled lines between the nodes. The nodes represent important concepts; the lines are relations between the concepts (Nesbit & Adesope, 2006, p. 415; Novak & Cañas, 2008, p. 1). Relations are also referred to as linking phrases, because the lines representing them are labeled with a word. This means that in one CM there are usually many different relations, each with a different word label to describe it. Two concepts and a relation form a proposition. A proposition is the basic unit of meaning in a CM and the smallest unit that can be used to judge the validity of the relation (line) drawn between two concepts (Ruiz-Primo & Shavelson, 1996, p. 570).

The term concept map was coined by Novak and colleagues (e. g. Novak & Gowin, 1984). CMs were developed in the framework of a longitudinal study of school children trying to understand if their cognitive limitations came from genetically determined processes of childhood development or rather from previous learning in the context of schooling (Novak, 2002; 2005). However, graphical notations of language, like CM can be traced back to the 1960s, especially the fields of linguistics and computational linguistics (Sowa, 2008). In the field of psychology, early models of CM (knowledge networks) were developed by Collins and Quillian (1969), Rumelhart and Norman (1978), or Minsky (1990). While in the 1960s the models focused on the structure of knowledge since the 1970s researchers tried in addition to model processes which operate on the structure.

The most important cognitive theories underlying CMs are on the one hand the theory of semantic networks (e. g. Collins & Quillian, 1969; Dansereau et al., 1979) as in the early psychological models mentioned above. On the other hand Ausubel's (1968) learning theory based on assimilation can be mentioned. Consistent with models of semantic networks CMs as external models are assumed to be structurally consistent with knowledge as internal model. Therefore, concept-mapping may help students on the one hand to externalize and on the other hand to construct and elaborate their cognitive structure. Ausubels's (e. g. 1968) learning theory focuses on assimilation as learning process. His theory implies a hierarchical memory structure and explains learning as subsumption process. Based on Ausubel's theory, Novak and Gowin (1984) suggest that CMs should have a hierarchical structure displaying subordinate und superordinate relationships. So-called crosslinks (links between different sections of the hierarchy) represent integrative connection between different domains of the hierarchy (Ruiz-Primo & Shavelson, 1996, p. 571). However, dependent on the respective question, in many studies CMs are used in a more flexible way and do not have a hierarchical but a network structure.

A couple of other theoretical approaches have been quoted in order to explain the efficacy of CM, among them dual coding theory (Paivio, 1986) and the learning strategies approach (for an overview see Nesbit & Adesope, 2006, p. 417ff.). According to dual coding theory verbal and visuo-spatial information reside in different memories. The memories can be interlinked, and the links provide additional retrieval options for both kinds of information. In addition, verbal and visuo-spatial information can be processed in different channels at the same time. This might lead to deeper and more efficient information processing than working exclusively with verbal data, e. g. texts. CMs may comprise verbal and visuo-spatial information and thus may enable effective processing. Closely connected with this line of argumentation is that the format of CMs represents information in a structured graphic, whereas texts represent information in a linear order. Thus CM display one concept and all propositions integrating this concept only once, whereas texts may contain the same concept several times. Thus diagrams may support encoding and comprehension of information better than text (Larkin & Simon, 1987). Last, but not least CMs can function as learning strategy, especially as organization or elaboration theory (Weinstein & Mayer, 1986). In cases students are requested to create or modify CMs they have to group information and by that actively process information and reach a deep understanding.

CMs are mainly used for two purposes: 1. as instructional tool or learning strategy in order to foster meaningful learning, that is to say help students integrating new information with existing prior knowledge; 2. as measure to assess structured knowledge and knowledge development. Both purposes can be combined (Horton et al., 1993; Sowa, 2000; Nesbit & Adesope, 2006). Over the years, CMs are widely used in educational settings, but also for knowledge management purposes (Novak & Cañas, 2008; Novak, 2010; 2011)

In educational research, CMs are often used in order to find out about the effectiveness and quality of the complex learning tasks by assessing students' structured knowledge respectively the development of their knowledge before and after an intervention. In order to assess the CMs different approaches can be distinguished. Dependent on the respective aim, they range between ideographic and nomothetic, qualitative and quantitative, or descriptive and normative analyses. In the course of ideographic analyses usually the most important features of individual CMs are verbally described whereas nomothetic analyses aim at comparing all CM of a test sample and then draw general conclusions. Qualitative approaches aim at referring to features of the content and are therefore often combined with descriptive approaches. In contrast, quantitative approaches aim at scoring components of the map or the entire map, such as the number, existence of concepts and/or propositions, coherence or diameter of the map. The descriptive approach considers maps of test persons gained in the respective study and describes them qualitatively and/or quantitatively. The normative approach takes overlaps between students' maps and a criterion map (e. g. expert's reference map) into account (Ruiz-Primo & Shavelson, 1996).

Especially the development of scoring techniques has attracted attention of researchers since the 1990s, both concerning manual scoring and automated computer-supported scoring. Afamasaga-Fuata'i (2004), for example, used a scoring scheme developed by Novak and Gowin (1984), which focuses on the structural differentiation (hierarchical depth) and integration (cross-links) between valid concepts and propositions, according to the guiding theory of learning. Simon and Levin (2012) report a method which compares and scores CMs in four dimensions: spatial structure (how well organized is the diagram?), consolidation (the degree of integration expressed by the links between concepts), focus (prominence of specific concepts inside the CM), and depth and wealth of ideas. Cañas et al. (2006) developed a topological taxonomy for CMs, which takes into account the use of single name concepts (over chunks of text, which reveal poor appropriation of the content by the individual) and structural aspects (concept count, links count, the ramification and the hierarchical depth. The software CMap Analysis was developed to automate the necessary computations (Cañas & Reiska, 2010); it is currently used by researchers (Derbentseva, 2012).

Some limitations of existing scoring measures can be identified. Often, qualitative and quantitative measures are not related. Quantitative indicators like number of propositions do not legitimate researchers to draw inferences on the quality of knowledge. In turn, qualitative measures, e. g. the frequency of special propositions, lose sight of the semantics. Therefore, the work already done can be improved by using models and measures strongly combining qualitative and quantitative research tradition. With the help of those measures congruencies and differences between individual maps of a test sample or between individual maps and a criterion map can be judged both qualitatively and quantitatively. In the course of the analyses the semantic information of the maps, that is to say the propositions and their interrelationships (i. e. the content structure), is kept and does not disappear behind scoring indicators. For that purpose all maps of a sample can be represented, evaluated and statistically assessed by only one, e. g. a modal network. A modal network contains those propositions named commonly and most frequently by the test persons

(Oldenbürger et al., 1992). Besides this descriptive approach, congruencies and differences between all individual maps and a criterion map, e. g. an experts' map of the contents can be identified, in order to follow a normative approach. The reliability and the degree of representativeness of modal map and criterion map can be judged by the internal consistency of a congruence scale measuring the overlap between maps. The internal consistency is indicated by Cronbach's α, and the congruence scale should have a high internal consistency (reliability). The calculations are based on a person x proposition matrix (Fürstenau et al., 2009; 2012b). The results allow defining more content valid and concrete starting points for more effectively improving teaching-learning processes.

This method has been applied in a number of cases related to starting a company (Fürstenau et al., 2009) or based on management simulation games (Ryssel & Fürstenau, 2011). It has also been used to assess the advantages of CM over alternative means of knowledge articulation (Fürstenau et al., 2010; 2012a).

There have been attempts at using other comparison methods, especially the Pathfinder networks (Torres Carvalho et al., 2012); however, such methods, which do not distinguish between different link types, cannot be applied on CM without losing relevant information.

3 Concept maps and system dynamics diagrams

3.1 Symbols and usage

The purpose and background of system dynamics (SD) is helping decision makers to design better decision policies by providing a simulation-based testing environment (Forrester, 2007). It assumes that (social) systems are dynamic in nature and driven by feedback loops – logically closed paths of causation. Such loops consist of accumulation variables ("stocks") and flow rates adding to or draining from stocks (Forrester, 1969). The structure of such a system can further be divided into the "physics" – that which is going on independently of the decision maker – and the decision policies by which the decision maker tries to influence the system's behavior over time. Such policies are expressed as sets of intermediate steps between stocks and flow rates, and so-called auxiliary variables help to express them clearly.

Stocks, flow rates and auxiliaries conform differential equations which enable to simulate the thus modeled system. Originally, system diagrams were only used to communicate the causal structure of simulation models, but with the advent of graphical user interfaces for personal computers, new software products allowed to formulate system models by developing "stock-and-flow" diagrams (Schaffernicht, 2009). Later on, the simplified symbolic language of "causal loop" diagrams focused attention on the causal loops, partly be leaving out the difference between the types of variables (Lane, 2008). Together, stock-and-flow diagrams (SFD) and causal loop diagrams (CLD) have become a standard toolset for the qualitative formulation SD models, even though SD also includes quantitative work based on equations (Lane, 2008; Schaffernicht, 2010). "Hybrid" diagrams (HD) combine the advantages of both diagram types by inserting causal link polarity and loops into SFD (Sterman, 2000), but do not add new symbols.

From its very conception, SD is based upon the assumption that most relevant knowledge about a social system is in the minds of those who live and act inside them (Forrester, 1961); therefore the "mental database", as well as the challenges of eliciting and improving it – learning – have been main topics in SD (Morecroft and Sterman, 1994). The intention to elicit and improve knowledge as well as the use of diagrams constitutes a bridge between SD and CM, despite other differences.

3.2 Corresponding components

Diagrams of the three types – CLD, SFD and HD - can easily be converted into a CM, as the following tables illustrate.

CLD	***CM***
Variable	Concept
Positive causal link without delay	Relation of type „+“
Positive causal link with delay	Relation of type „+ D“
Negative causal link without delay	Relation of type „-“
Negative causal link with delay	Relation of type „- D“

Table I: converting a CLD into a CM

As shown in Table I, a CLD maps into one concept and four relationship types. A CLD has only one type of variable, but the causal links can have two different polarities and an optional delay mark, which gives four possible linking-phrases to build propositions like "motivation –+-> effort".

SFD	***CM***
Stock variable	Concept of type "stock"
Flow variable	Concept of type "flow"
Intermediate variable (auxiliary, converter)	Concept of type "intermediate"
Information flow	Relation „is-used-by“

Table II: converting a SFD into a CM

Table II associates CM components to each component of a SFD. SFD distinguish three types of variables, but instead of several types of causal links the only type of relations are information flows (thin arrows); one can think of an illustrative label like "is used by".

HD	*CM*
Stock variable	Concept of type “stock”
Flow variable	Concept of type “flow”
Intermediate variable (auxiliary, converter)	Concept of type “intermediate”
Positive causal link without delay	Relation of type „+“
Positive causal link with delay	Relation of type „+ D“
Negative causal link without delay	Relation of type „-“
Negative causal link with delay	Relation of type „- D“

Table III: converting a HD into a CM

Last not least, Table III shows how HD are converted into a CM; they combine the SFD variable types with the CLDs’ causal links, and therefore constitute the most differentiated symbolic language of SD.

It is immediately clear that any SD diagram can easily be “translated” into a CM, and any story implied by the propositions can be interpreted as the meaning of the mental model articulated in the diagram. This ease is explained by the fact that by allowing for any kind of concept and any kind of relationship, the “language” of CM does not impose specific types of concepts or relationships. On the other hand, SD does only allow the specific types of variables and links which have been presented above. On top of this specificity, SD has a set of rules limiting the syntactically allowed connections; for instance, only a flow rate can influence a stock, and therefore causal links from stock to stock or from auxiliary to stock are prohibited. Another important epistemic rule is that only stocks can be directly observed; therefore it is syntactically wrong to posit a causal link from a flow rate to an auxiliary or another flow rate.

Such restrictions do not have a counterpart in CM. It follows that one can construct a CM containing concepts which are not variables (but “objects”), and therefore not all syntactically well-developed CM can be translated into a SD diagram.

The comparatively strict syntactical rules in SD, together with a larger set of symbols (for expressing more specific meanings), is not an end in itself: it has the purpose to focus the modeler’s mind on important aspects of a dynamic system and to help him. In this context, let us recall that one of the systems thinking skills held in high esteem in the SD community is “operational thinking”, meaning that the recount we develop of a dynamical phenomenon should reveal how the studied behavior pattern is created (Richmond, 1993). While the term “systems thinking” as used inside the SD community sadly collides with its general interpretation, it has received a growing amount of attention and has its own stream of publication (see Maani & Maharaj, 2004 and Sweeney & Sterman, 2007), A detailed discussion of these skills and habits is beyond the scope of this paper – some details can be found in the appendix. However, SD reasoning analyzes problems or systems such as to generate comprehension of all causal mechanisms required to endogenously reproduce and then influence the dynamic system. The symbolic language and the meanings it supposes (and obliges to use) are thought as a help for inquiry.

We should then suspect that the development of SD-diagrams would lead to unearthing operational details of the analyzed phenomenon, together with a conceptual boundary which includes the relevant factors and privileges an endogenous explanation. Since CM does not become so specific, typical SD-diagrams should reveal more of those aspects than CM.

As far as this supposition holds true, SD diagramming and modeling would be a good candidate for the type of learning envisaged by Novak, and thus an attractive complementary approach to knowledge articulation and structuring.

We will now discuss some illustrative examples meant to reveal this potential complementarity.

3.3 Some illustrative examples

We will now discuss some illustrative examples taken from the context of the growth and collapse of the original Easter Island population; this is a well-known case which has been treated in SD education (Fisher, 2007; for another example see the systems wiki [3]. At the Lewis & Clark College [4] the same subject has been explored using CM.

The first example (Figure 1) translates a SF diagram inspired by Fisher's (2007) exercise into a CM. There are two stocks – *Population* and *Trees*. Population changes due to the *births* and the *deaths* flows, while Trees only diminish due to the *consumption* flow, which uses (is determined by)the *Population* size. On the other hand, the *deaths* (flow) depend on Population, but also on the number of Trees (passing by *available trees per person*, *sufficiency of trees* and the *death rate*.

[3] http://www.systemswiki.org/index.php?title=Mysteries_of_Easter_Island (3/12/2013)
[4] http://www.lclark.edu/

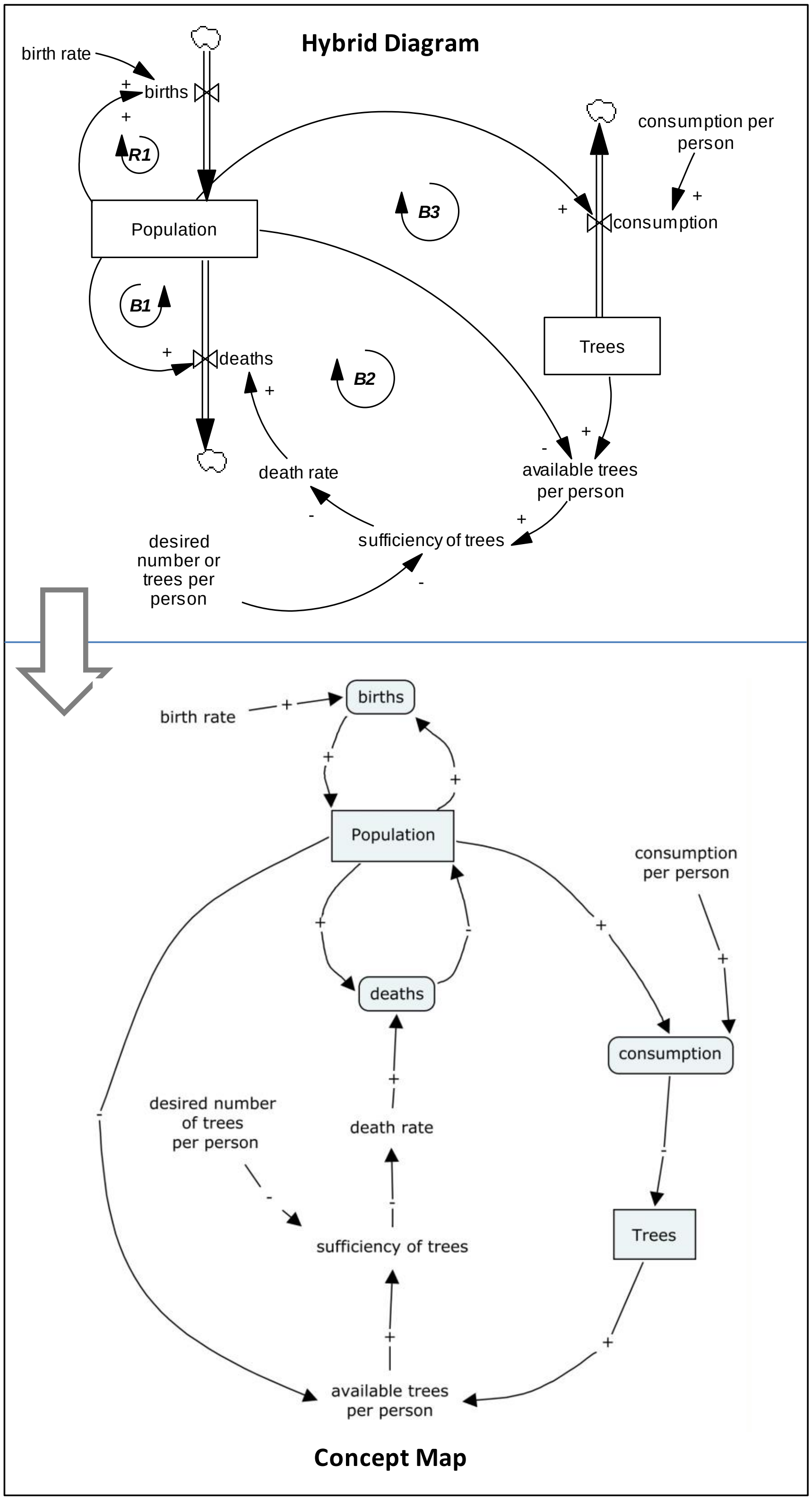

Figure 1: translating a HD into a CM

This CM has three types of concepts: stocks are represented by rectangles, flows by rounded rectangles and intermediate variables are just words. The linking sentences are simple “+” and “-“. The diagram can be transformed into the list of propositions displayed in Table IV:

Propositions		
First concept (cause)	**Linking phrase**	**Second concept (effect)**
Population	+	deaths
sufficiency of trees	-	death rate
Trees	+	available trees per person
deaths	-	Population
death rate	+	deaths
consumption per person	+	consumption
birth rate	+	births
births	-	available trees per person
Population	+	consumption
births	+	Population
desired number of trees per person	-	sufficiency of trees
available trees per person	+	sufficiency of trees
consumption	-	Trees
Population	+	Births

Table IV: the set of propositions

Even though the CM language does not have a symbol for feedback loops (which do not play a specific conceptual role), such loops can be detected and conceptualized as chains of propositions. It is also interesting to note that a propositions’ list like the one shown in Table IV above contains the same information as an adjacency matrix, which would be created for each relation and would have the following content. The following Table V represents the corresponding adjacency matrix:

Adjacency matrix	Population	births	birth rate	deaths	death rate	available trees per person	sufficiency of trees	desired number of trees per person	consumption per person	consumption	Trees
Population		1		1		-1				1	
births	1										
birth rate		1									
deaths	-1										
death rate				1							
available trees per person							1				
sufficiency of trees					-1						
desired number of trees per person							-1				
consumption per person										1	
consumption											-1
Trees						1					

Table V: adjacency representation of the model

Since we have a case with 11 variables, the matrix has a 11 X 11 structure. By default, all the matrix elements are equal to zero. When there is a causal link from a variable *a* to another variable *b*, then the element for row *a* and column *b* is set to a non-zero value. We have used a "1" to represent positive polarity, and a "-1" to express negative polarity. For instance, the first proposition from above – "Population + deaths" is now represented by the "1" in row 1, column 4. The "-1" in row 1, column 6 represents the third proposition in Table IV.

This means that the loop detection methods based on the exploitation of an adjacency matrix can also operate on the CM. In our case, the loops are shown in the following Table VI:

Loop	Pol.	Delay	Variables					
R1	+	0	births	Population				
B1	-	0	Population	consumption	Trees	available trees per person	sufficiency of trees	death rate deaths
B2	-	0	Population	available trees per person	sufficiency of trees	death rate	deaths	
B3	-	0	Population	deaths				

Table VI: the feedback loops as proposition chains

If we can translate a HD without losing relevant information, the same can be done with CLDs and SFDs. Thus mathematical methods developed for CMs and the proposition sets (like the one displayed in Table IV – especially the computations for constructing a reference net (model) and then using statistical processing to compare large sets of models – are applicable to SD models and mental models of dynamic systems (MMDS). We could even bypass the graphical translation and transform a MMDS' adjacency matrix directly into a propositions' list (which we have already done in an exploratory case).

In conclusion, it is argued here that SD educators and researchers interested in the learning of SD can benefit from collaboration with educational researchers from the CM field.

Turning now to the transformation of a CM to a SD diagram, let us analyze a CM available from the Lewis & Clark College[5], which also focuses on why the Easter Island original population collapsed. It turns out that this is not possible without taking design decisions at several points, because either a concept or a linking phrase cannot be directly represented in a SD diagram.

In the case of the CM shown in the following Figure 2, the *Easter Island Population* is clearly a central concept, and it is *reduced* by four factors: *slave trade*, *diseases* (which are *increased* by *slave trade*), *diminished agricultural capabilities* and *ecosystem collapse*. The two latter problems are *caused* by *soil fertility/health* which is *reduced* by the *deforestation of the coconut palm*. At the same time, the *Easter Island Population builds Statues* which results in the *deforestation*.

Since the concepts in this CM are of undefined type, the translator has to take a series of decisions in order to create a corresponding Hybrid Diagram. In this case, *Easter Island Population* and *Statues* are the obvious stocks; however, *Disease* – understood as the number of sick people – and *Slave trade* – as dumber of sequestered people- are interpreted as stocks, too, as are *Agricultural capabilities*. Of course, this means that *diminished agricultural capabilities* is split up in a stock and the *diminished* part is put as an outflow.

[5] http://enviro.lclark.edu:8002/rid=1235441584719_936506269_114/Easter%20Island.cmap (3/12/2013)

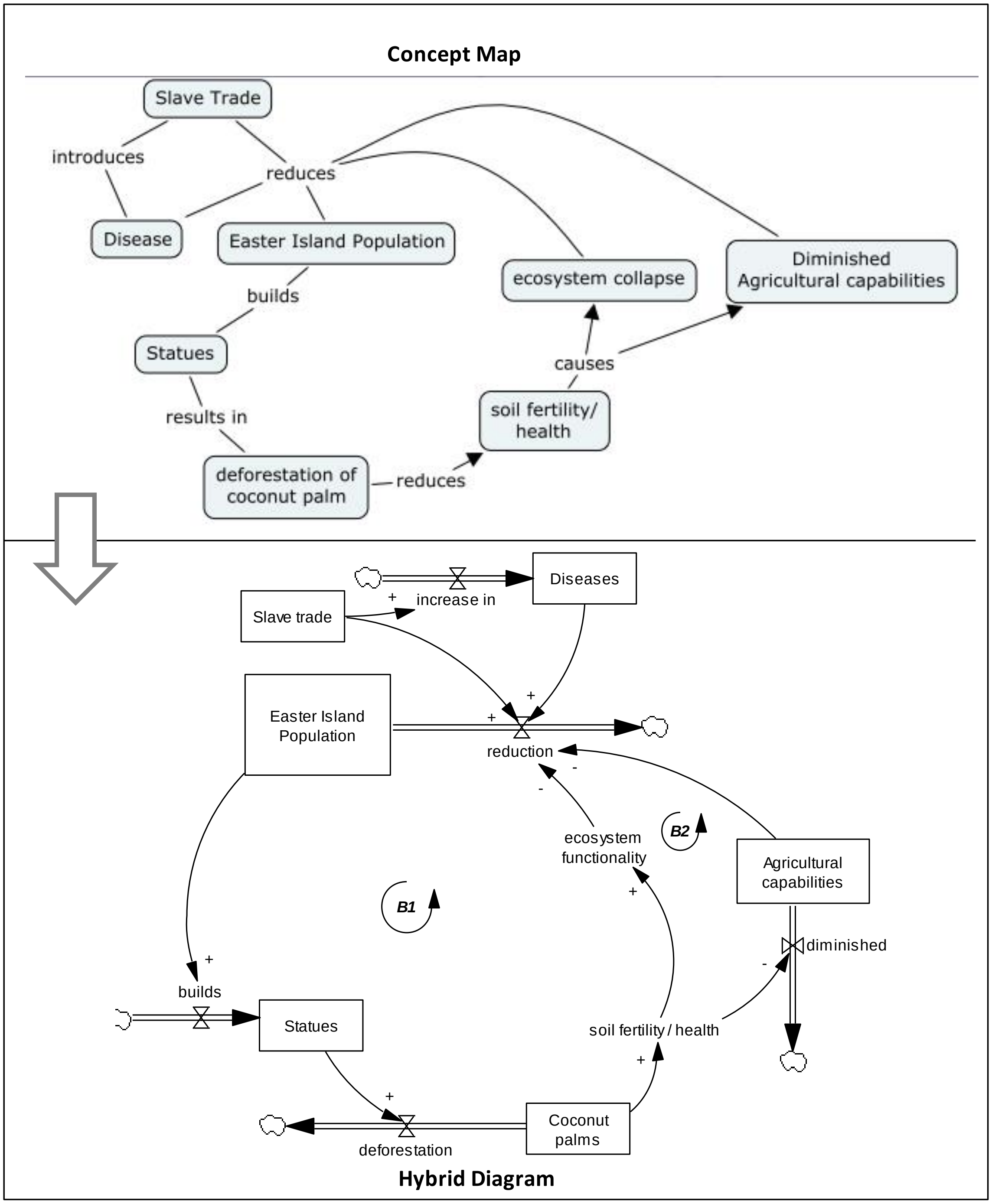

Figure 2: translating a CM into a HD

In a similar manner, the *deforestation of the coconut palm* is split into a *Coconut palm* stock and a *deforestation* flow. Additionally, the linking phrases *increases*, *reduces* and *builds* are represented as flow variables.

It is noteworthy how many operational details were implicit in the CM and are only articulated because we have to decide if a concept is a stock or a flow variable, and then comply to the rule that stocks can only be influenced by flow variables. By imposing stricter rules and restrictions on the modeler, SD leads him or her to articulate his or her understanding of the situation in a way which automatically corrects ideas which could not work in the represented situation. On top of this, the modeler is held to recognize the feedback loops, which leads to the discovery that the population collapse was self-inflicted.

The re-translation into a CM and comparison with the original CM illustrates the gain in relevant aspects:

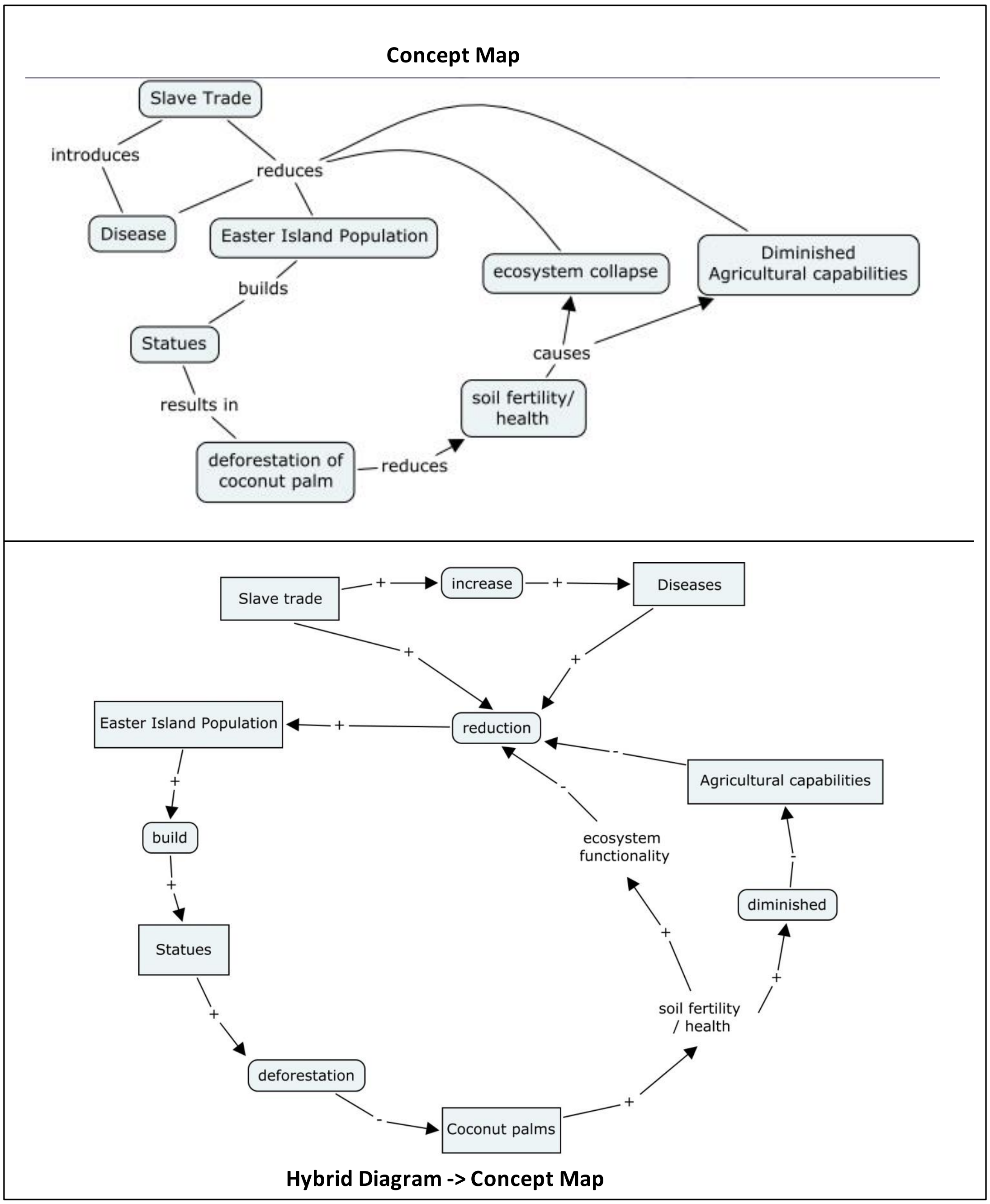

Figure 3: translating a CM into a CLD

Visual inspection reveals that the translated HD has more components, and there are three types of concepts (implicitly treating the recognition of the different types of variables as *superordinate* learning). This also shows in the propositions table, where we have replaced the linking words *reduces* with "-" and *builds*, *causes*, *results in* and *introduces* by "+".

Propositions of the original CM			
#	First concept (cause)	Linking phrase	Second concept (influenced)
1	deforestation of coconut palm	-	soil fertility / health
2	Diminished Agricultural capabilities	-	Easter Island Population
3	Disease	-	Easter Island Population
4	Easter Island Population	+	Statues
5	ecosystem collapse	-	Easter Island Population
6	Slave trade	-	Easter Island Population
7	soil fertility / health	+	ecosystem collapse
8	soil fertility / health	+	Diminished Agricultural capabilities
9	Statues	+	deforestation of coconut palm
10	Slave trade	+	Disease

Propositions of the reconstructed CM			
#	First concept (cause)	Linking phrase	Second concept (influenced)
1	build	+	Statues
2	Coconut palms	+	soil fertility / health
3	deforestation	-	Coconut palms
4	ecosystem functionality	-	reduction
5	soil fertility / health	+	diminished
6	diminished	-	Agricultural capabilities
7	Agricultural capabilities	-	reduction
8	soil fertility / health	+	ecosystem functionality
9	Easter Island Population	+	build
10	reduction	+	Easter Island Population
11	Slave trade	+	increase
12	Diseases	+	reduction
13	Slave trade	+	reduction
14	Statues	+	deforestation
15	increase	+	Diseases

Table VII: comparison of propositions

The Hybrid Diagram converted into CM not only has more details; most of the propositions of the original CM have become a chain or propositions:

Original CM	Reconstructed CM
1	3, 2
2	7, 10
3	12, 10
4	9, 1
5	4, 10
6	13, 10
7	5, 6
8	8
9	14, 3
10	11, 15

Table VIII: corresponding propositions

This is a trace of what individuals are led to do when developing a HD, but not those who develop a CM: if one has to decide if a concept is a stock or another type of variable, then one also has to identify the relevant flows. This remains implicit in CM, and therefore the structure of the situation has more operational clearness in a HD.

4 Discussion

Section 3 has shown two areas where the SD field can advance by collaborating with researchers from the CM field. First, since a SD diagram is supposed to express knowledge about a dynamic problem and can be translated into a CM without losing relevant information, the methods used to analyze and compare CM are applicable to SD diagrams. This is a methodological statement which should be considered by those using SD to trigger and support learning. Specifically the interpretation of causal links and chains of causal links as propositions and chains of propositions creates a link with the educational research field. This is of high relevance for methodological aspects of research concerning mental models of dynamic systems. This is a kind of mental models under research in SD (Groesser & Schaffernicht, 2012; Schaffernicht and Groesser, 2011). Also, initial steps towards taking into account paths (sequences of causal links) in the analysis of such mental models are under way (Schaffernicht & Groesser, 2013).

As we have argued in the second part, using SD diagramming and its rules facilitates the development of operationally accurate diagrams; as far as one accepts that such diagrams represent knowledge and that developing them also develops our knowledge, this means that whenever the focus question involves a dynamic system, SD will be an enrichment for the CM field, and its advantages should be detectable with the same analysis methods.

Both aspects seem to point at a new field of scientific collaboration for the advancement of knowledge about how we learn about and know dynamic systems. Two research questions shall be proposed here:

1) Can the methods for analyzing CMs qualitatively and quantitatively applied to the analysis of MMDS? Is it, for example, possible to apply the modal map and the criterion map (reference map) approach developed in CM to SD, and consequently define modal MMDs or a reference MMDS based upon expert opinions for MMDS and teaching cases? And would it be possible to assess the quality of individual MMDS by applying this approach?
2) Does the development of SD diagrams and models improve the quality of concept maps, where dynamical phenomena are studied? Are there more operational details? Are there more feedback loops? Are the explanations provided by the diagrams more endogenous?

Conclusions

In this conceptual inquiry, we have asked if there are compatibilities and complementarities between CM and SD. We have then shown that the representational tools are compatible: any SD diagram can be interpreted and represented as a CM. However, specific additional rules are required if one wants to develop a CM which can be interpreted and represented as a SD diagram. As shown, this has the benefit of facilitating the development of more operationally accurate knowledge and representations. SD diagrams from experiments with large numbers of individuals can – and shall – be analyzed using CM methods to improve our understanding of how people learn about dynamic systems.

This is, of course, only a conceptual contribution with methodological implications. Only practical investigations will reveal more information about the fruitfulness of this line of work for both communities. Thus we conclude by inviting researchers to take up the research questions and report back from their endeavors.

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Appendix: systems thinking

According to Richmond (1993):

1. *Dynamic thinking*: “Dynamic thinking is the ability to see and deduce behavior patterns rather than focusing on, and seeking to predict, events. It's thinking about phenomena as resulting from ongoing circular processes unfolding through time rather than as belonging to a set of factors.” (p. 122)
2. *System-as-cause thinking* (closed-loop thinking): “When exercising closed-loop thinking, people will look to the loops themselves (i.e., the circular cause-effect relations) as being responsible for generating the behavior patterns exhibited by a system. This is in contrast to holding some set of external forces responsible: external forces tend to be viewed as precipitators rather than as causes.” (p. 124)
3. *Forest thinking* (generic thinking): “Just as most people are captivated by events, they are generally locked into thinking in terms of specifics” (p. 124)
4. *Structural thinking*: “Structural thinking is one of the most disciplined of the systems thinking tracks. It's here that people must think in terms of units of measure, or dimensions. Physical conservation laws are rigorously adhered to in this domain. The distinction between a stock and a flow is emphasized.” (p. 125).
5. *Operational thinking*: “Thinking operationally means thinking in terms of how things really work—not how they theoretically work, or how one might fashion a bit of algebra capable of generating realistic-looking output.” (p. 127)
6. *Continuum thinking*: reasoning in terms of continuous processes rather than discrete events.
7. *Scientific thinking*: striving for quantification rather than precise measurement. Developing hypothesis and being rigorous about testing them.

Habits of minde

The systems thinker’s habits of mind according to Linda Booth Sweeney (http://www.lindaboothsweeney.net/thinking/habits)

1. Sees the Whole: sees the world in terms of interrelated “wholes” or systems, rather than as single events, or snapshots;
2. Looks for Connections: assumes that nothing stands in isolation; and so tends to look for connections among nature, ourselves, people, problems, and events;
3. Pays Attention to Boundaries: “goes wide” (uses peripheral vision) to check the boundaries drawn around problems, knowing that systems are nested and how you define the system is critical to what you consider and don’t consider;
4. Changes Perspective: changes perspective to increase understanding, knowing that what we see depends on where we are in the system;
5. Looks for Stocks: knows that hidden accumulations (of knowledge, carbon dioxide, debt, and so on) can create delays and inertia;
6. Challenges Mental Models: challenges one’s own assumptions about how the world works (our mental models) — and looks for how they may limit thinking;
7. Anticipates Unintended Consequences: anticipates unintended consequences by tracing loops of cause and effect and always asking “what happens next?”

8. Looks for Change over Time: sees today's events as a result of past trends and a harbinger of future ones;
9. Sees Self as Part of the System: looks for influences from within the system, focusing less on blame and more on how the structure (or set of interrelationships) may be influencing behavior;
10. Embraces Ambiguity: holds the tension of paradox and ambiguity, without trying to resolve it quickly;
11. Finds Leverage: knows that solutions may be far away from problems and looks for areas of leverage, where a small change can have a large impact on the whole system,
12. Watches for Win/Lose Attitudes: is wary of "win/lose" mindsets, knowing they usually makes matters worse in situations of high interdependence.

Habits of mind according to the Waters Foundation (http://watersfoundation.org/systems-thinking/habits-of-a-systems-thinker/):

1. Big picture: Seeks to understand the big picture
2. Change over time: Observes how elements within systems change over time, generating patterns and trends
3. Systems' structure: Recognizes that a system's structure generates its behavior
4. Interdependencies: Identifies the circular nature of complex cause and effect relationships
5. Changes perspectives: Changes perspectives to increase understanding
6. Assumptions: Surfaces and tests assumptions
7. Considers issue fully: Considers an issue fully and resists the urge to come to a quick conclusion
8. Mental models: Considers how mental models affect current reality and the future
9. Leverage: Uses understanding of system structure to identify possible leverage actions
10. Short term / long term consequences: Considers both short and long term consequences of actions
11. Unintended consequences: Finds where unintended consequences emerge
12. Time delays: Recognizes the impact of time delays when exploring cause and effect relationships
13. Successive approximation: Checks results and changes actions if needed