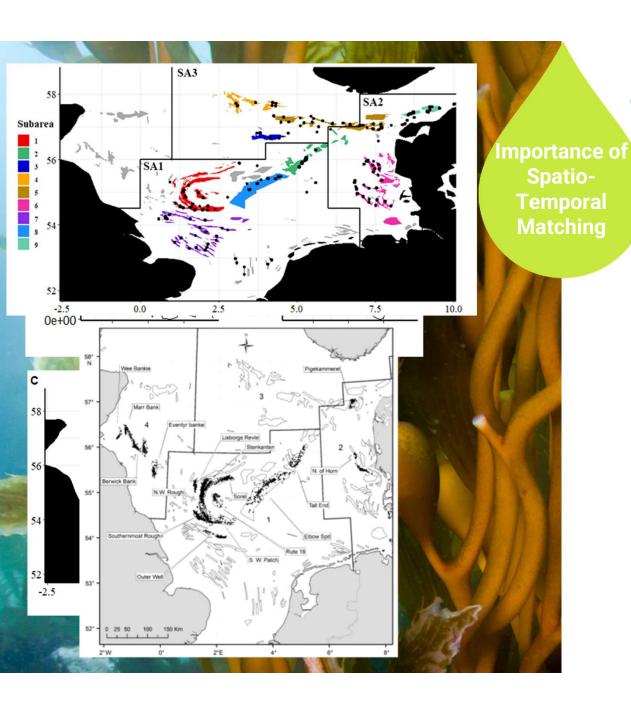


Importance of Spatio-Temporal Matching

Aligns environmental data with biological processes, (e.g. recruitment and growth).

Akimova et al. (2016):

- Analyzed spatially-resolved correlations between North Sea stock estimates (recruitment & SSB) and environment (temperature and salinity) of nine commercially important fish stocks
- Correlations were examined across regions to identify areas where environmental variables most strongly influenced recruitment.
- Recruitment of cod and plaice was negatively correlated with temperature in the northwestern North Sea and the German Bight, respectively.
- Novel patterns also emerged, e.g. sprat R and SSB and salinity



Importance of Spatio-Temporal Matching

Aligns biological data with environmental processes

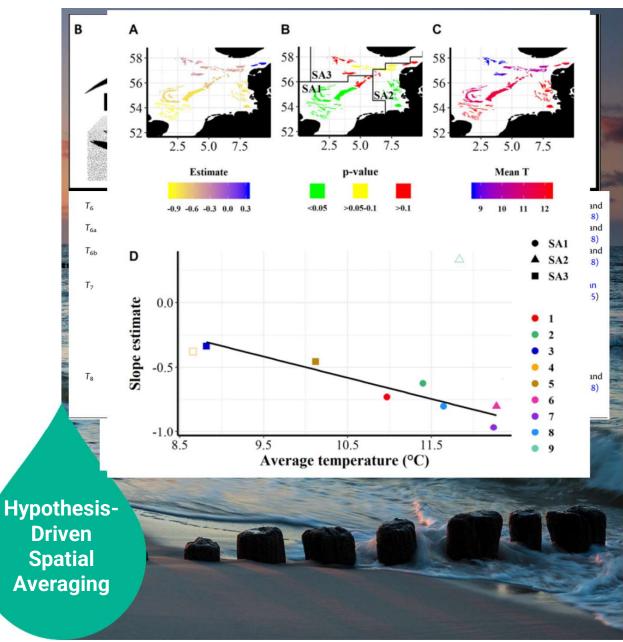
- Stock assessment model outputs measures of R (early life) and SSB (adults)
- Drawbacks:
 - Integrated across large areas with limited seasonal resolution
 - Adult estimates are always biased by fishing efforts
 - The connection and relationship with important life history events can be difficult to detect
- Alternative data sources with better spatial and seasonal resolution
 - Survey data
 - Fisheries data

Hypothesis-Driven Spatial Averaging

This approach involves selecting environmental variables and scales that match biological data based on established knowledge.

Henriksen et al. (2021)

- Averaging environmental data over biologically relevant spatial and temporal scales.
- Related sandeel to bottom temperatures, revealing age-dependent responses.
- Warmer temperatures inhibited overwintering survival, demonstrating the biological relevance of spatial resolution
- Advantage: Ensures that the environmental data closely match the biological spatiotemporal scales of interest.
- **Disadvantage:** May overlook environmental patterns in other scales that could be biologically relevant.



OC2 OC3 Depth-averaged currents (anom.) Ocean color type 1 (anom.) 0.001** 0.001** **Data-Driven Dimension** Reduction 2015 2000 2005 2010

Data-Driven Dimension Reduction

Techniques like Principal Component Analysis (PCA, EOFs) and clustering methods (e.g. SOMs) are used to reduce data complexity by identifying dominant patterns.

Taylor et al. (2021)

- Reducing data complexity using clustering and EOFs.
- Used Ocean Color satellite-data: Identified four main OC types in the North Sea
- OC types correlated strongly with bio-optical, physical, and zooplankton community variables.
- OC types varied seasonally and interannually, often linked to large-scale processes such as the strength of local wind-driven currents and variability in the Subpolar Gyre Index.
 - Advantage: Effectively captures major patterns in the data, potentially revealing unexpected environmental influences.
 - Disadvantage: The resulting patterns may not correspond to the specific spatial or temporal scales relevant to the biological process under study.

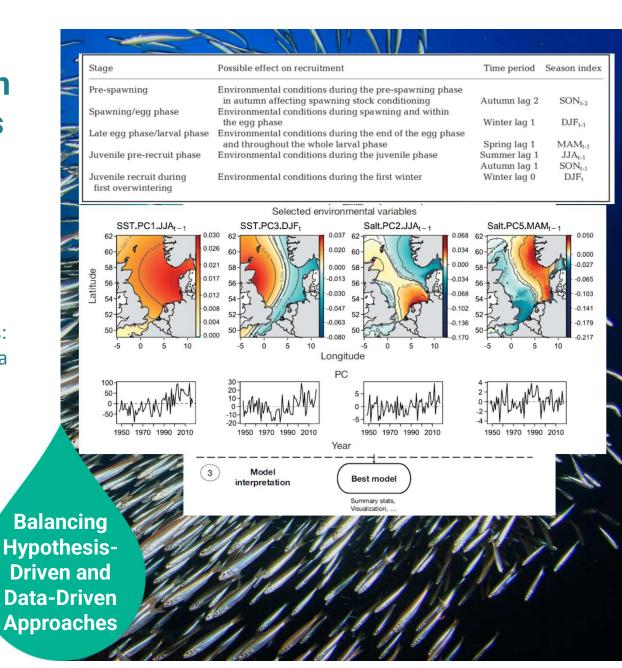
Balancing Hypothesis-Driven and Data-Driven Approaches

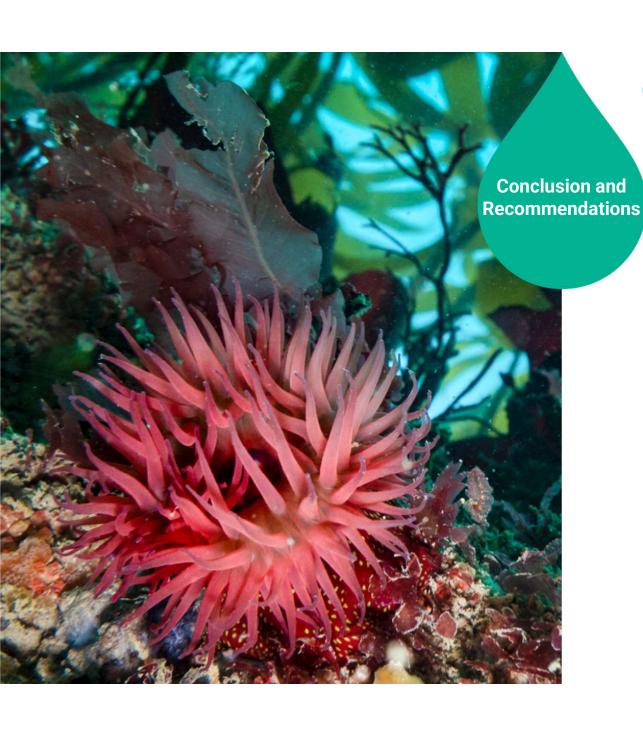
Combining both approaches can provide a comprehensive understanding.

Kühn et al. (2021)

- Applied PCA (EOFs) and clustering (SOMs) and machine learning to identify spatio-temporal
- Environmental data tailored predefined hypothesis:
 SST and salinity anomalies were linked to North Sea cod recruitment.
- This approach identified nonlinear relationships between environmental factors and life stages

Bridging hypothesis-driven frameworks with data-driven models enables tailored insights.





Conclusion and Recommendations

- Resolution decisions depend on species-specific biology, lifecycle stages, and environmental drivers.
- Hypothesis-Driven: Ideal for wellstudied populations/stocks
- Data-Driven: Suited for systems with high variability or less biological knowledge.
- A combined approach provides robust, biologically relevant summaries.