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Chapter 4

Bridging Qualitative and Quantitative Methods in Foresight

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4.1 Introduction

There is a long-lasting and controversial discourse on the role of quantitative and qualitative data and methods in science, at least since the “Newtonian turn” in physics in the 17th century. After this successful step in the mathematical formalization of a large branch of physics, nowadays called “classical mechanics”, it was used as a kind of paradigmatic case by many theorists of science. Thereby, standards for scientific processes and theory structures were imposed on realms of science dealing with dramatically different subjects, and having different purposes than classical mechanics. This was controversially discussed within the debate on positivism, but it still has a strong influence on our understanding of science.
Why is this relevant for the discussion of quantitative and qualitative concepts in foresight?
Firstly, this paradigmatic case deals with the motion of objects in space (planets, cannonballs, cars), i.e. it deals explicitly with the time dimension. Therefore, a new kind of mathematics was developed by Newton and Leibniz: the differential calculus. The general laws of motion could then be formulated as a set of differential equations which calculate the (observed or future) time courses of the object’s location from given initial (and boundary) conditions. These laws of motion described a number of observations and experiments so well that, at the beginning of the 19th century, a mechanistic world view was formulated, assuming that, once set in motion, the universe would work like clockwork, following eternally

the Newtonian laws of motion (theological complications could be resolved[1]). Although this extreme view was revised for several reasons[2], the relation between the explanation of phenomena and their prediction is still a vital point for the controversial understandings of foresight.

Secondly, the cited paradigmatic case is a fully quantitative theory where each basic concept (like “length”) is operationalized by a measurement procedure (“compare with the ‘mètre des archives’ in Paris”) which assigns the respective variable (“s”) a real number (“5.51m”). This constitutes a clear-cut relation between the quantitative theory and its real-world subject, and makes a variable-oriented approach to scientific explanation and prediction very appealing.

Thirdly, the Newtonian laws of motion are valid for a huge number of different experimental and observed situations (all macroscopic mechanical phenomena with relative velocities significantly less than the speed of light). This implies that science is able to find general laws with very wide ranges of applicability.

In the next section we analyse the shortcomings of epistemological approaches to prediction which are oriented to the above paradigmatic case, while it appears as a more or less singular stroke of luck in the history of science. In the following section we then discuss the role of quantitative models in foresight studies. After a short overview of the four main approaches to foresight according to Kreibich (2006) we proceed with a discussion of qualitative concepts compared with quantitative concepts in science, and conclude with some approaches which bridge the gap between the two traditions.

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[1] E.g. by reformulating the laws of motion as a variational principle by Lagrange (18th century), implying more a (divine) purpose of the whole trajectory/history than reducing the options of God to defining the initial condition and the Newtonian laws.

[2] Even by inner-physical reasons like macroscopic irreversibly or, later, deterministic chaos.

4.2 Explanation and Prediction

As mentioned above, within the epistemological position of logical positivism, there is no difference in the inferential pattern between explanation and prediction. Following the argumentation of Aligica (2003) this can best be demonstrated by the position of one of the proponents of the “nomologico-deductive” school of explanation:
“An explanation (...) is not complete unless it might as well have functioned as a prediction; if the final event can be derived from the initial conditions and universal hypotheses stated in the explanation, then it might as well have been predicted, before it actually happened, on the basis of a knowledge of the initial conditions and general laws” (Hempel, 1963).
Thus the explanation of a phenomenon includes the information about antecedent conditions and general causal laws. Hempel called these “covering-laws” or “nomologico-deductive” argument when an observed phenomenon can be reconstructed along these lines.
The main arguments against the above concept as a general structure of valid science (Rescher, 1998; Aligica, 2003) include historical but also purely logical aspects:

- there are generally accepted and important scientific explanations without predictive power (e.g. the mechanisms which generate earthquakes or the evolutionary explanations of the emergence of new species);
- there are successful predictive methods without any explanatory content like time series analysis and correlational or analogical approaches;
- the history of science shows many examples of successful predictions based on poor or even wrong explanations, as well as wrong predictions based on good explanations.

The latter emphasizes the role of explanatory scientific theories as steps in an ongoing process instead of being already “close to the truth”, and reflects on the fact that empirical theories (in contrast to mathematical statements) cannot be proved in a strictly logical

sense but, according to Popper (2004), only be falsified.
This makes clear that – at least for a large part of relevant scientific predictive endeavours – the nomologico-deductive approach is not the most promising one: possibly either no general laws exist or the number of observed instances is, for systematic reasons, too low to perform a significant formal falsification procedure.
Aligica (2003) summarizes: “In the prediction’s domain even the best confirmed theories are no more than reasonable and provisional estimates of the truth.” And he concludes by stressing the principal epistemic difference between explanation and prediction (or retrodiction[3]):
“Explanations try to reveal connections between events, phenomena and states and if possible to reveal the fact that they are part of larger patterns, regularities and laws.
The primary function of predictions and retrodictions is to acquire and offer more knowledge of specific, concrete events and occurrences. The idea is to export from premises the necessary epistemic weight needed to gain credibility. The primary function of such arguments is simply to establish or prove the conclusion. Consequently in a prediction or retrodiction argument, the application of general laws is not essential. An argument that makes appeal to general laws is always welcome but still it is as good as any other argument; and thus in the last instance it is inessential. Using the covering-law model to make a prediction or retrodiction is sufficient, but not necessary. Statements of restricted regularities, quasi-laws, statistical laws, the so-called common sense generalizations or accidental generalizations can viably be employed in projective arguments.”
Even if this argumentation seems self-evident to many practitioners in Future Studies it becomes crucial in foresight projects which include researchers from those disciplines where a covering-law type-understanding of science is (still) dominant. In climate change, economic or ecological theories quantitative (dynamic) modelling plays

[3] Retrodiction means the prediction of an event in the past from initial situations and conditions even further in the past.

a widely accepted role, and these models are often assumed by their authors to operationalize Hempel's general laws, allowing for explanation and prediction at the same time – consequently they are hardly inclined to accept that their model-based predictions play a comparable role to "common sense generalizations" in foresight.

4.3 The Role of Quantitative Modelling in Foresight

Indeed, the argument has to be handled with care: some of these predictive models are closer to the above-mentioned epistemological "stroke of luck" than others, in particular the atmospheric climate forecast models (known as Atmospheric General Circulation Models) which incorporate a great deal of Newtonian mechanics and can dispose of a large (and increasing) amount of standardized data for validation via retrodiction. Of course the future could in principle falsify the model, but it is anchored very deeply in systematically accumulated empirical evidence. But already the next step to answer the question what the global climate will look like under a given human impact scenario requires more complex physical earth system models which integrate oceans, the kryosphere and biogeochemical cycles. Although these additional components are still purely subject to the laws of nature, the data situation for validation becomes more critical and (consequently?) the underlying theories more controversial. Here the argument certainly becomes more relevant: that our current theoretical understanding may be more a historical phase than already "close to the truth". The fact that the theory has the same form (a dynamic quantitative model) as others which are closer to Hempel's paradigm should not be of any relevance in this context – its role in foresight exercises becomes relativized and in this case: "An argument that makes appeal to general laws is always welcome but still it is as good as any other argument" (Aligica, 2003).
To stay with the forecast-example of global climate change as-

sessments the next step using what are called Integrated Assessment Models (IAMs) is to incorporate human actions and reactions into the formal model on the basis of the plausible argument that (anthropogenic) changes in the physical environment will have feedbacks on human actions – a relation which questions the possibility of reasonable a priori definitions of, for example, scenarios of anthropogenic CO_2 emissions. This means that socio-economic theories enter the physical earth system models and with them all specific problems like reflexivity and the related problem of the separation of the observer (modeler) from its subject (e.g. society). While quantitative modelling approaches are well established in economics, these are highly contested in sociology and policy science. But, even in economics – is similar to the situation described for physical earth system models – the quantified theory is far from Hempel's paradigm: independent of the obviously poor quality of predictions[4] the basic hypotheses of mainstream theory are still used to guide economic policies.

IAM modellers are well aware of these shortcomings in the predictive ability of their integrated models, and make attempts to quantify the uncertainty of their forecasts. Meanwhile, there are classifications of the sources of uncertainty in quantitative models, ranging from numerical failures to uncertainties in the choice of relevant variables and their interactions (structural uncertainties[5]). This also spans the range of the possibility of a formal uncertainty assessment from "manageable" to "almost impossible".

To deal with this situation, Jan Rotmans, an experienced IAM modeller (Rotmans and de Vries, 1997) originally called for a proper interpretation of quantitative forecasts of large integrated models: "Don't trust the numbers, just trust the trends". This seems to be a possibility for a more careful interpretation of quantitative prediction, although it is not clear under which conditions totally uncertain

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[4] Poor predictions of the economic cycle, wrongly predicted convergence of developing and developed countries, etc.

[5] For an interesting approach to deal with structural uncertainty, see Van Asselt and Rotmans (2002). They suggest a systematic exploration of different combinations of modules of an IAM along ideas of cultural theory.

numbers produce trustworthy trends.

From our experience in predictive formal modeling activities – mostly for purposes of policy assessment (e.g. Petschel-Held and Lüdeke, 2001; Eisenack et al., 2006) – we would argue that the whole modelling process – not only the resulting prediction – is the relevant input into an assessment or foresight exercise. If all assumptions underlying the model are made explicit and transparent, mathematics (supported by computers) is an unrivalled means for correct and comprehensive logical deduction. A model used in this manner in a foresight process provides more "food for thought" than a black box, and contributes to reasonable projections.

This understanding of the role of quantitative modelling in foresight has far-reaching consequences as it demands that a model used in foresight

- can either be made fully transparent with respect to its underlying assumptions to everybody who interprets its predictions
- or is close to the paradigmatic case of classical mechanics (see the preceding section), and has proved its predictive capacity in many instances under widely varying conditions.

In the "integration"-section we present an approach to dynamic modelling which is intrinsically appropriate to fulfill the first requirement.

So far we have discussed the role of the most complex quantitative concept, dynamic modelling based on assumptions on mechanisms and interactions. This is mathematically realized either in the form of deterministic/ stochastic ordinary/partial differential equations or their discrete counterparts. Our starting point was the critique of the generalization of the epistemic identity of prediction and explanation, a position which is oriented at a quantitative theory exactly of this form.

As mentioned already, there are quantitative methods relevant for foresight without explanatory pretensions, e.g. correlational approaches and time series analysis. Particularly in situations where only poor mechanistic knowledge is available, these open the possibility for temporal extrapolation. But one should keep in mind that virtually all of these statistical extrapolation methods are implicitly related to classes of mechanistic assumptions. To take a simple example, to choose a linear extrapolation instead of a quadratic one, even if the first reproduces the observed time series a bit better, implies the assumption that there is no significant positive feedback, and that this will be also the case in future. We would therefore argue that the mechanistic assumptions which underlie the predictions should be made transparent whenever possible.

4.4 Approaches to Foresight

From the practice of foresight, Kreibich (2006) identifies four different approaches, which show that the paradigm discussed above covers only a small part of relevant predictive abilities:

- *The explorative empirical-analytical approach* based on available explicit knowledge and actual data, probable and possible future developments are systematized under explicit assumptions and boundary conditions. These developments are then analysed according to specific rules.
- *The normative-intuitive approach* Experience and more generally, partly tacit knowledge are used in an imaginative and creative way to generate desirable visions of the future.
- *The planning approach* Here the focus is the process of shaping the future towards a desirable vision. Stocks of knowledge and experience are used creatively to suggest new communication, decision-making, participation and implementation processes.
- *The communicative-participative approach* The integration of actors from different societal sectors increases the amount of knowledge on possible future developments. In particular the aspects of shaping and implementation possibilities become substantiated. The same is valid for the normative aspect (desirability).

Practical foresight exercises show that usually a combination of the above approaches is applied. For example, in their future study on global sustainability *The great transition*, Raskin et al. (2002) applied a combination of the first three approaches, which is nicely documented by the structure of their final report. It starts in an explorative empirical-analytical manner by analysing historical transitions and developing from these global scenarios (see Figure 4.1) by applying a defined set of philosophies[6].

There is some overlap to the normative-intuitive approach as the set of applied philosophies is not sufficient to define the different future visions, and there is a strong normative component in imagining the "new sustainability paradigm".

After that the "planning approach" is applied, asking how the desirable scenario could be implemented – the results are clearly represented in Figures 4.2 and 4.3.

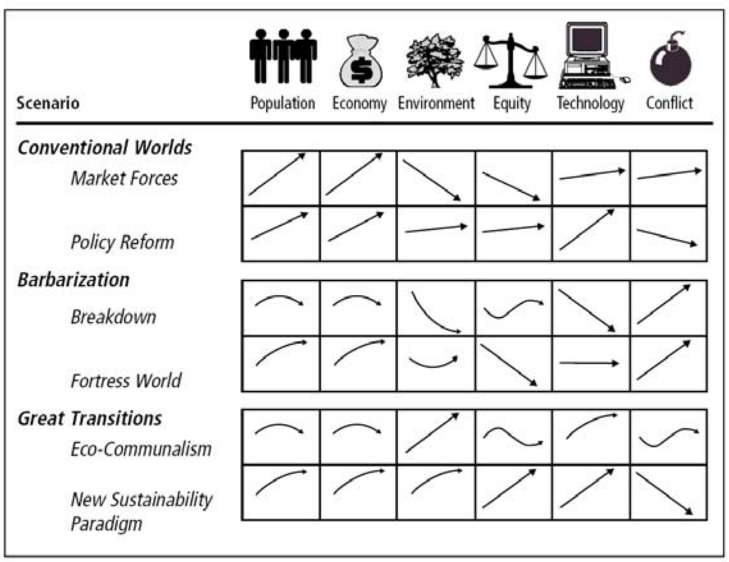

Figure 4.1 Scenario structure with illustrative patterns (after Gallopín et al., 1997)

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[6] Smith, Keynes, Malthus, Hobbes, Morris, Mill.

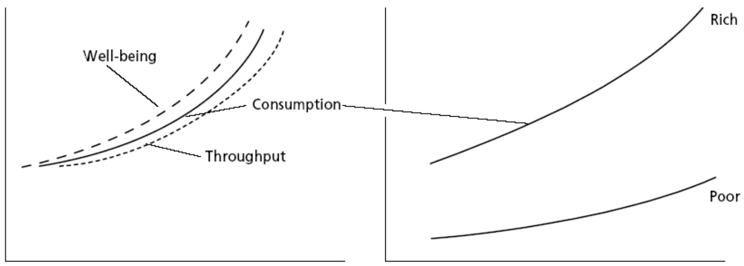

Figure 4.2 “Market forces”-scenario, where well-being, consumption and material/energetic throughput increase in parallel, while the consumption gap between the rich and the poor is increasing

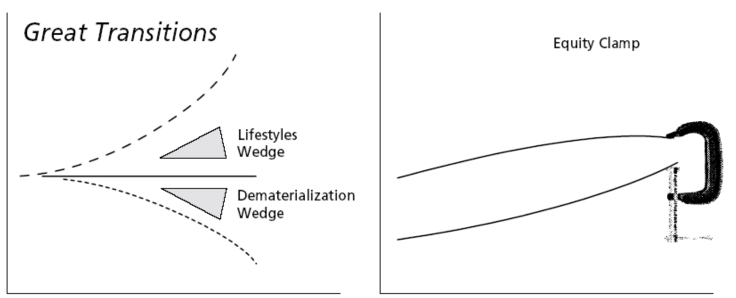

Figure 4.3 “Instruments” for a transition to sustainability: the “lifestyles wedge”, decoupling well-being from consumption; the “dematerialization wedge”, decoupling consumption from material/energetic throughput; and the “equity clamp”, forcing the redistribution of wealth on the globe (after Raskin et al., 2002)

With respect to the choice of qualitative and quantitative methods in this future study – as in many others – a mix was applied, ranging from the citation of results from models as discussed in the preceding two sections to qualitative arguments, while the use of quantitative approaches is concentrated in approaches (i) and (iii). However, it is instructive to have a brief look at some of the specifics of these two methodological schools in order to sharpen the view for the problem of the most satisfactory choice of method.

4.5 Qualitative Versus Quantitative Methods

A common property of all quantitative methods in foresight – from complex dynamic modeling to simple statistical correlations – is that they are variable-oriented. This has far-reaching consequences. Firstly, all of these methods begin after the variables are defined – so the obviously crucial step of variable definition lies outside their scope.

Related to this, the concept of the quantitative variable is two-edged: on the one hand, it is clearly operationalized by a specific measuring process, thereby standardized and highly comparable, independent of the location and time of its measurement. On the other hand, this has to be paid for by "context stripping", i.e. it is abstracted from the original context in which it had a specific meaning.

However, when using quantitative variables the systematic comparison of a large number of cases becomes feasible – which is important for the explorative empirical-analytical approach in foresight. With respect to the statistical evaluation of data intended to provide a basis for temporal extrapolation or to obtain relations between variables which can, for example, be used in dynamic system models, one specific point has to be stressed: "outliers are no problem". This means that it is assumed to be irrelevant when the identified interrelation is invalid for some of the observed cases.

The statistical use of quantitative variables has to be distinguished from their use in system analytic models. Here the time-courses of the variables are deduced from their hypothesized interrelations which allow complex feedback nets to be evaluated. This is applicable in foresight if one can formulate explicitly and quantitatively the mechanisms which contribute to the process which has to be predicted. A further condition is that the assumed interrelations stay valid, and the chosen variables stay relevant during the forecast period.

Quantitative variables may be measured on different scales, allowing for different mathematical operations:

a. ratio – all mathematical operations;
b. interval – differences;
c. ordinal – greater than, less than;
d. nominal – discrete, no ordinal relation.

The less is the demand for measurement the fewer the number of mathematical operations which are possible on the variables. System-theoretical models need variables on a ratio scale while statistical evaluations are possible for all scales.

The characteristics of qualitative data and methods are significantly different. The form of the data is much richer – one can almost state that every type of information which is not a variable is qualitative data. Typical examples are a text, a photo, a movie, etc. The character is exactly the opposite of the "context-stripped" variable: which is a "meaningful but complex configuration of events and structures" or a "singular, whole entity purposefully selected".

Retrieval techniques for such qualitative data are, amongst others, interviews, observations, oral history, focus groups, and Delphi groups, which establishes the link to the communicative-participative approach in foresight.

Data analysis techniques are hermeneutics (evaluating text and context), grounded theory (identify concepts across different texts), and others. One important aspect in qualitative methodology is the concentration on each single case. It may even be productive to look for the extreme cases rather than for the typical – in clear contrast to the treatment of "outliers" in quantitative statistical approaches.

The related process of thinking is a more circular one: during the process of foresight activities definitions, and even aims, may be modified if appropriate – this, again, is in clear contrast to variable-oriented foresight which is more linear, in the sense that, after the initial variable definitions are made, the process has to stay with them – at least for a considerable time.

4.6 Integration of Qualitative and Quantitative Methods

One way to integrate the different methodological traditions is on the level of the organization of foresight projects, which allows the results of different quantitative and qualitative methods to be integrated. This is certainly a step forward, but does not guarantee the mutual understanding of the reasoning behind these results – which is a severe shortcoming in the communication process. Therefore, it seems to be valuable to look for existing methods at the interface between the qualitative and the quantitative tradition.

One class of these “interface-methods” retains the variable-orientation (including a more linear research process), but tries to deal with weaker scales (as far as is known the following methods cover the main ideas in this realm):

Here one possibility is statistics with multidimensional nominal data: as a two-valued nominal variable is already very close to a qualitative concept (something is either green or not), a, for example, cluster algorithm on multidimensional nominal data yields qualitative constellations rather than quantitative cluster centroids. On the other hand, we still have the typical characteristics of ignorance with respect to single outliers which is unacceptable for important traditions of qualitative research.

This problem disappears if modified system analytical approaches on weaker scales are chosen. One example is the qualitative case study analysis (QCA) after Ragin (1994) on the basis of Boolean Algebra: this uses Boolean variables (with the values true/false) to transparently deduce rules applicable for several cases. On the other hand, it is still variable-oriented with the typical consequences for the research process.

A more explicitly time-related approach in this class is systems analysis with ordinal variables (QDEs) after Kuipers (1994): this method allows possible future trend combinations to be deduced from very loosely characterized feedback structures – it makes the advantages of systems analysis available for only weakly quantified systems. As this approach is rather new, it will be described in some more detail in the followings paragraphs.

QDEs are based on system theoretical process thinking, i.e. the state of a system is related to its rate of change. In the realm of usual quantitative modelling, this is formalized by differential (since Leibnitz and Newton) or difference equations, where explicit numerical relations between the variables and their rates of change are needed. In contrast, QDEs try to deduce the time development of the variables from a much weaker: namely, a "qualitative" understanding of the interactions of the system elements. This qualitative understanding can be characterized by the following hierarchy of determination:

1) Which elements are directly related (e.g. A and B are directly related, A and C are not: A – B) ?
2) What is the direction of the influences (e.g. B influences A: A <- B)?
3) Is it a strengthening or diminishing influence (e.g. B diminishes A)?
4) Is it an influence on the variable or on its rate of change (e.g. B diminishes the change of A)?

Levels 3 and 4 above imply that it is possible to describe the elements of the system by ordinal scale variables, i.e. a "greater/less than" relation can be defined.

At level 4 of determination, QDEs can be applied and will generate the time course of the variables by their trends and trend changes. As QDEs are a generalized system analytic method, the boundaries of the system, its elements, their qualitative relationships, and exogenous drivers have to be identified. In all cases where this can be done, at least in parts, the method is applicable.

With respect to the mathematical representation, a QDE can be understood as a whole class of ordinary differential equations (ODEs), which are solved simultaneously. In its simplest form the right-hand sides of the ODEs are only defined by their monotonicities, i.e. only the signs of the Jacobi matrix elements are known. The results one can obtain from such a weak systems characterization (compared with a numerical model) are combinations of trend directions of the variables and sequences of such combinations. Depending on the input, branching and/or cyclic time developments may be the result, i.e. different possible futures. Branching points identify critical stages in the development: depending on influences which are beyond the functional resolution of the assumed model, different paths may be entered.

QDEs can be considered as a kind of automatic phase space analysis which yields possible sequences of monotonicity cells. The algorithm works like a filter: starting with one trend combination, all possible successor combinations are generated. Then the algorithm filters all transitions which are not in accordance with the given system, i.e. the given Jacobi matrix. For the remaining ones, again all valid successors are generated, and so on. This results in a “tree” where each branch represents a possible sequence of trend combinations or “qualitative trajectory”.

To apply QDEs, it is necessary to construct an influence diagram which depicts the system’s elements and their qualitative relationships. To obtain this, techniques of qualitative data collection (interviews, oral history, focus groups, Delphi groups) and data analysis (hermeneutics, discourse analysis, grounded theory) can be applied (for the potential role of these techniques in the different stages of model development and the interpretation of model results, see Luna-Reyes and Andersen, 2003).

The method was originally applied by Kuipers and his group on qualitative physics and human physiology. In the realm of sustainability science it was applied on smallholder agriculture in developing countries, urban development, fisheries management and industrial agriculture. In these cases, it was the aim: to calculate possible future developments from qualitative systems understanding; to choose from these a set of possible futures, i.e. the desirable ones; to identify critical branching points; and to assess policy options to influence the development positively.

The strength of QDEs is that powerful mathematical system theoretical methods become available even if only qualitative knowledge of the interactions of the system’s elements is available, for example, in the form of an influence diagram. This allows us to fulfill the requirement of the transparency of the model assumptions for the interpreter of the results as formulated earlier in the Section 4.3 on the role of quantitative modeling in foresight

One disadvantage is that, in some cases, the result, i.e. the qualitative trajectories, may be very ambiguous, in the sense that very many branching points occur. The extreme case would be that the filtering ability of the qualitative model is so weak that almost every future development is possible. But this simply means that the input – our knowledge of the system – is insufficient to make any forecasts.

Another class of "interface-methods" deals with the systematization of a research or forecasting process that integrates quantitative and qualitative methods. A relevant example based on our own research experiences is the use of qualitative data retrieval and analysis to construct and validate/falsify system analytical models (Luna-Reyes and Andersen, 2003): the purely deductive part of the whole forecast process is done via systems analysis (e.g. the above-mentioned QDE approach) while the – extremely important – remaining steps are done with qualitative methods. As the qualitative steps interact with the system-analytic process at several points, the danger of insufficient mutual understanding of systems scientists and qualitative researchers is minimized. This method can be interpreted as an elaborated version of triangulation (Denzin, 1970), which follows the idea of corroborating a result by obtaining it with different methods.

4.7 Conclusions

We started with the discussion of the most important paradigm of quantitative foresight: the concept of quantitative dynamic modeling. Its promises, limitations, and chances were elaborated. From the limitations, the importance of alternative, inter alia qualitative methods, became clear. With respect to the chances, the transparency of the underlying assumptions and/or a long-standing, successful history of validation are identified.
Obviously the approaches to foresight are necessarily too diverse to be subsumed under the nomologico-deductive concept. As one more satisfactory possibility to frame the broad field of foresight activities, the systematization of Kreibich (2006) was adopted and – for illustration – applied to the “great transition” study of SEI. It occurred that – at first sight – in this study the explorative empirical-analytical (i) and the planning approach (iii) were used. Closer inspection showed that also normative-intuitive aspects (ii) played an important role. So, only one of the four approaches, the communicative-participative approach was definitely not used in this study. Quantitative methods were mainly used in approach (i) and to some extent in (iii). For approach (ii), quantitative methods are clearly less appropriate, while they may have a role in the communicative-participative approach.
After a description of the important properties of quantitative and qualitative data and methods, a hierarchy of integration depth of the “two cultures” was identified: the most superficial way is the collection of qualitative and quantitative “black box” results gained by different members of the foresight activity – the danger of unrecognized inconsistencies in the basic assumptions leading to the respective results is obvious. Then, for a somewhat deeper integration, two classes of “interface-methods” were suggested: the very fast alternating application of qualitative and quantitative steps (e.g. Luna-Reyes and Andersen, 2003) and the use of variable-oriented methods working with data on weaker than ratio scale.

As a very promising example for the latter interface-methods the system analysis with ordinal variables was presented in more detail. It occurs that models (and projections) constructed with this method fulfill the above-mentioned precondition of transparency for all members of the foresight activity and allows us to map the uncertainty or ambiguity of assumptions, of course resulting in possibly very weak and ambiguous projections. In general, this example shows that there are current developments within mathematical systems theory which concentrate more on uncertainties in the system definition and, with respect to projections, more on corridors than on trajectories. This paper tried to show that this offers the chance of deeper integration of quantitative and qualitative methods in foresight activities.

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