# Supplementary Material for "Skilful decadal-scale prediction of fish habitat and distribution shifts " 

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Supplementary Figure 1| Forecasts of distribution drivers skilfully predict the absolute value. As for Fig. 1 but showing mean squared-error skill score (MSESS) (rather than Pearson correlation) as a measure of forecast skill. Predictive skill of physical variables underlying habitat forecasts showing a) sea surface temperature (SST) in August and b) sub-surface ( $250-600 \mathrm{~m}$ ) salinity in March with a lead time of five years. Each grid point is coloured according to the local MSESS estimate. Forecast skill is for the grand ensemble mean forecast, i.e., averaged across the individual realisations from all model systems, covering the period 1960-2018 for SST and 1985-2018 for salinity. Regions where the MSESS is not significantly greater than 0 (at the $95 \%$ confidence level, as estimated from bootstrapping) are crosshatched. Lines mark the polygons over which the area of suitable habitat is calculated in subsequent analyses.







| Key Metrics | Individual Models | Signif. test |
| :--- | :--- | :--- |
| — Grand Ens. | - CESM DPLE | p $<0.005$ |
| — Persistence | - ECEarth3 | * $\mathrm{p}<0.01$ |
|  | - HadGEM3 | $+\mathrm{p}<0.05$ |
|  | - MPI-ESM1.2-HR | Not Signif. |
|  | - NorCPM |  |

Supplementary Figure 2| The absolute values and probabilistic distributions of habitat metrics can also be skilfully forecast. As for Fig. 2 but showing additional metrics of forecast performance. The ability to correctly estimate the absolute habitat area is indicated by the Mean Squared Error skill score (MSESS) (panels a-c), while the Continuous Ranked Probability skill score (CRPSS) (panels d-f) indicates the probabilistic skill of the forecast distribution. Skill is shown for the habitat area of mackerel (panels a and d), bluefin tuna (b and e) and blue whiting ( $c$ and f). Skill metrics between the forecast and observed habitat areas are plotted as a function of forecast lead-time into the future, calculated across the appropriate comparison periods. Forecast skill is shown for the individual members of the model ensemble (light weighted lines) and for the grand-ensemble forecast (heavy red line). The skill of persistence forecasts (heavy blue lines) are also shown for reference where it can be defined (i.e. for MSESS): shaded areas for both these key metrics denote the $90 \%$ confidence interval estimated from bootstrapping. The hypothesis that the ensemble mean forecast outperforms persistence (i.e. a one-tailed test) is tested for each lead time, and denoted with symbols at the bottom of the MSESS panels. It is not possible to define a CRPSS metric for a persistence forecast and therefore no such results (or significance tests) are presented here. Both MSESS and CRPSS skill scores are calculated relative to the climatological statistics of each metric.


Supplementary Figure 3 | Habitat predictions from initialised climate models outperform forecasts based on uninitialized projections. The significance of habitat forecast skill when compared against the skill of habitat forecasts based on uninitialized forecasts (rather than persistence forecasts) for lead times of 0-10 years is shown for all species and for a) Pearson correlation coefficient, b) the mean-squared error skill score (MSESS) and c) continuous ranked probability skill scores (CRPSS). Significance levels ( $1-\mathrm{p}$ values) are plotted on the vertical axis for a onesided test that the given skill of the decadal forecast system is greater than the uninitialized skill. Note the non-linear (probability) scale on the vertical axis. Significance levels outside the axis ranges are plotted at the top or bottom of each panel.

Supplementary Table 1| Habitat models used in this study

| Species | Region | Environmental <br> Variable and Month <br> of Interest | Habitat model | References |
| :--- | :--- | :--- | :--- | :--- |
| Mackerel <br> (Scomber <br> scombrus) | Greenlandic <br> exclusive <br> economic zone, <br> south of 70 N | Sea surface <br> temperature in <br> warmest month <br> (August) | Suitable habitat is <br> warmer than $11^{\circ} \mathrm{C}$ | 1,2 |
| Bluefin tuna <br> (Thunnus <br> thynnus) | Irminger Sea, <br> Denmark Strait <br> and waters south <br> of Iceland. | Sea surface <br> temperature in <br> warmest month <br> (August) | Suitable habitat is <br> warmer than $8.5^{\circ} \mathrm{C}$ | $3-5$ |
| Blue whiting <br> (Micromesistius <br> poutassou) | Rockall Trough <br> and Rockall Bank, <br> west of Great | Salinity between 250 <br> and 600 m depth <br> (March) | Statistical habitat <br> model. Optimal <br> salinity between 35.3 <br> and 35.5 psu | $6-8$ |

Supplementary Table 2|Forecast systems and ensemble sizes used in this study

| Forecast Centre | Model Name | Ocean Resolution | Start dates <br> Ensemble size | References |
| :--- | :--- | :--- | :--- | :--- |
| Bjerknes Center for <br> Climate Research, <br> Norway | NorCPM1 | Tripolar, $1^{\circ}$ grid, 53 <br> vertical levels on density <br> coordinates | $1960-2018$ <br> 20 members | 9 |
| Danish <br> Meteorological <br> Institute, Denmark | EC-Earth3 | Tripolar $1^{\circ}$ grid with <br> meridional refinement <br> down to $1 / 3^{\circ}$ in the <br> tropics; 75 levels | $1960-2018$ <br> 10 members | 10,11 |
| Max Planck Institute <br> for Meteorology, <br> Germany | MPI-ESM-1.2-HR | Tripolar, $\sim 0.4^{\circ}$ grid. 40 <br> vertical levels. | $1960-2018$ <br> 5 members | 12,13 |
| Met Office Hadley <br> Centre, UK. | HadGEM3-GC31- | Tripolar $\sim 0.25^{\circ}$ grid, <br> 75 vertical levels | $1960-2018$ <br> 10 members | 14 |
| National Center for <br> Atmospheric <br> Research, USA | CESM DPLE | Nominal $1^{\circ}$ horiz. with <br> meridional refinement <br> down to $\sim 0.3^{\circ}$ at the <br> Equator; 60 vertical <br> levels | $1955-2018$ <br> 40 members | 15,16 |

Supplementary Table 3|CMIP6 models and representative variants used as uninitialized models. Ticks indicate that the given model, variant and gridded product were used for uninitialized forecasts of either sea surface temperature (SST) or salinity. In total, $\mathbf{3 5}$ models were used for salinity and 44 for SST.

| Source ID | Institution ID | Variant Label | Grid Label | SST | Salinity |
| :---: | :---: | :---: | :---: | :---: | :---: |
| ACCESS-CM2 | CSIRO-ARCCSS | rlilplfl | gn | $\checkmark$ |  |
| ACCESS-ESM1-5 | CSIRO | r1ilplfl | gn | $\checkmark$ |  |
| BCC-CSM2-MR | BCC | r1ilp1fl | gn | $\checkmark$ | $\checkmark$ |
| CAMS-CSM1-0 | CAMS | r1ilplfl | gn | $\checkmark$ | $\checkmark$ |
| CanESM5 | CCCma | r1ilp1fl | gn | $\checkmark$ | $\checkmark$ |
| CanESM5-CanOE | CCCma | r1ilp2f1 | gn | $\checkmark$ | $\checkmark$ |
| CAS-ESM2-0 | CAS | r1ilp1f1 | gn | $\checkmark$ |  |
| CESM2 | NCAR | r4ilp1fl | gn | $\checkmark$ |  |
| CESM2-WACCM | NCAR | r1ilplfl | gn | $\checkmark$ |  |
| CESM2-WACCM | NCAR | rlilplfl | gr |  | $\checkmark$ |
| CIESM | THU | rlilplfl | gn | $\checkmark$ | $\checkmark$ |
| CMCC-CM2-SR5 | CMCC | r1ilp1f1 | gn | $\checkmark$ | $\checkmark$ |
| CMCC-ESM2 | CMCC | r1ilp1f1 | gn | $\checkmark$ | $\checkmark$ |
| CNRM-CM6-1 | CNRM-CERFACS | r1ilp1f2 | gn | $\checkmark$ | $\checkmark$ |
| CNRM-CM6-1-HR | CNRM-CERFACS | rlilplf2 | gn | $\checkmark$ | $\checkmark$ |
| CNRM-ESM2-1 | CNRM-CERFACS | rlilp1f2 | gn | $\checkmark$ | $\checkmark$ |
| EC-Earth3 | EC-Earth-Consortium | r1ilp1f1 | gn | $\checkmark$ | $\checkmark$ |
| EC-Earth3-CC | EC-Earth-Consortium | r1ilp1fl | gn | $\checkmark$ | $\checkmark$ |
| EC-Earth3-Veg | EC-Earth-Consortium | rlilplfl | gn | $\checkmark$ | $\checkmark$ |
| EC-Earth3-Veg-LR | EC-Earth-Consortium | r1ilp1fl | gn | $\checkmark$ | $\checkmark$ |
| FGOALS-f3-L | CAS | rlilp1f1 | gn | $\checkmark$ | $\checkmark$ |
| FGOALS-g3 | CAS | r1ilp1f1 | gn | $\checkmark$ | $\checkmark$ |
| FIO-ESM-2-0 | FIO-QLNM | rlilplfl | gn | $\checkmark$ | $\checkmark$ |
| GFDL-CM4 | NOAA-GFDL | rlilp1f1 | gn | $\checkmark$ | $\checkmark$ |
| GFDL-ESM4 | NOAA-GFDL | rlilp1f1 | gn | $\checkmark$ | $\checkmark$ |
| GISS-E2-1-G | NASA-GISS | rlilp1f2 | gn | $\checkmark$ | $\checkmark$ |
| HadGEM3-GC31-LL | MOHC, NERC | r1ilp1f3 | gn | $\checkmark$ | $\checkmark$ |
| HadGEM3-GC31-MM | MOHC | rlilp1f3 | gn | $\checkmark$ | $\checkmark$ |
| IITM-ESM | CCCR-IITM | r1ilp1f1 | gn | $\checkmark$ |  |
| INM-CM4-8 | INM | r1ilp1f1 | gr1 | $\checkmark$ | $\checkmark$ |
| INM-CM5-0 | INM | rlilp1f1 | gr1 | $\checkmark$ | $\checkmark$ |
| IPSL-CM6A-LR | IPSL | r1ilp1f1 | gn | $\checkmark$ | $\checkmark$ |
| KACE-1-0-G | NIMS-KMA | rlilp1fl | gr | $\checkmark$ |  |
| KIOST-ESM | KIOST | rlilplfl | gr1 | $\checkmark$ |  |
| MCM-UA-1-0 | UA | r1ilp1f2 | gn | $\checkmark$ | $\checkmark$ |
| MIROC-ES2L | MIROC | r1ilp1f2 | gn | $\checkmark$ |  |
| MIROC6 | MIROC | rlilp1f1 | gn | $\checkmark$ |  |
| MPI-ESM1-2-HR | MPI-M | rlilp1f1 | gn | $\checkmark$ | $\checkmark$ |
| MPI-ESM1-2-LR | MPI-M | r1ilp1f1 | gn | $\checkmark$ | $\checkmark$ |
| MRI-ESM2-0 | MRI | r1ilp1f1 | gn | $\checkmark$ | $\checkmark$ |
| NESM3 | NUIST | rlilp1f1 | gn | $\checkmark$ | $\checkmark$ |
| NorESM2-LM | NCC | rlilp1f1 | gn | $\checkmark$ |  |
| NorESM2-LM | NCC | rlilp1f1 | gr |  | $\checkmark$ |
| NorESM2-MM | NCC | r1ilp1f1 | gn | $\checkmark$ |  |
| NorESM2-MM | NCC | r1ilp1f1 | gr |  | $\checkmark$ |
| TaiESM1 | AS-RCEC | r1ilp1f1 | gn | $\checkmark$ | $\checkmark$ |
| UKESM1-0-LL | MOHC, NERC, NIMS-KMA, NIWA | r1ilp1f2 | gn | $\checkmark$ | $\checkmark$ |

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