西北农林科技大学
Northwest A&F University

生态仿真优化实验室
Simulation Optimization Lab

Understanding Scientific Reasoning

Research Process in Biometrics and Operations Research

Prof. Dr. Tianjian Cao

Simulation Optimization Lab

Northwest A & F University

cao@nwsuaf.edu.cn

Outline

- Main Steps or Phases in Research Process
- The Nature of Causal Models and Their Testing
- Examples from Biometrics and Operations Research

Main Steps/Phases in Research Process

- Giere’s six-step programs

- A guide-dog approach

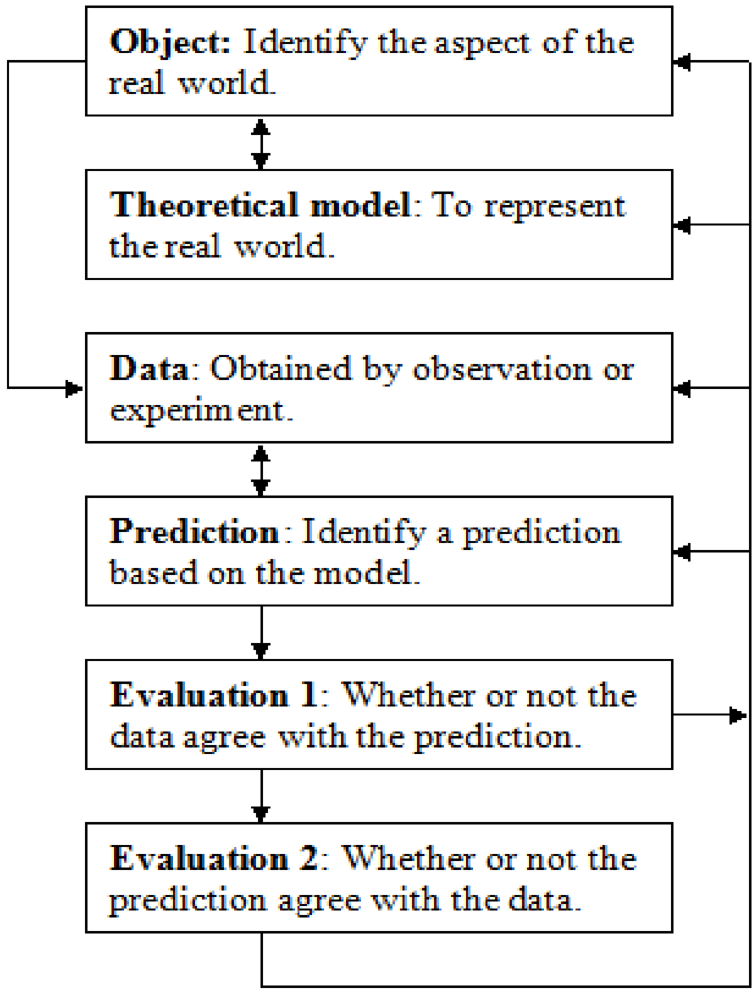
Giere’s six-step programs

- Giere’s six-step programs for evaluating **theoretical** hypotheses

- Giere’s six-step programs for evaluating **statistical** hypotheses

- Giere’s six-step programs for evaluating **causal** hypotheses

Evaluating theoretical hypotheses



- **Fig. 1** Giere's six-step program for evaluating theoretical hypotheses (Giere 1991, p.38-39)

Theoretical, con't

- The first step is to identify the real world object.
- And the second step is to identify a theoretical model used to represent the real world.
- Step 3 identifies data that obtained by observation or experiment involving the real world objects of study.
- Based on the model, the fourth step, a prediction is conducted, the prediction says what data should be obtained if the model actually provides a good fit to the real world.

Theoretical, con't

- The next part is evaluation. Giere (1991) divided the evaluation part into two steps.
  - The first step of evaluation part answers whether or not the data agree with the prediction.
  - If not, conclude that the data do not fit the real world. If the data do agree with the prediction, go on the next evaluation step.

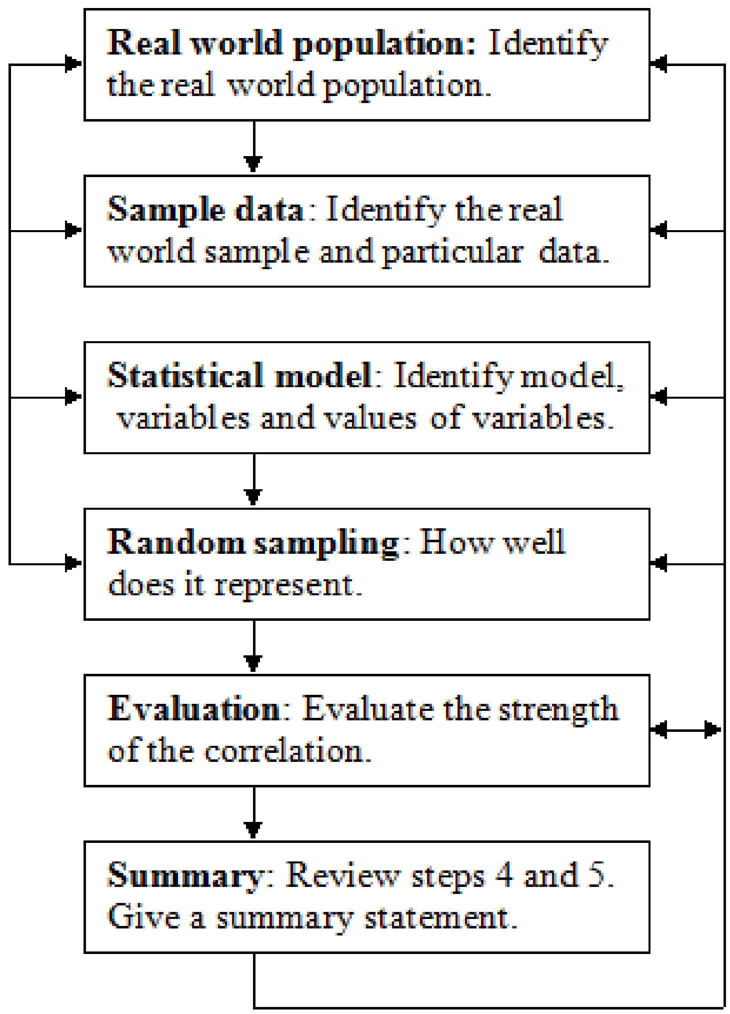
Theoretical, con't

- The second evaluation step checks the validity of prediction by answering the following question:
  - “Was the prediction likely to agree with the data even if the model under consideration does not provide a good fit to the real world?”

- If the answer is “no,” then the data do provide good evidence that the model does fit the real world.

- If the answer is “yes,” then the data are inconclusive regarding the fit of the model to the real world.

Evaluating statistical hypotheses



- **Fig. 2** Giere’s six-step program for evaluating statistical hypotheses (Giere 1991, p.128, p.186-187)

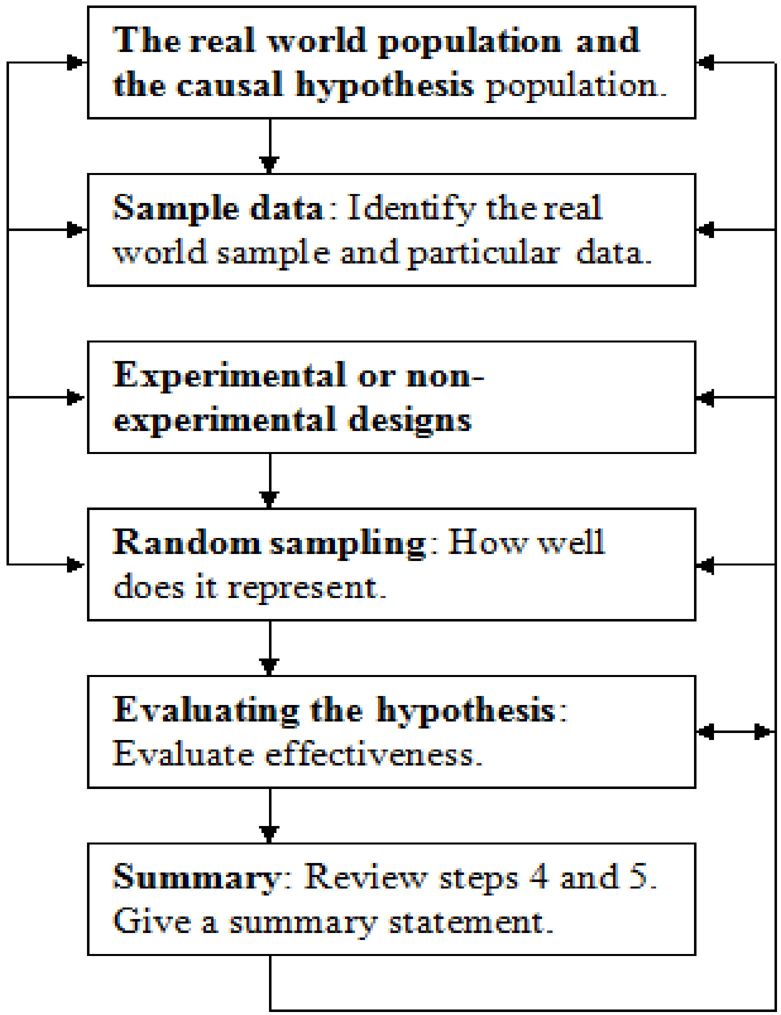
Statistical, con't

- Firstly, the real world population which is the intended object of the study should be identified.
- Secondly, we need to identify the real world sample and the particular data.
- The third step is to identify the statistical model of the population, the relevant variables and the values of these variables.
- Step 4, random sampling, provides answers to the question – “How well does a random sampling model represent?”

Statistical, con't

- By evaluating the strength of the correlation, step 5 analyzes the random sampling model, whether or not it is applicable.
  - In this step, the statistical model in step 3 is checked if a correlation is possible.
- Finally, the last step summarizes the statistical hypotheses, particularly by reviewing analyses in steps 4 and 5.

Evaluating causal hypotheses



- **Fig. 3** Giere’s six-step program for evaluating causal hypotheses (Giere 1991)

Causal, con't

- As shown in Fig. 3, there are three types of experimental designs, i.e.,
  - prospective,
  - retrospective,
  - and randomized experimental designs.

- Compared to prospective and retrospective designs, randomized experimental designs provide the best evidence for the existence of a genuine causal factor (Giere 1991).

A guide-dog approach

- Theory construction
- Data generation
- Data analysis
- Scientific inference

A guide-dog approach, con't

- In research philosophy, research methodology can be grouped as
  - empiricism, inductivism, and hypothetism.
- Arguments among hypothetical-deductive approach, inductive or empirical approach, and anti-empiricism have been raised in the past decades.
- Compared to inductivism and hypothetism, empiricism has been a common methodological background assumption in ecology.
- The hypothetical-deductive method was widely applied in the modern ecology (Tuomivarra et al. 1994).

A guide-dog approach, con't

- “In ecology the central problem is not the lack of theory or the lack of data but the lack of research able to link them systematically and critically.” (Tuomivaara et al. 1994).
- By accepting the criticism of the anti-empiricists, Tuomivaara et al. (1994) developed an approach of research philosophy called Guide-Dog Approach for ecology research.
- This approach formulates the research process as an integrated whole consisting of conceptual and theoretical thinking, mathematical modelling, designing of instruments and experiments, data generation, statistical analysis, and scientific inference.

Theory construction

- The aim of theory construction is to conceptualize the ecological theory using the method of
  - idealisation
  - and concretisation

Theory construction, con't

- The first step is to conceptualize the bases of the research problem and the ideas.

- The second step is to identify the basic elements and relationships of the research object.

- The third step is to enrich the core model with additional elements and relationships.

- In the fourth step the theoretical model is solved by applying the relevant analytical or numerical calculation methods.

Data generation

- In data generation, whether or not the theoretical model corresponds to its object is tested (Tuomivaara et al. 1994).

- Several problems should be taken into account in the data generation process, such as
  - operationalization,
  - quantification and measurement,
  - design of the arrangements
  - or setting up data generation,
  - and analysis.

Data generation, con't

- The first step results in a conceptual model in which the basis of the theoretical model and all factors are conceptualised or identified.
- The second step is to simplify the conceptual model, and to formalise it into the form of a core model of data generation.
- In the third step the operational model takes additional concepts and assumptions concerning instrumentation and arrangements into account.
- By fixing values of parameters and initial conditions, a special case model of data is developed in the fourth step.

Data analysis

- In ecology statistical analysis is widely used for data analysis.
- Distributional assumptions and independence of observations are key factors in the statistical analysis.
- Because these factors may affect the precision of the estimates.

Data analysis, con't

- According to Tuomivaara et al. (1994), the critical point in the evaluation of the statistical model is the amount of error variation.

- Increasing sample sizes may easily reduce error variation.

- At the mean time, however, the relative efficiency of additional observations decreases.

- A more efficient way is to identify and eliminate the sources of variation.

Scientific inference

- Scientific inference means the process of drawing conclusions from results concerning the validity of theory (Tuomivaara et al. 1994).

- According to Popper (1959,1963,1983), the more severe the test, the higher the degree of evidential support the data gives to the theory.

Scientific inference, con't

- Firstly, the correctness of theories is strongly supported by evidential data and other accepted knowledge;
- Secondly, the theories should be clearly, strongly and definitely formulated, and the theories must be severely tested so that we can find actual data;
- Thirdly, before conclusions, possible sources of error in data generation should be critically analysed;
- Finally, we should realise that all models, theories, data, tests and conclusions in science remain conjectural or tentative by their nature.

Nature of Causal Models and Testing

- The nature of causal models
- Experimental and non-experimental testing
- Comparison of experimental and non-experimental testing
- Examples from Biometrics

The nature of causal models

- Correlation or causation
- Deterministic or stochastic
- Individuals and populations
- Effectiveness of causal factors

Correlation or causation

- “One of the most common mistakes in statistical reasoning is inferring the existence of a causal connection from a known correlation.” (Giere 1991).
- In fact, causation and positive correlation are very different.
- Correlation is symmetrical relationship, in contrast, cau
- A symmetrical relationship means, “if A is positively correlated with B, then B will be positively correlated with A, and vice versa.”
- However, “if being an A causes you to be a B, it does not follow that being a B would cause you to be an A.”

Correlation or causation, example

- In forest ecological modelling some ecologists use ‘age’ as a dependent variable very often (e.g. Lehtonen 2005).
- For example, in a whole-stand tree growth model tree growth can be formed as a function of time.
- The volume growth of forest is positively correlated with age.
- Clearly, age **does not** cause volume growth.

Deterministic or stochastic

- In a deterministic model an individual will be characterized by a set of variables.
- Among the variables characterizing an individual, one variable that will represent a single characteristic that is under consideration as being a causal factor related to another single characteristic, a possible effect.
- Given the residual states S, the presence or absence of causal variable C completely determines the presence or absence of the possible effect E in the individual I.

Deterministic or stochastic, example

- Consider an individual forest stand. Among the residual states of the stand are #tree, Hdom, age, BA, H100, etc.
- To say that initial density is a positive causal factor for optimal thinning frequency in the stand, given its residual state, is to say that if the stand is given dense planting initially the stand will get frequent thinnings.
- And if the stand is not given dense planting initially the stand will not get frequent thinnings. Vice versa.
- Therefore, planting density is either a positive or negative causal factor (deterministic) for optimal thinning frequency in an individual forest stand.
- The variables planting density and optimal thinning frequency are causally related.

Deterministic or stochastic, example

- There is, however, another approach. This is to assume that risks, such as
  - butt rot,
  - forest fire,
  - wind throw, or
  - snow break in forest management is to be represented
    - not by deterministic,
    - but by stochastic,
    - or probabilistic models.
- In such models what the value of the causal variable does is change the probability of the value of the effect variable.

Deterministic or stochastic, example

- For instance, butt rot is a negative causal factor (stochastic) for timber production in an individual tree (Möykkynen et al. 2000), characterized by residual state,
- if the probability of timber production given butt rot is less than the probability of timber production given 'No butt rot'.
- For a different residual state the probabilities could be different.

Individuals and populations

- For many causal relationships, for instance, those studied in the biometrics, it is impossible to investigate the causal relationship by studying just individuals.
- The only way to get at the causal relationship is to study large groups of individuals.
- So models of causality that can be applied to populations are needed.

Individuals are deterministic

- A model for causation in a population will consist of a set of individuals, each of which is modelled by a deterministic model of causation in individuals.

- The basic idea is that the variables C and E are causally related in the population U, if there are any individuals in U for whom C and E are causally related.

Individuals are deterministic, con't

- In the original population U, the percentage of members exhibiting the effect E is the probability of E in the population U, Pu(E).
- In the hypothetical population X (all individuals have C), the percentage is the probability of E in X, Px(E), and Px(E) will be greater than Pu(E).
- Similarly, in the hypothetical population K (no individuals have C), the percentage is the probability of E in K, Pk(E), and Pk(E) will be less than Pu(E) (Giere, 1991).

Individuals are stochastic

- Compared to the above deterministic model of causal factors in populations,
- if the individuals are stochastic, the only difference is that Px(E) and Pk(E) are no longer definite numbers,
- but only averages over probabilities.

Individuals are stochastic, example

- For example, there is exactly one individual tree in a forest stand for which butt rot is a negative causal factor for timber production.
- On a deterministic model of that one forest stand, the number of cases of butt rot damage in population X, all trees in the forest stand damaged by butt rot, will definitely be greater by one than the number in population U, real forest stand.
- On a stochastic model of that one individual tree all we can say is that there is some probability that the number of cases of E in X will be greater than the number in U.

Effectiveness of causal factors

- On a deterministic model of individuals, there are only three grades of effectiveness:
  - positive causal factor,
  - negative causal factor,
  - and intermediate case – causal irrelevance.

- On a stochastic model of individuals, there is a full range of degrees of effectiveness.

Effectiveness of causal factors, con't

- The simplest definition of the effectiveness of C in producing E, Ef(C,E), in an individual I,
  - is the simple difference between P(E/C) and P(E/Not-C) for I.

- This measure has maximum value +1 and minimum value -1, with zero effectiveness corresponding to causal irrelevance between the variables C and E (Giere, 1991).

Effectiveness of causal factors, con't

- For a population model assuming a deterministic model for individuals,
- the simplest measure of the effectiveness of a causal factor in population U
  - is the difference between Px(E) and Pk(E).

- This measure again ranges from -1 to +1, with zero effectiveness corresponding to causal irrelevance (Giere, 1991).

Experimental and non-experimental

- Randomized experimental designs
- Prospective designs
- Retrospective experimental designs

Experimental research

- “The experiment is a situation in which a researcher objectively observes phenomena which are made to occur in a strictly controlled situation where one or more variables are varied and the others are kept constant.”
- An experimental research study is conducted for the researcher’s interest which is always in determining cause and effect.
- The causal variable is the independent variable and the effect or outcome variable is the dependent variable.
- Experimental research allows us to identify causal relationships because we observe the result of systematically changing one or more variables under controlled conditions.

Non-experimental research

- Non-experimental research is needed because there are many independent variables that we cannot manipulate (Johnson and Christensen 2000).

- For example, in forest risk management one could not do the following experiment: Randomly assign 500 new plantations to experimental and control groups, where the experimental group must have fungi (butt rot effects) and the controls do not have.

Non-experimental, con't

- Nonexperimental is conducted for many reasons. The three most common objectives are description, prediction, and explanation (Johnson and Christensen 2000).
  - Descriptive nonexperimental research is used to provide a picture of the status or characteristics of a situation or phenomenon.
  - Predictive nonexperimental research is used to predict the future status of one or more dependent variables.
  - Explanatory nonexperimental research is used to explain how and why a phenomenon operates as it does.

Randomized experimental designs

- Because of the large number of the whole of any population, it is impossible to examine the whole population.
- Thus, in scientific research a set of samples are usually set and then infer from the sample back to the population.
- By randomly selecting a sample from the real population, then randomly dividing it into two groups.
- Two hypothetical populations can be created from real samples. These two groups are experimental (x) and control (k) groups.

Randomized, con't

- In randomized experimental designs, random sampling occurs in two places.
  - First, the whole sample of subjects should be randomly selected from the whole population of interest.
  - Second, the division of the initial sample into experimental and control groups must be done randomly.

Randomized, con't

- Estimating the effectiveness of the causal factor is similar to estimating the strength of a correlation.
- One simply calculates the difference between the two nearest and two farthest ends of the estimated intervals for Px(E) and Pk(E).
- The resulting interval is the estimate of the effectiveness of the causal factor in the population (Giere 1991).

Prospective designs

- Unlike experimental studies, the subjects are not assigned to the two groups by the researchers.
- Prospective studies are more like tests of correlations in that they are based on samples from the actual population as it exists.
- The overall strategy in prospective studies is to get two groups that are, on the average, similar in every feature except the expected causal factor.
- If there is a statistically significant difference in the frequency of the effect, then that provides evidence for the causal hypothesis (Giere 1991).

Retrospective experimental designs

- A retrospective design is backward looking – unlike both experimental and prospective designs, which are forward looking.
- Random sampling plays almost no role in retrospective studies.
- In retrospective studies, the roles of the cause and effect variables are reversed.
- Thus, one can almost always tell when a reported study is retrospective.

Retrospective, con't

- Retrospective studies offer the frequency of the cause in groups with and without the effect.
- There is no way to use these frequencies to estimate the effectiveness of the causal factor.
- Therefore, retrospective studies suffer from a further failure to fit a random sampling model (Giere 1991).

Experimental vs. non-experimental

- Causal models with experimental research data are stronger than causal models with nonexperimental data (Johnson and Christensen 2000).
- Giere (1991) compared the characteristics of experimental and non-experimental testing for evaluating causal hypotheses (see Table 1).

Experimental vs. non-experimental

Table 1. Comparison of experimental and non-experimental testing.

	Random assignment	Random sampling	Other control variables	Description of groups	Description of percentage data	Estimate of effectiveness
Randomized experimental testing	Yes	Maybe	Not necessary	X-all C K-all Non-C	%E	Possible
Prospective testing	No	Maybe, sometimes not	Possible	X-all C K-all Non-C	%E	Possible
Retrospective testing	No	Maybe, usually not	Possible	X-all E K-all Non-E	%C	Not Possible

Source: Giere (1991), p.257.

Experimental vs. non-experimental

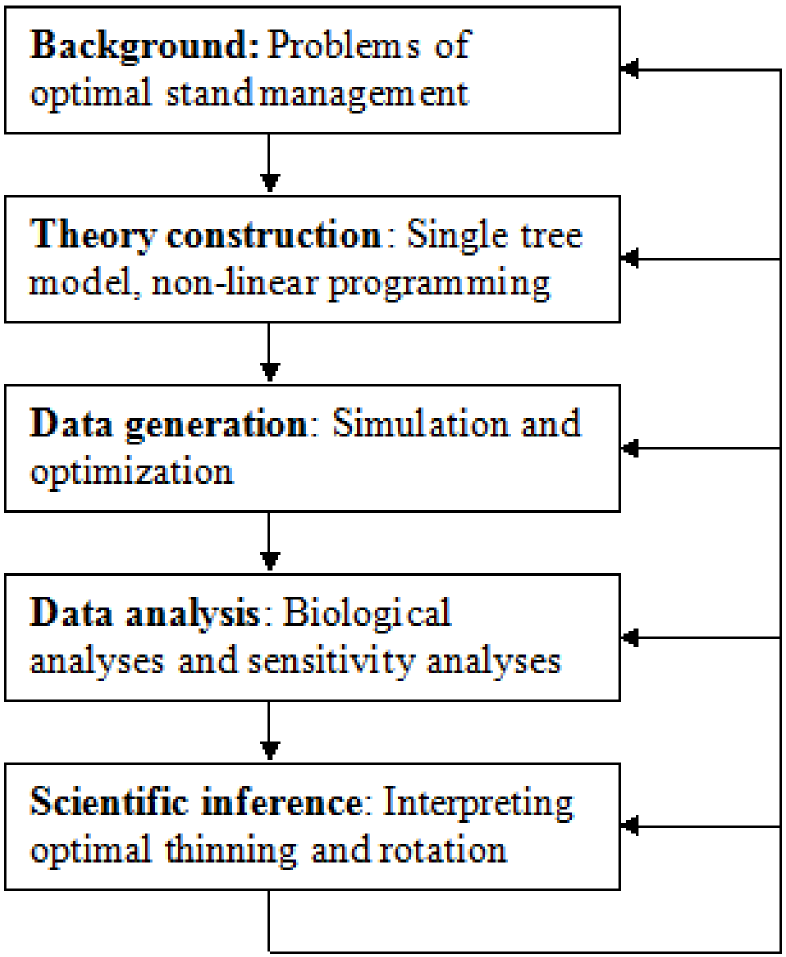
- Randomized experimental designs provide much better evidence for a causal hypothesis than prospective designs (Giere 1991).
- There is an additional disadvantage to retrospective studies.
- The data they yield allow no estimate of the effectiveness of the causal factor.
- Evidence for causal hypotheses based on retrospective data alone cannot be regarded as being as good as evidence based on prospective or experimental studies.

Optimal thinning, an example

- An optimization study of forest stand management by Cao et al. (2006) extend earlier research on optimal thinning patterns and rotation periods for even-aged Norway spruce stands.

- The main aim of this study was to investigate how initial stand structures affect optimal thinning and rotation for even-aged Norway spruce stands.

Optimal thinning, con't



- **Fig. 4** The main research phases for effects of initial states on optimal stand management according to the Guide-Dog Approach.

Optimal thinning, con't

- By applying Giere's six-step program for evaluating causal hypotheses (Fig. 3) to the study by Cao et al. (2006). The six steps are:
- Step 1. The real world population and the causal hypothesis.
  - The population of interest consists of simulation and optimization of Norway spruce stands management.
  - The cause variable is exposure to harvesting schedules,
  - and the effect variable is stumpage earnings.
  - The hypothesis at issue is that initial states are positive causal factors for stand management in the population of sample plots.

Optimal thinning, con't

- Step 2. The sample data.
  - The overall sample stands, including
    - MT and OMT sites,
    - initially dense,
    - medium density
    - and sparse stands,

    - show that initial states may have positive impact to stand management.

Optimal thinning, con't

- Step 3. The design of the experiment.
  - The design fits a model for prospective.
  - It is not experimental because there was no random division into experimental and control groups.
  - The subjects selected themselves into the categories of initial states, such as, initial density, age, dominant height, and so on.
  - All subjects were originally free of the effect, optimal thinning and rotation.

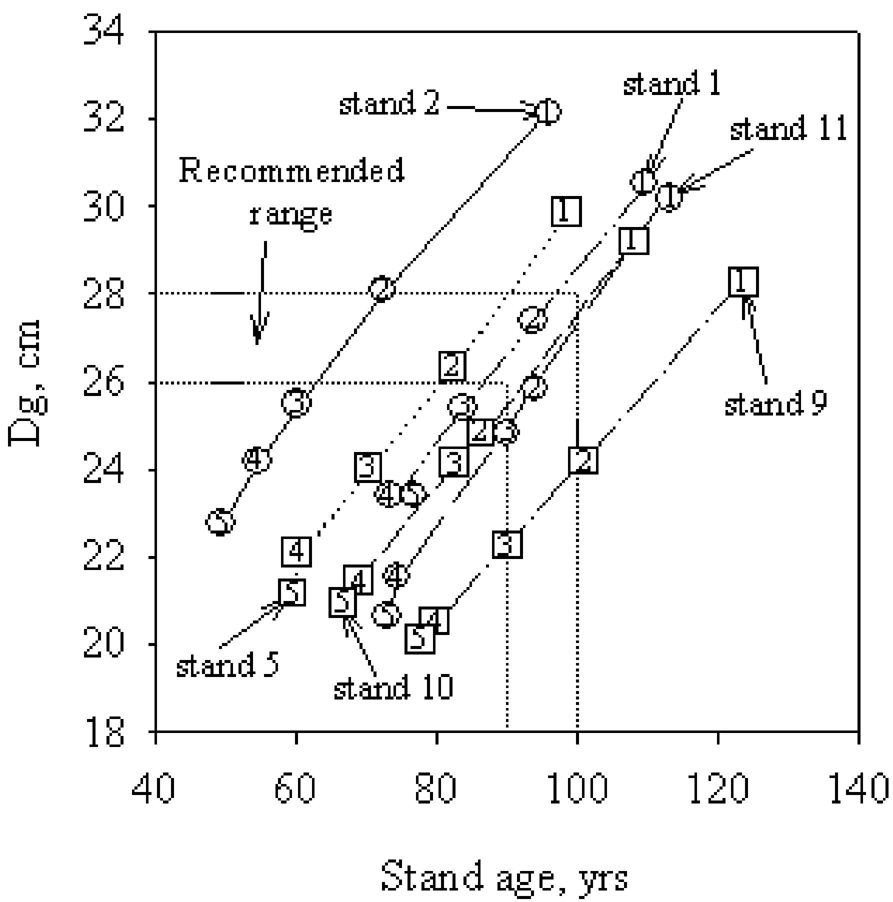
Optimal thinning, con't

- Step 4. Random sampling:
  - In this example sample stands are not random samples of all Norway spruce stands.
  - Within the sample stands, however, the sampling was randomly done.
  - There was no mention of any other variables controlled for in the data presented.

Optimal thinning, con't

- Step 5. Evaluating the hypothesis.
  - Fig. 5 exhibits a diagram of the resulting data.
  - There is good evidence that initial states is a positive causal factor for optimal rotation.
  - For the data, optimal rotation periods vary from 61 to 92 years at 3% rate of interest.
  - High variation is due to sensitivity of optimal rotation to site qualities, initial stand structure and density.

Optimal thinning, con't



Note: Numbers inside symbols denote interest rate.

- **Fig. 5** Optimal rotation period and average diameter at rotation age in MT sites.

Optimal thinning, con't

- Step 6. Summary.
  - This is clearly a careful study in line with prospective and random sampling models.
  - The study indicates that optimal thinning patterns and rotation period not only depend on site quality, but also initial stand characteristics.
  - Obviously, more severe tests may make stronger evidence in favour of the causal hypothesis.

References

- Peter Checkland, Systems Thinking, Systems Practice. New York: John Wiley & Sons 1981.
- Eugene S. Ferguson, Engineering and the Mind's Eye. Cambridge: The MIT Press 1992.
- James H. Fetzer, Philosophy of Science. New York: Paragon House 1993
- J.C. Gibbings, The Systematic Experiment. A Guide for Engineers and Industrial Scientists. Cambridge: Cambridge University Press 1986
- Ronald N. Giere, Understanding Scientific Reasoning, third edition. Chicago: Holt, Rinehart and Winston Inc. 1991
- Frederick Grinell, The Scientific Attitude. Second ed. New York: The Guidford Press 1992.
- Ernst Mayr, This is Biology – The Science of Living World. 1997.
- Elliot Sober, Philosophy of Biology. 1993.
- Steward Richards, Philosophy & Sociology of Science. An Introduction. Oxford: Basil Blackwell 1985.
- Timo Tuomivaara, Pertti Hari, Hannu Rita, Risto Häkkinen, The Guide-Dog Approach: A Methodology for Ecology. Helsingin yliopiston metsäekologian laitoksen julkaisuja 11. Helsinki 1994.