

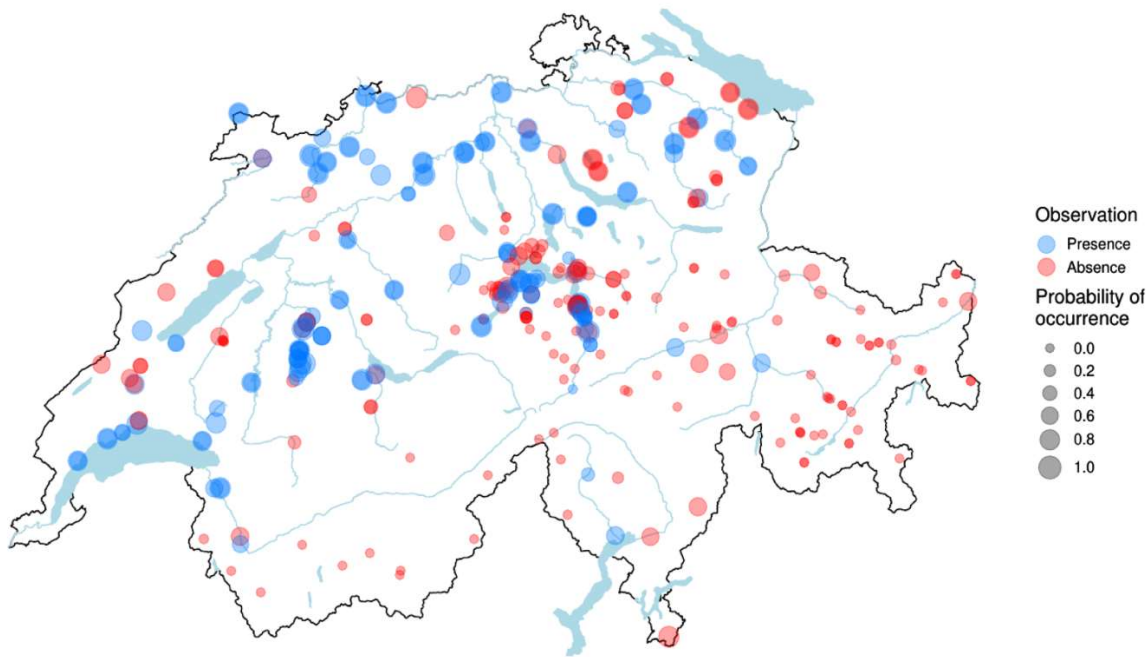
# **Probabilities are probably not enough**

## **Causal Inference: Formalization of Reasoning**

**Andreas Scheidegger**



# Species Distribution Model – a typical ML application



$$\text{Prob}(\text{fish} \mid A, B, C)$$

$$p(\text{fish density} \mid A, B, C)$$

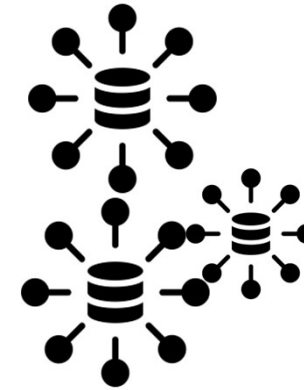
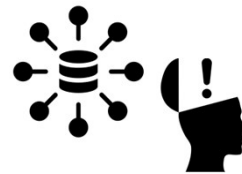
# Predictions and Generalization

## Prediction

- Well defined problem, we know how to assess a model
  - Data splitting, X-validation, ...
- We have a clear metric for model selection
- In principle, we can always figure out which model is better

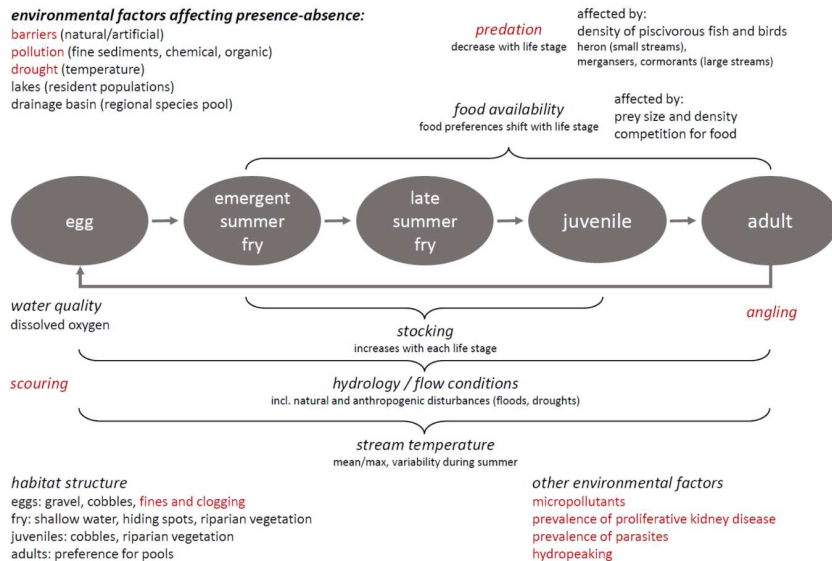
## Generalization

- In principle, we need just more data



→ Follow the standard protocol for predictive modeling

“...to better inform stream management” Caradima, et al. (2021)



“The importance of including **environmental conditions that have a direct, mechanistic effect** on species distributions has been emphasized as a means to improve model interpretability [...] (Austin, 2002). This [...] is especially important **when the models are intended to inform stream management.**”

**Which variables should be included in the model?  
 Which variables must not be included in the model?**

## Management: deciding on interventions

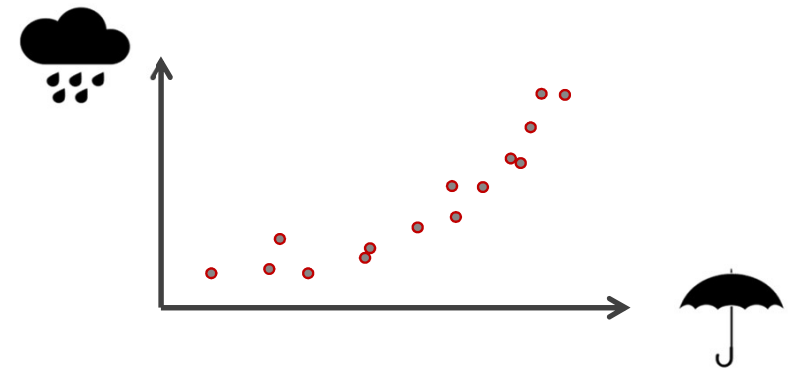
Predictive question:

*What do I know about outcome Y if I **know** X?*

Management question:

*What do I know about outcome Y if I **do** X?*

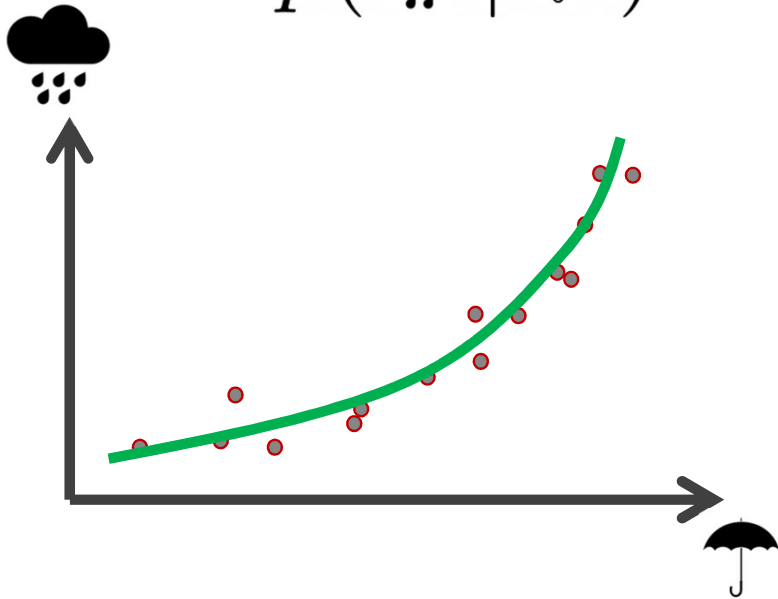
$$\text{Prob}(Y | X) \stackrel{?}{=} \text{Prob}(Y | \text{do}\{X\})$$



# Observational vs. Interventional Distribution

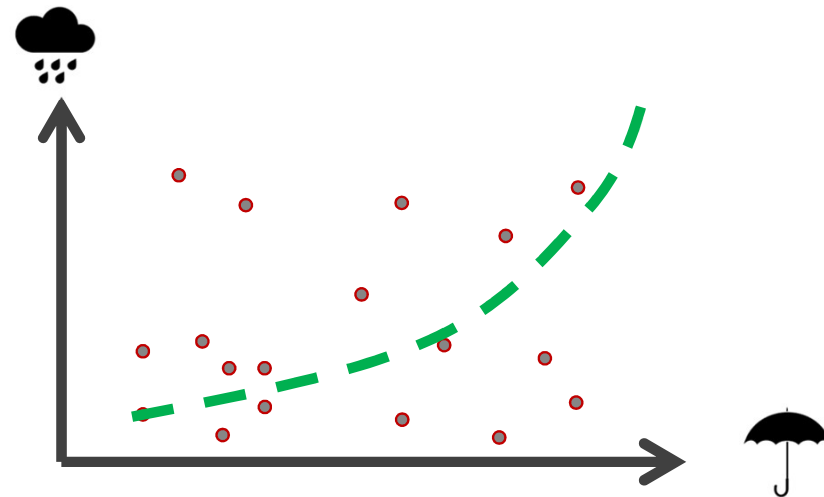
observation

$$p(\text{☁} \mid \text{☂})$$

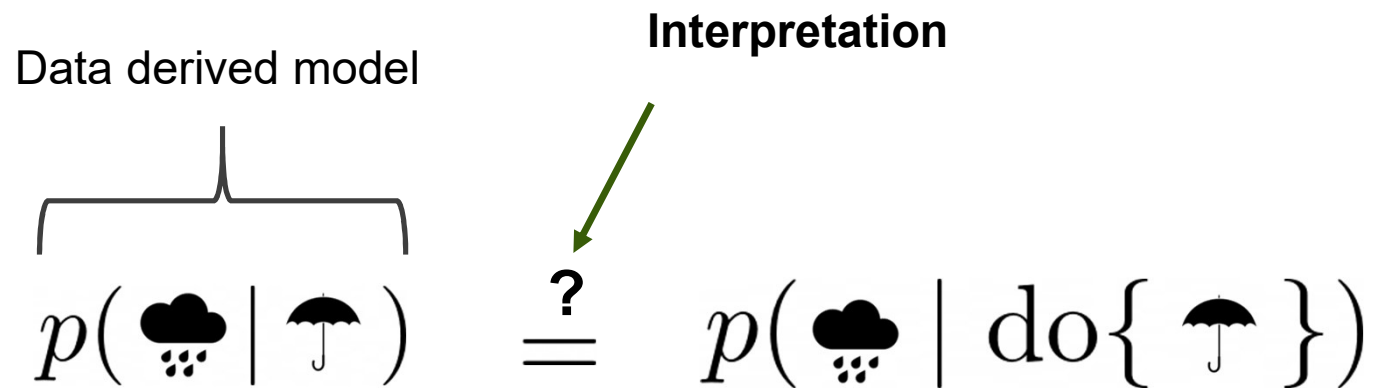


intervention

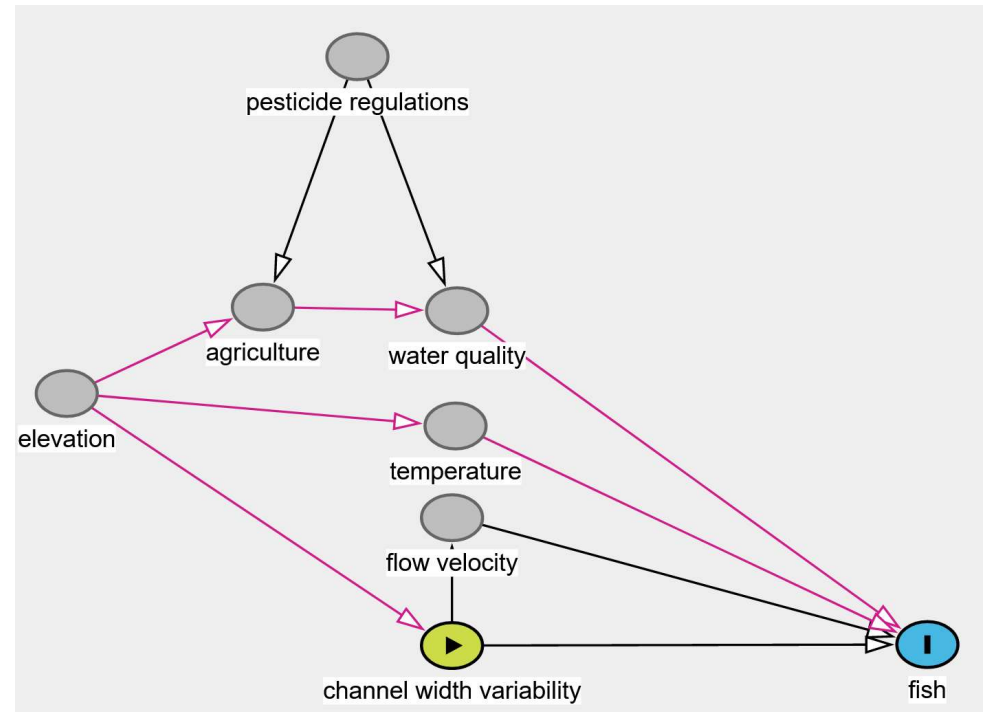
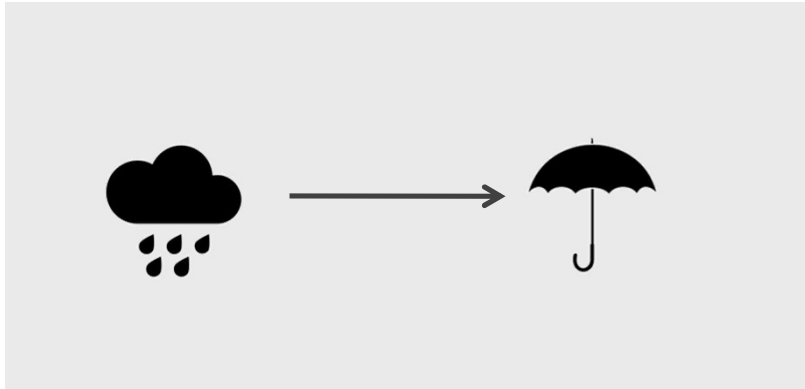
$$p(\text{☁} \mid \text{do}\{\text{☂}\})$$



# Causal Inference: Observational distributions = Interventional distribution?

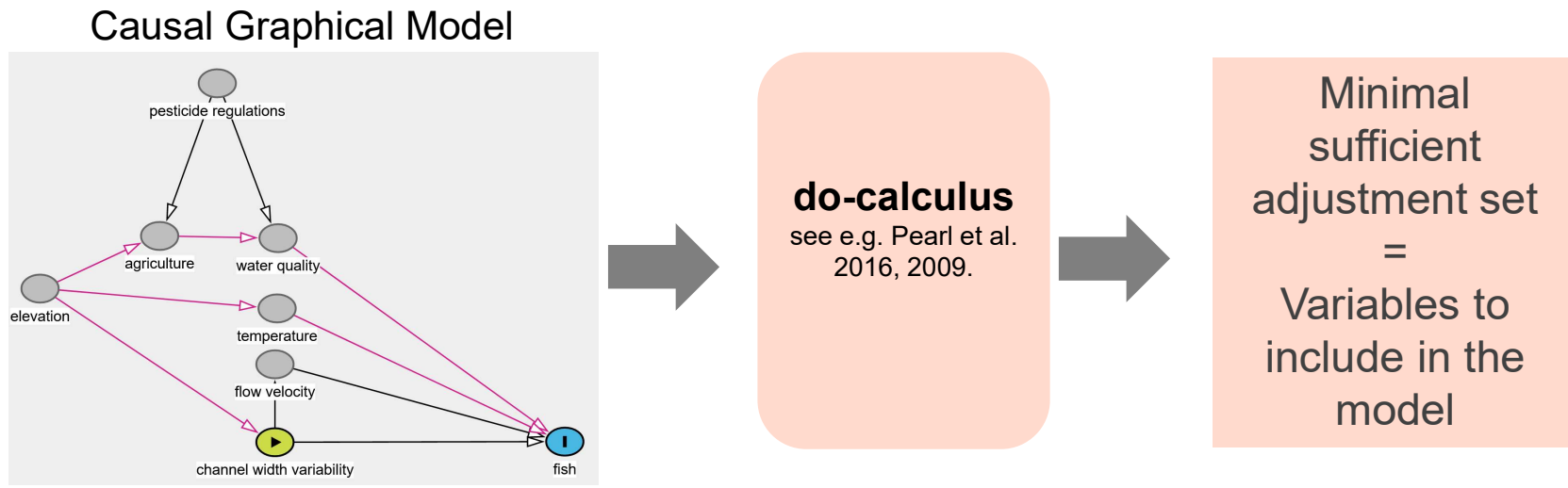


# Causal Graphical Model: encode our world-view as DAG





# do-calculus: symbolic analysis of the causal graphical model



Note, no linearity or distributions assumptions are made! Only the graph is analyzed.



Judea Pearl

## Minimal Sufficient Adjustment set $\rightarrow$ variable selection

What happens to  $Y$  if I change  $X$ ?

$$\text{Prob}(Y \mid \text{do}\{X\}) = \text{Prob}(Y \mid X) \text{ ?}$$

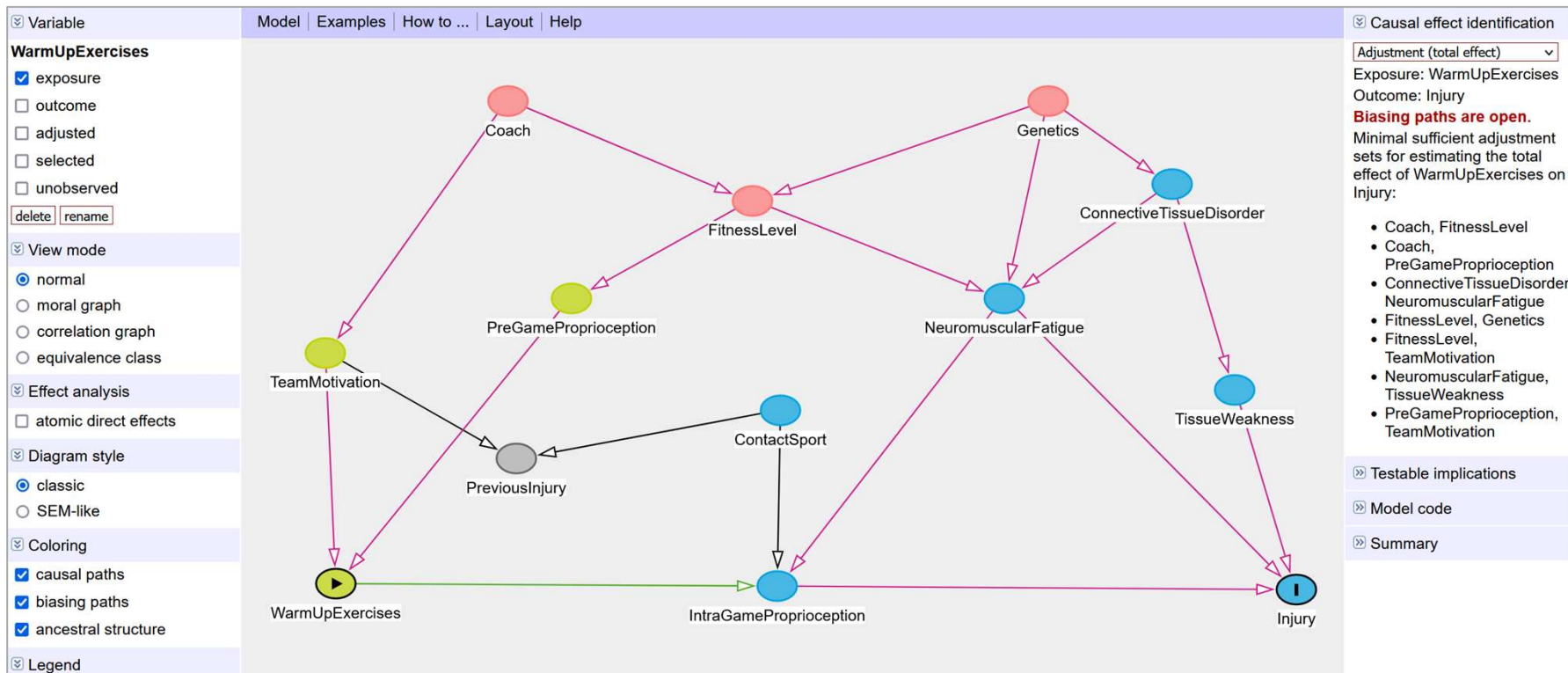
Maybe I need to condition on additional variables  $S_i = \{X, Y, \dots\}$ :

$$\text{Prob}(Y \mid \text{do}\{X\}, S_i) = \text{Prob}(Y \mid X, S_i)$$

$S_i$  is a minimal sufficient adjustments set, i.e. a set of variables to include in our model

<https://dagitty.net>

<https://cran.r-project.org/web/packages/dagitty/index.html>



## Causal Inference Workflow

1. Define outcome and interventions variables
2. State the your *strong assumptions* as Causal Graphical Model (DAG)
3. Identify the *Minimal Sufficient Adjustment* sets with do-calculus
4. Pick a MSA set
5. Fit and assess a model based on your *weak assumptions*
6. (Test robustness of conclusion by modifying the DAG)

- The Causal Graph is analyzed symbolically:
  - Model independent
  - No linearity or distributional assumptions
  - No observations are involved
- It does *not* identify causal relationships!

## Model selection criteria

Prediction, Calibration

Predictions of the  
effects of interventions

Predictions of  
unobserved states

Insights from the model

Aesthetics & Simplicity

## Model selection criteria

Prediction, Calibration

traditional predictive modeling: X-val, AIC, ...

Predictions of the  
effects of interventions

Causal inference

Predictions of  
unobserved states

Insights from the model

Aesthetics & Simplicity

# Model selection criteria

Prediction, Calibration

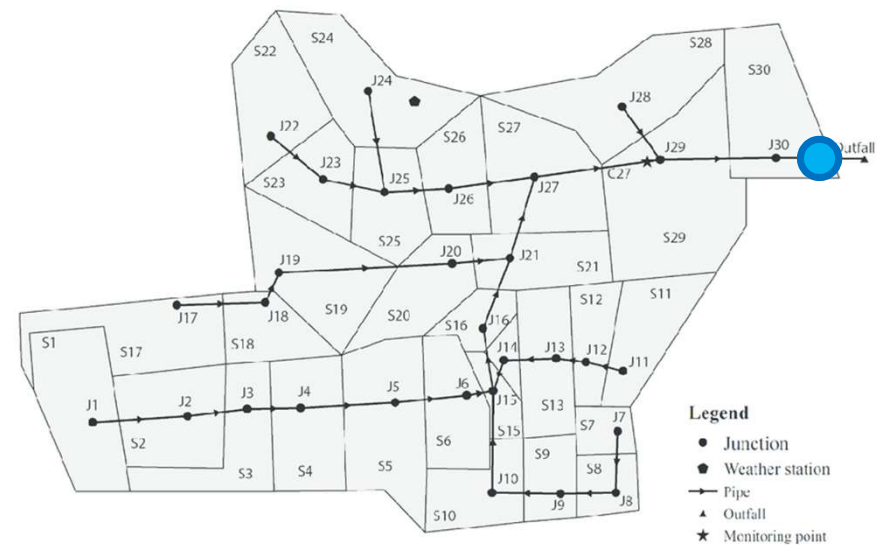
Predictions of the effects of interventions

Predictions of unobserved states

Insights from the model

Aesthetics & Simplicity

Observations and points of interest do not match



## Model selection criteria

Prediction, Calibration

Predictions of the  
effects of interventions

Predictions of  
unobserved states

Insights from the model

Aesthetics & Simplicity

*“The problem with machine learning is that the machine is learning and not you”*

– somebody from on the internet

Mathematical tools may help us to find insight.  
→ but we still must decide what counts as insight!

*“Environmental systems are incredible complex. I want a model that is easy to understand.”*



## Model selection criteria

Prediction, Calibration

*“Beauty is the first test: there is no permanent place in the world for ugly mathematics.”* - Hardy G.H., 1941.

Predictions of the effects of interventions

*“The only physical theories that we are willing to accept are the beautiful ones.”* – A. Einstein

Predictions of unobserved states

Insights from the model

*“The miracle of the appropriateness of the language of mathematics for the formulation of the laws of physics is a wonderful gift which we neither understand nor deserve”* – Wigner, E., 1960

Aesthetics & Simplicity

*“We should not expect scientific explanations always to be intuitive and satisfying.”* – Anil Seth, 2021



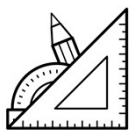
data  
observations



Where is the information from?




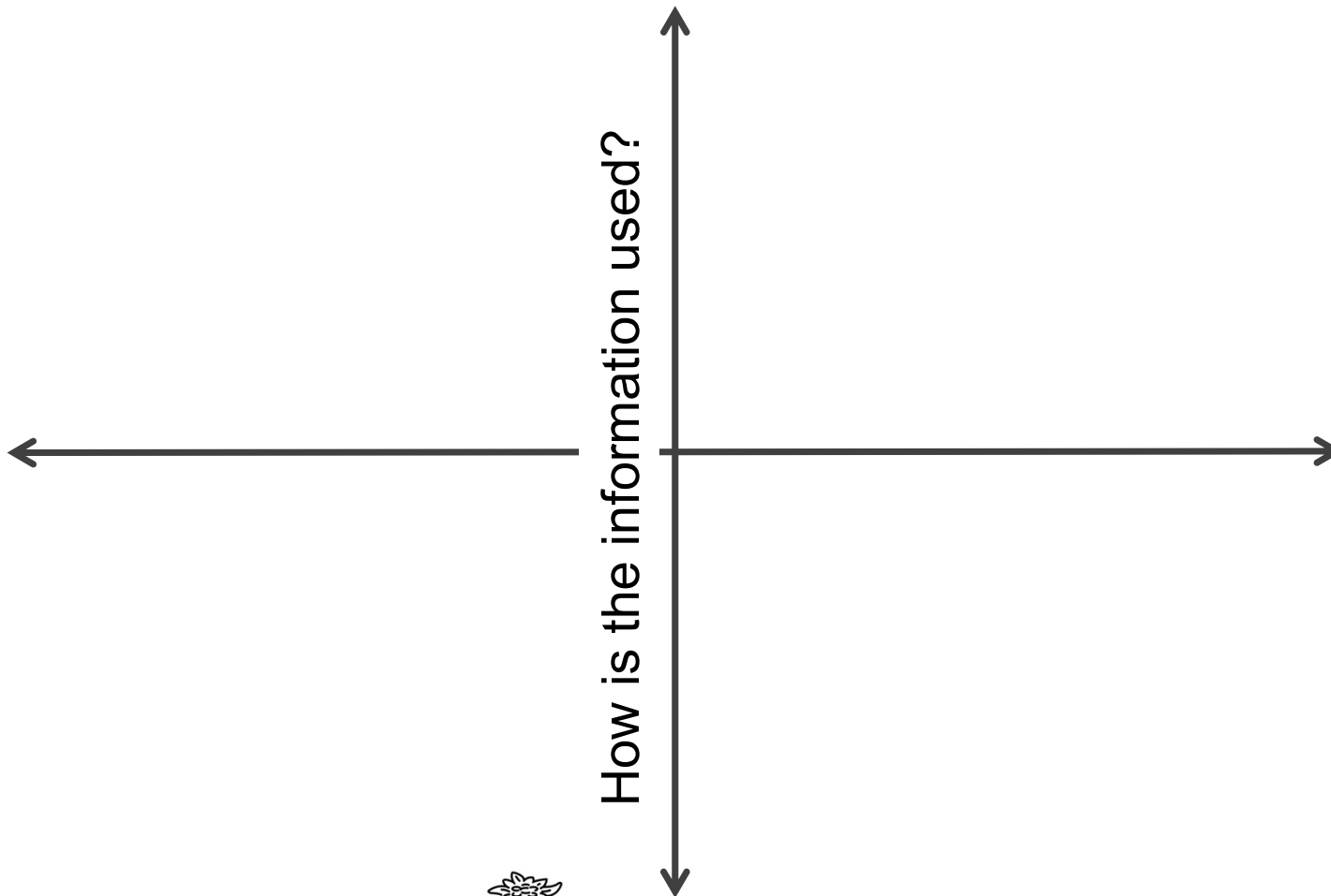
intuition, experience,  
human judgment



formal  
(mathematical)

**eawag**  
aquatic research ooo

  
data  
observations

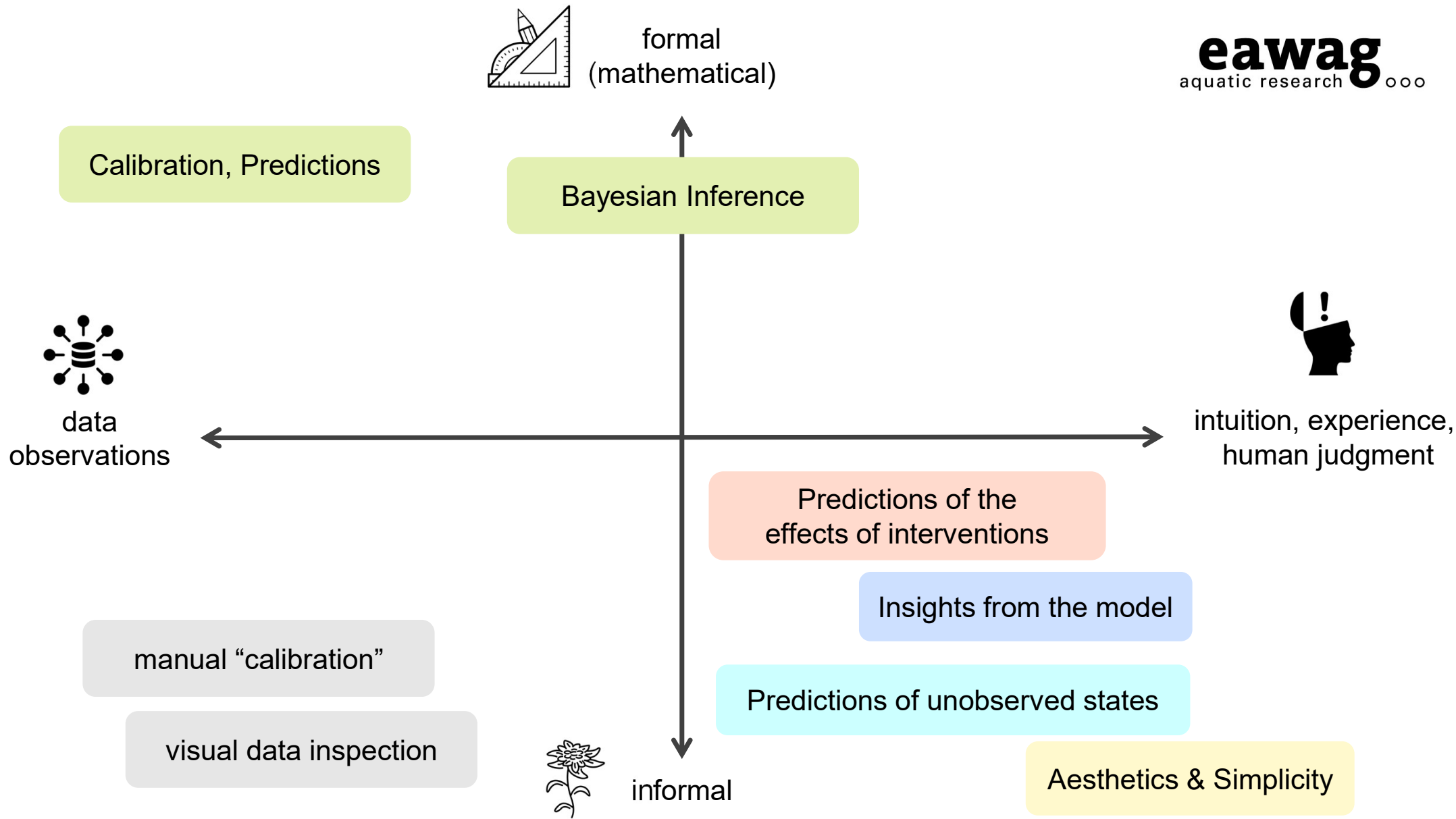


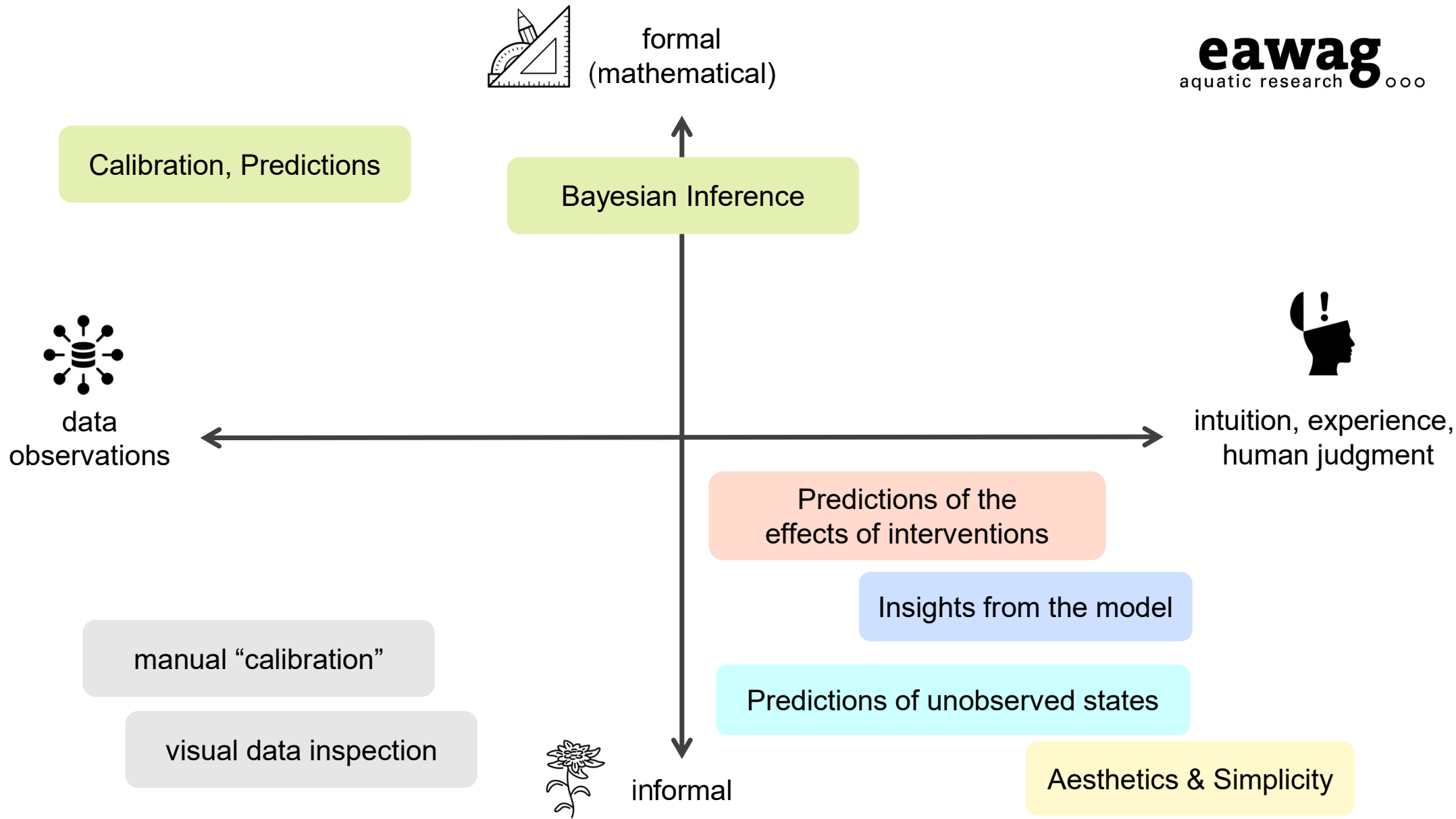
How is the information used?

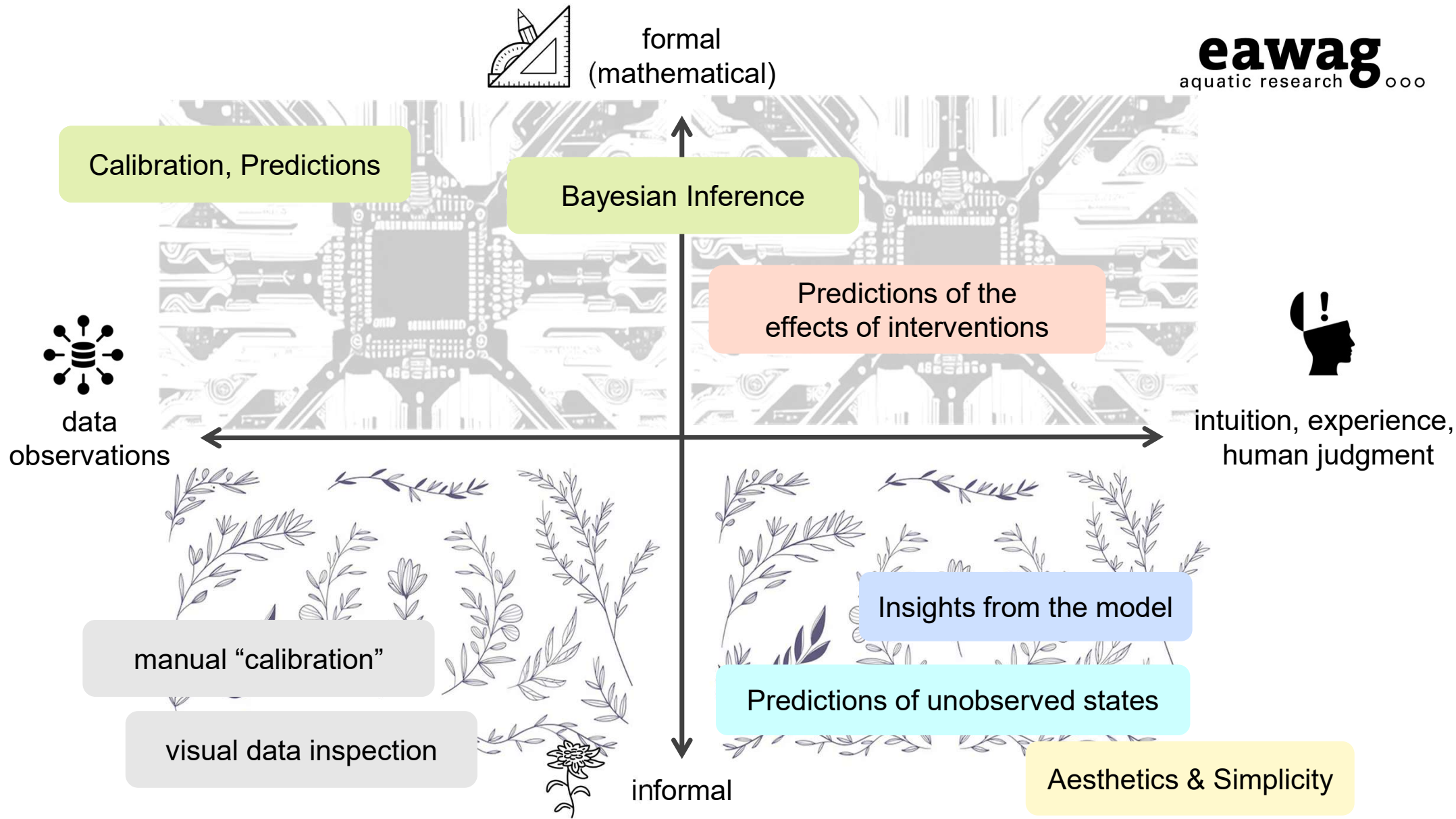
informal

  
intuition, experience,  
human judgment









# The Elephants in the Room: LLMs GPT, Gemini, Claude, LLaMA, ...

Image from Stable Diffusion: *A large language model visits scientists on the Zugspitze.*



# ChatGPT4: Please give me the casual graphical model

AN Please draw the causal DAG with the nodes: ice cream, sun, drowning.  
first reasons about all potential a causal connection why they exist or why not. Then draw the graph based on you conclusions

Alright, let's reason about the potential causal connections between the nodes: ice cream, sun, and drowning.

1. **Ice Cream and Sun:**

- **Reasoning:** On hot and sunny days, people are more likely to buy and consume ice cream. So, the sun can be a cause for increased ice cream sales.
- **Conclusion:** There's a causal connection from "Sun" to "Ice Cream".

2. **Ice Cream and Drowning:**

- **Reasoning:** There isn't a direct causal relationship between ice cream consumption and drowning. However, on hot days when ice cream sales are high, more people might go swimming, increasing the risk of drowning incidents. This is a classic example of a confounding variable (the sun) that affects both ice cream sales and drowning incidents.
- **Conclusion:** There's no direct causal connection between "Ice Cream" and "Drowning".

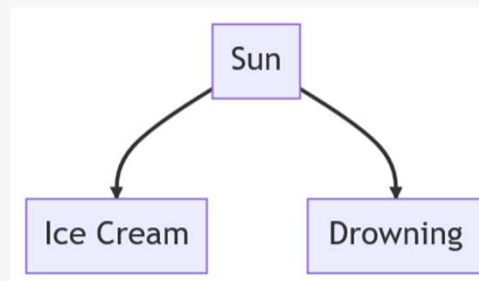
3. **Sun and Drowning:**

- **Reasoning:** On sunny days, more people might decide to go swimming or participate in water-related activities, which could increase the risk of drowning incidents.
- **Conclusion:** There's a causal connection from "Sun" to "Drowning".

Let's draw the graph based on these conclusions.

Used **Diagrams:** Show Me ▼

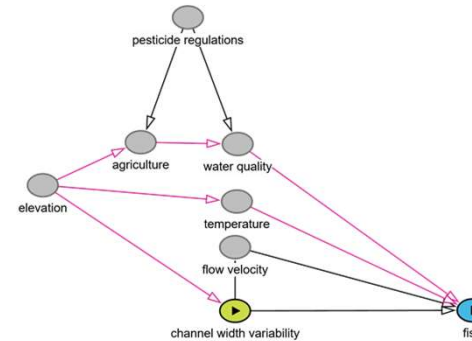
Here's the causal DAG based on our conclusions:





## Summary: Causal Inference

Under what conditions can we predict the effect of interventions from observational data?



- Causal Inference is model agnostic
- No assumptions about linearity or distributions are made
- Causal Inference protects us from logical fallacies
- Causal Graphical Models are great for communication of assumptions

- Causal Inference is **not** about finding causalities!
- Feedback loops are troublesome
- Does not help with small sample size
- Does not guarantee extrapolation

# Summary: Model Selection

Prediction, Calibration

Bayesian Inference

Predictions of the effects of interventions

## Formalized Reasoning

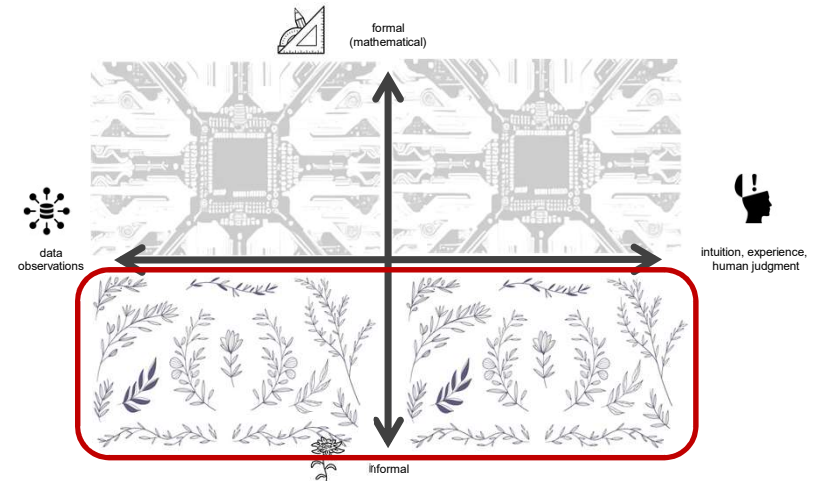
- Makes assumptions explicit
- Can be automatized

Predictions of unobserved states

Insights from the model

Aesthetics & Simplicity

## Informal Reasoning



LLM's can do informal reasoning

→

We need to fundamentally rethink how we do modeling!

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*Are mechanistic models always causal by construction?*

*How much of the “art” of modeling can be done by LLM’s? What will be left for the scientists?*

*Is our preference for aesthetic models more about our cognitive limitations rather than about nature?*

*Is it a good idea to prioritize the learning of the scientist over the learning of the model?*