Application of Bayesian Networks in the examination of on-farm fish welfare indicators.

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Introduction

The recent upsurge of interest in fish welfare has led to increased demand for systems for the assessment of fish welfare in commercial production.

Bayesian Networks (BN) are an increasingly common multivariate modelling technique, which has evolved from specialist machine learning applications into a powerful tool for analysing highly complex data, as demonstrated by its rapid adoption into fields such as genetics (1,2).

This study uses a BN approach to examine the relationship between fish welfare and environmental variables in commercial rainbow trout (*Oncorhynchus mykiss*) farming systems.

Materials and Methods

Seven participating farms were followed up from July 2002 to November 2003 with six week interval visits.

On each visit 24 fish were randomly selected and several parameters associated with fish welfare were measured. Also at that time water quality measurements and farm husbandry factors were recorded.

Welfare indicators and fish measurements investigated:

- Haematocrit
- Plasma glucose
- Plasma cortisol
- Lysozyme activity
- Fish length
- Relative length of rayed fins; pectoral, ventral; dorsal, anal and caudal See Fig. 1.
- Fish weight
- Condition factor

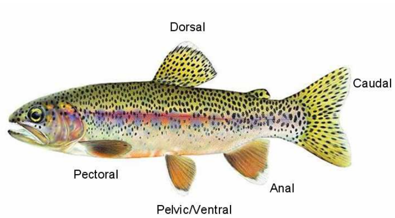

Fig 1. Trout fins description.

Water quality analysis measurements and farm husbandry factors recorded:

- Stocking density
- Flow-rate
- Loading rate
- Biomass
- Water temperature
- pH
- Dissolved oxygen
- Ionized ammonia
- Unionized ammonia

Multivariate associations among farm measurement and welfare indicators were analysed using a BN.

A BN is a type of graphical model which depicts the (estimated) joint probability distribution of a given dataset. The joint probability distribution of a dataset contains all the information required for formal statistical inference, and in this respect a BN is vastly richer than other multivariate techniques such as Principal Components Analysis. However fitting a BN to data is highly computational intensive and requires the use of specialist techniques such as optimisation heuristics or Markov chain Monte Carlo simulation in order to estimate robust models (3).

After running 1615 model search heuristics we selected the dependencies between variables (arcs) that were selected with a frequency of over 50% to create the majority consensus network.

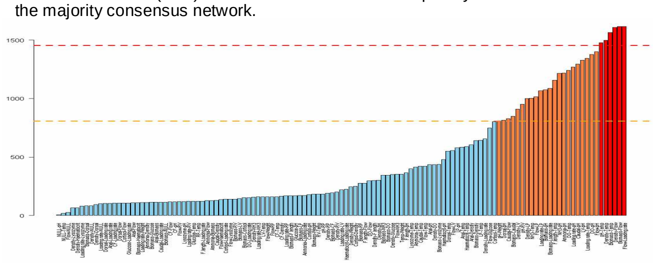

Fig. 2. Frequency of undirected arcs. The red line (top) represents the cut off point for those arcs with frequency over 90%. The orange line (middle) represents the cut off point for those arcs with frequency over 50%.

Results

Arcs with frequency over 90%.

The diagram below (Fig. 3) represents the majority consensus network reflecting the main dependencies between water quality variables and farm husbandry factors. Density, flow, biomass and temperature compose a close circle reflecting direct and indirect associations among these four factors. This circle openly turns its links to pH and Loading rate.

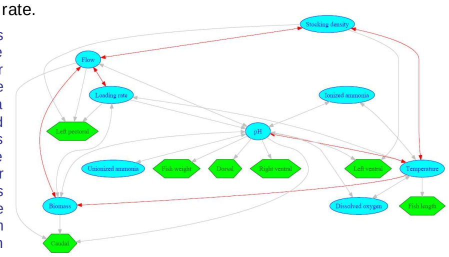

Fig 3. The majority consensus network highlighting in red the arcs with a frequency over 90%. In grey appear those undirected arcs with a frequency between 50% and 90%. Direction in the arrows is based on biological knowledge and plausibility. Water parameters and farm factors are coloured in blue. Welfare indicators and fish measurements are coloured in green.

Arcs with frequency from 50% to 90%.

Some welfare indicators appear at this level (Fig. 4). The relative length for dorsal, caudal, left ventral and right ventral fins appears associated with the pH.

Density appears associated with both ventral and pectoral left relative fin length.

Flow and loading rate are associated with left pectoral relative fin length.

pH appears associated with both ionized and unionized ammonia.

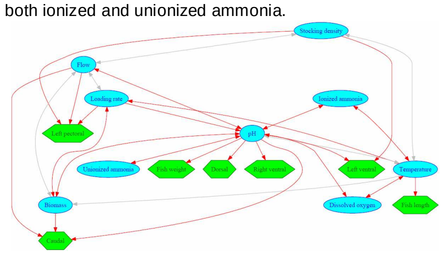

Fig 4. The majority consensus network highlighting in red the arcs with a frequency between 50% and 90%. In grey appear those undirected arcs with a frequency over 90%. Direction in the arrows is based on biological knowledge and plausibility. Water parameters and farm factors coloured in blue. Welfare indicators and fish measurements are coloured in green.

Conclusions

As expected the more consistent associations are those related to farm husbandry, as these factors are adjusted as part of the farm management control. This greatly increases our confidence in the results of our BN modelling and reinforces the internal validity of the study.

Out of all the possible welfare indicators considered under the study; the relative fin length appears co-dependent with a number of water quality and farm management practices. They are part of it, changing when the farm conditions change, which suggests that they would be the first choice as welfare indicators.

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