



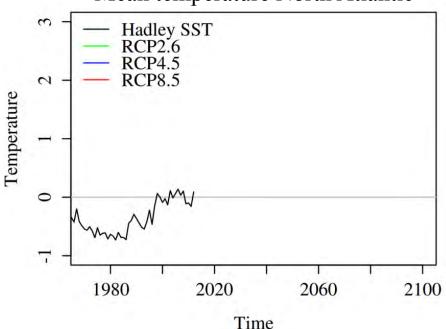
# THE PREDICTIVE POTENTIAL OF SPECIES DISTRIBUTION MODELS FOR PLANKTON

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Santos, 26th of March 2015

# Climate change and future predictions

#### Mean temperature North Atlantic

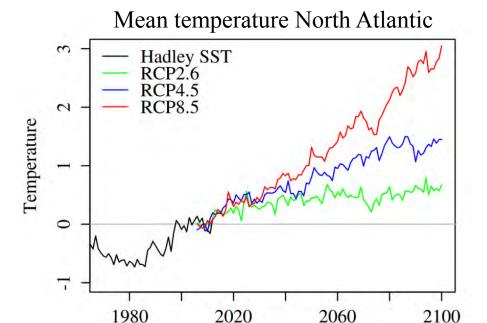


#### Leading edge range expansions:

- Phytoplankton: 470 km dec<sup>-1</sup>
- Zooplankton: 142 km dec<sup>-1</sup>
- Bony fish: 278 km dec<sup>-1</sup>



# Climate change and future predictions

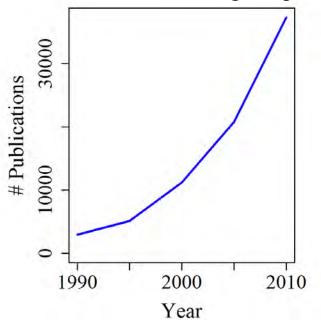


#### Leading edge range expansions:

Time

- Phytoplankton: 470 km dec<sup>-1</sup>
- Zooplankton: 142 km dec<sup>-1</sup>
- Bony fish: 278 km dec<sup>-1</sup>

#### Studies on climate change impact



Brander et al. 2013

- Predictions are inherently risky
- May gain large public attention
- Need to be carefully validated!

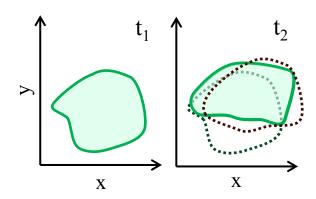


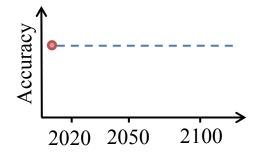
### Aim

# Real-world test of species distribution model (SDM) predictions for plankton in the North Atlantic



Are SDM predictions about changes in biogeography useful?



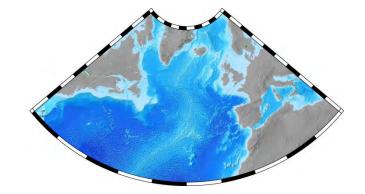




Does model performance stay constant when models are projected into more distant times?



Is model performance spatially homogenous?



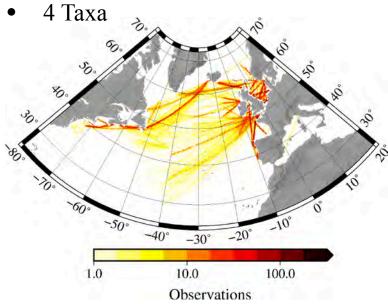
# Concept

1950 2000 Calibration **Testing** data data Environmental observations SDM fitting SDM predictive Validating Biological observations

## Data

### **Biological**

- Continuous Plankton Recorder
- > 200 000 observations
- 1958-2012



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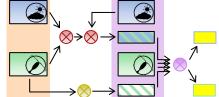
	Taxonomic Group	Observed prevalence
Calanus finmarchicus	Copepods	37 %
Pseudocalanus spp.	Copepods	12 %
Ceratium tripos	Dinoflagellates	16 %
Coscinodiscus wailesii	Diatoms	1 %

#### **Environmental**



- Temperature
- Salinity
- Depth

- Day length
- Daytime





## Methods



#### **SDMs**

- MaxEnt (presence-only)
- Generalized additive models (GAM) (presence/absence)
- Random forest (presence/absence)



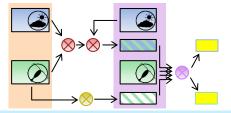
#### Spatial interpolations

Inverse distance



#### Model-validation metrics

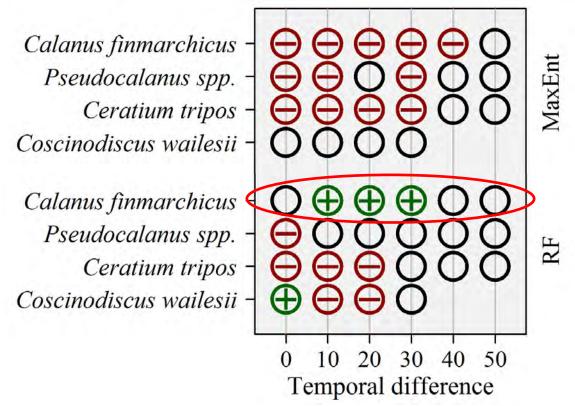
- Precision of presence predictions (PPV)
- Overall performance (TSS)
- Prevalence error

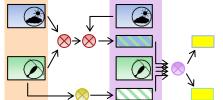


# Comparative performance

SDM predictions versus assuming constant distribution

Two-sided, paired *t*-tests ( $p \le 0.05$ ) of overall performance (TSS)





➤ Most SDM-predictions perform equally or worse than «no-change» scenarios

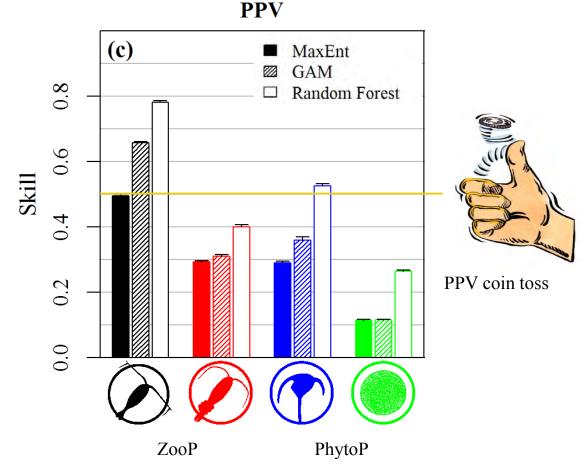
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# Potential precision

for SDMs with full training data 1958-2012

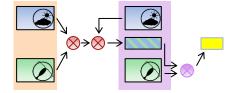
PPV: Probability of correctly predicting presences



> Relatively low precision of presence predictions



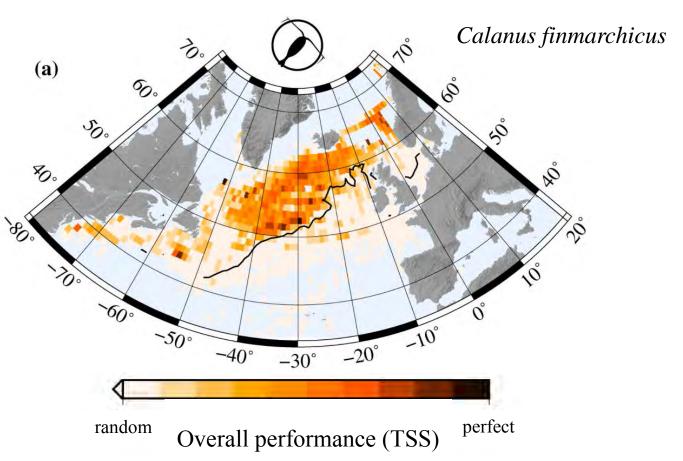
# Temporal extrapolations

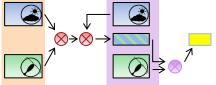


➤ Prevalence error increases for extrapolations with more temporal distance



# Spatial variations





> Strong spatial variations in model performance



# Reasons for low performance

#### Methodological

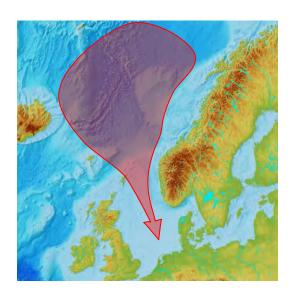
 Single overall performance metrics promote optimistic conclusions

#### **Ecological**

- Short generation times
- Neglect of biotic interactions
- Calanus finmarchicus depends on spring population

#### **Physical**

Lateral dispersal







# Summary

- 1. Most SDM-predictions perform equally or worse than «no-change» scenarios
- 2. The difference between predicted and observed prevalence increased for predictions with more temporal distance from their training dataset
- 3. Distinct spatial patterns in model performance

- ➤ Model validation against independent data sets is essential to assess future predictions of change...
- > ...but also a complex, multidimensional problem that needs to be approached from several angles

