Joint CPUE Standardization for Neon Flying Squid

Theory, motivation, and the jointCPUE model structure

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Why CPUE Standardization Matters for NFS

- Observed CPUE reflects both underlying NFS availability and fishery-specific catchability.
- NFS data are heterogeneous across fleets, regions, and seasons.
- Raw CPUE trends can therefore mix abundance signal with targeting, spatial coverage, and operational practices.
- A standardized index is needed before interpreting temporal change as a population signal.

Why Use a Joint Rather Than a Single-Fleet Model?

- A single-fleet model uses only one partial view of the stock and may be sensitive to sparse years or limited spatial coverage.
- A joint model pools information on the shared population process while allowing fishery-specific catchability differences.
- This is especially useful when fleets overlap only partially in space and time but still observe the same stock.
- The goal is not to force fleets to be identical, but to separate common abundance signal from fleet-specific observation processes.

Conceptual Decomposition

At a high level, jointCPUE treats observed CPUE as the product of latent population density and catchability.

$$CPUE_{f,s,t} = Biomass_{s,t} * q_{f,s,t}$$

$$\log(CPUE_{f,s,t}) = y_t + \omega_s + \varepsilon_{s,t} + q_{f,s,t}$$

- y_t: fixed time effect
- ω_s: time-constant spatial field
- $\varepsilon_{s,t}$: spatiotemporal field
- $q_{f,s,t}$: fleet-specific catchability

*** jointCPUE uses a log-normal observation model by default. For the aggregated NFS data, the proportion of zero catches is too low to support a stable delta-model parameterization (~5.8%).**

Population Component

- The latent population surface is represented by $\mathbf{y_t} + \boldsymbol{\omega_s} + \boldsymbol{\varepsilon_{s,t}}$.
- $\boldsymbol{\omega_s}$ captures persistent spatial structure, while $\boldsymbol{\varepsilon_{s,t}}$ captures time-varying spatial change.
- Spatial fields are represented with the SPDE approach on a triangular mesh, yielding sparse precision matrices.
- Anisotropy is incorporated through a geometric deformation of the spatial domain, allowing correlation range and strength to vary by direction.
- The standardized index is obtained by projecting the latent population surface to an extrapolation grid and integrating over area.

Catchability Component

- Fleet-specific catchability is represented through $\mathbf{q_{f,s,t}}$.
- The reference fleet is coded as fleetid = 0, and $q_{f,s,t}$ for that fleet are constrained to zero.
- Other fleets' $q_{f,s,t}$ are treated as deviations from the reference fleet.
- Systematic (q_f^{system}), temporal ($q_{f,t}^{\text{time}}$), and spatial ($q_{f,s}^{\text{space}}$) catchability deviations can be switched **on** or **off** depending on the application.

Systematic q-difference

$$q_f^{\text{system}} \begin{cases} = 0, & \text{fleetid} = 0 \\ \sim N\left(0, \sigma_f^2\right), & \text{fleetid} > 0 \end{cases}$$

Temporal q-difference

$$q_{f,t}^{\text{time}} = \begin{cases} 0, & \text{fleetid} = 0 \\ \gamma_{f,t} - \text{mean\_}t\left(r_{f,t}\right), & \text{fleetid} > 0\text{'} \end{cases} \quad \gamma_{f,t} \sim N\left(0, \sigma_\gamma^2\right) \text{ over observed times}$$

Spatial q-difference

$$q_{f,s}^{\text{space}} \begin{cases} = 0, & \text{fleetid} = 0 \\ \sim MVN\left(0, \sigma_\delta^2 R(\kappa)\right), & \text{fleetid} > 0 \end{cases}$$

Yearly and Monthly Standardized Indices

Yearly workflow

$$\eta_i = y_{t[i]} + \omega_{s[i]} + \varepsilon_{s[i],t[i]} + \boxed{m_{m[i]}} + q_{f[i]}^{\text{system}} + q_{f[i],t[i]}^{\text{time}} + q_{f[i],s[i]}^{\text{space}}$$

t indexes years.

An optional month fixed effect $\boldsymbol{m_m}$ can be added to account for uneven monthly sampling.

The month effect is constrained to sum to zero over observed months.

The month effect does not enter the yearly index itself.

Monthly workflow

$$\eta_i = y_{t[i]} + \omega_{s[i]} + \varepsilon_{s[i],t[i]} + q_{f[i]}^{\text{system}} + q_{f[i],t[i]}^{\text{time}} + q_{f[i],s[i]}^{\text{space}}$$

t indexes observed year-month combinations.

No separate month fixed effect is needed because month is already embedded in time.

Monthly indices track finer temporal variation but can be more sensitive to sparse coverage.

jointCPUE Workflow for the NFS Application

Prepare fleet-wise CPUE data → **Project coordinates and build mesh** → **Fit candidate joint models** → **Check diagnostics and compare indices**

- Joint spatiotemporal CPUE standardization in Template Model Builder (TMB)
- https://github.com/RujiaBi/jointCPUE
- The package standardizes CPUE by separating a shared latent population surface from fleet-specific catchability adjustments.
- Diagnostics focus on convergence, residual structure, and the plausibility of q-differences before interpreting indices.

jointCPUE Example Code

Yearly index:

```
fit_year <- jointCPUE(
  data_utm = data_utm,
  mesh = mesh,
  index = "yearly",
  month_diffs = "off",
  pop_spatial = "on",
  pop_spatiotemporal = "on",
  pop_spatiotemporal_type = "iid",
  q_diffs_system = "on",
  q_diffs_time = "off",
  q_diffs_spatial = "on",
  obs_sd = "fleet",
  ncores = ncores
)
```

Monthly index:

```
fit_month <- jointCPUE(
  data_utm = data_utm,
  mesh = mesh,
  index = "monthly",
  pop_spatial = "on",
  pop_spatiotemporal = "on",
  pop_spatiotemporal_type = "iid",
  q_diffs_system = "on",
  q_diffs_time = "off",
  q_diffs_spatial = "off",
  obs_sd = "fleet",
  ncores = ncores
)
```

Diagnostics:

```
check_convergence(fit_month)
calc_marginal_aic(fit_month)
```

Plot residual:

```
pred_month <- get_predicted(
  fit_month,
  data = data_utm,
  drop_floor = TRUE,
  floor_value = floor_value
)

plots_month <- plot_residuals(
  pred_month,
  observed_col = "cpue",
  x_col = "utm_x_scale",
  y_col = "utm_y_scale",
  residual = "log",
  bins = 40
)

plots_month$observed_predicted
plots_month$spatial_residual
```

Get index:

```
index_month  <- get_index(fit_month)
plot_index(index_month)
```

Plot q differences:

```
plot_q_diffs_system(fit_month)
plot_q_diffs_spatial(fit_month)
```

jointCPUE Application to Single Fleet

Yearly index:

```
fit_year <- jointCPUE(
  data_utm = data_utm,
  mesh = mesh,
  index = "yearly",
  month_diffs = "off",
  pop_spatial = "on",
  pop_spatiotemporal = "on",
  pop_spatiotemporal_type = "iid",
  q_diffs_system = "off",
  q_diffs_time = "off",
  q_diffs_spatial = "off",
  obs_sd = “shared",
  ncores = ncores
)
```

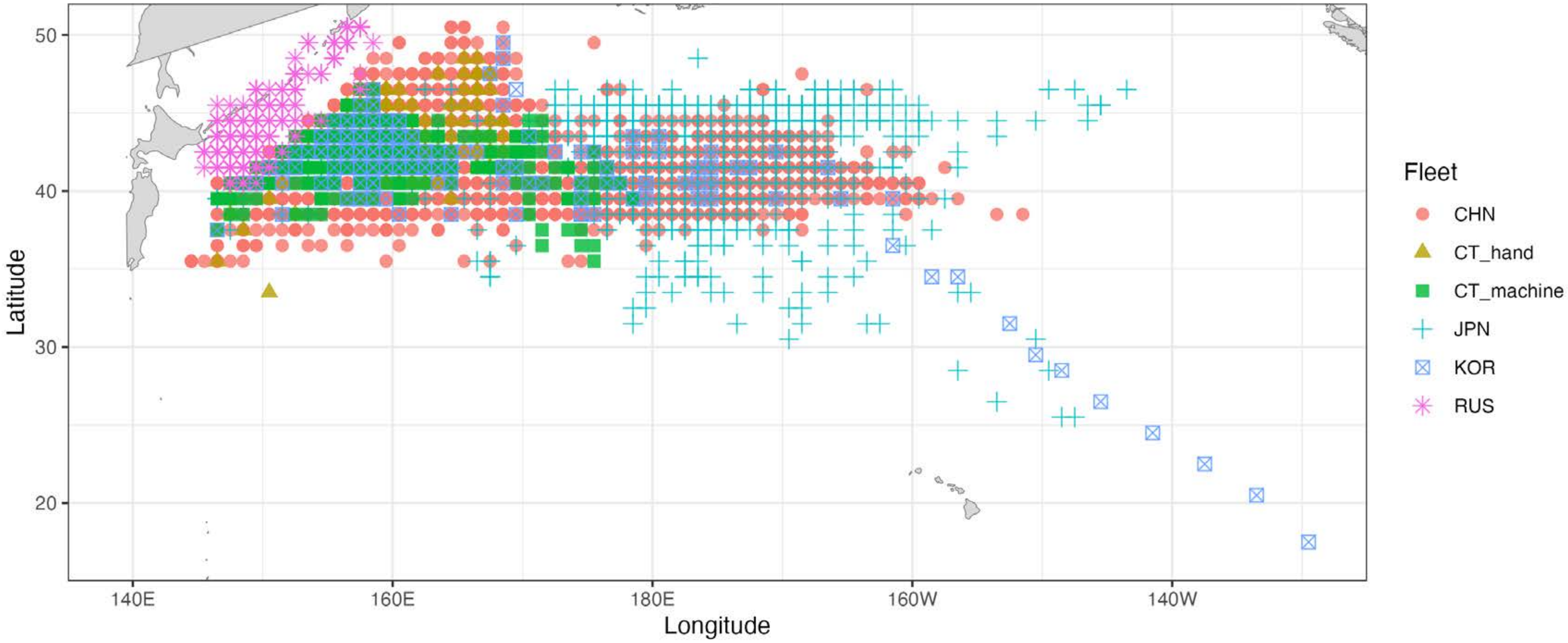
Monthly index:

```
fit_month <- jointCPUE(
  data_utm = data_utm,
  mesh = mesh,
  index = "monthly",
  pop_spatial = "on",
  pop_spatiotemporal = "on",
  pop_spatiotemporal_type = "iid",
  q_diffs_system = "off",
  q_diffs_time = "off",
  q_diffs_spatial = "off",
  obs_sd = “shared",
  ncores = ncores
)
```

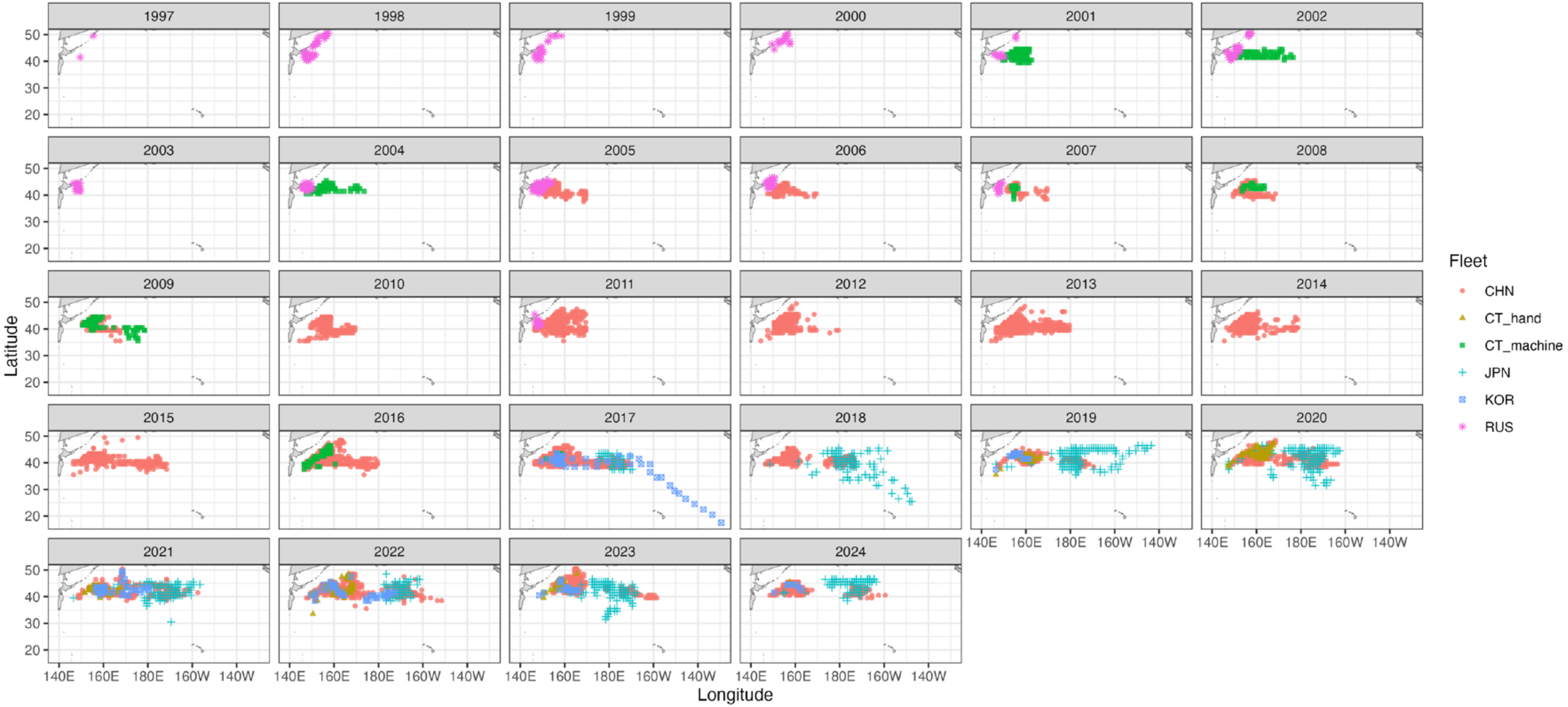
NFS Data Overview

Member	Gear type	Records	Temporal coverage	Effort	Note
China	Jigging	4,215	2005-2024; May-November	Operational days?	
Chinese Taipei	Handline , machine and mixed	1,018	2001-2009, 2011, 2016-2024; April-December	Machine-days, handline-days	Keep only handline or only machine (76 records with mixed gear types, 340 records without any gear or zero effort)
Japan	Jigging	932	2017-2024; January, February, April-December	Machine-days	Remove NW records with missing coordinates (22 records)
Korea	Jigging	180	2017, 2019, 2021-2025; June-November	Machine-days (impossible to distinguish whether handline or machine)	Use data until 2024
Russia	Drift-net	266	1997-2007, 2011; April-December	Vessel-days	

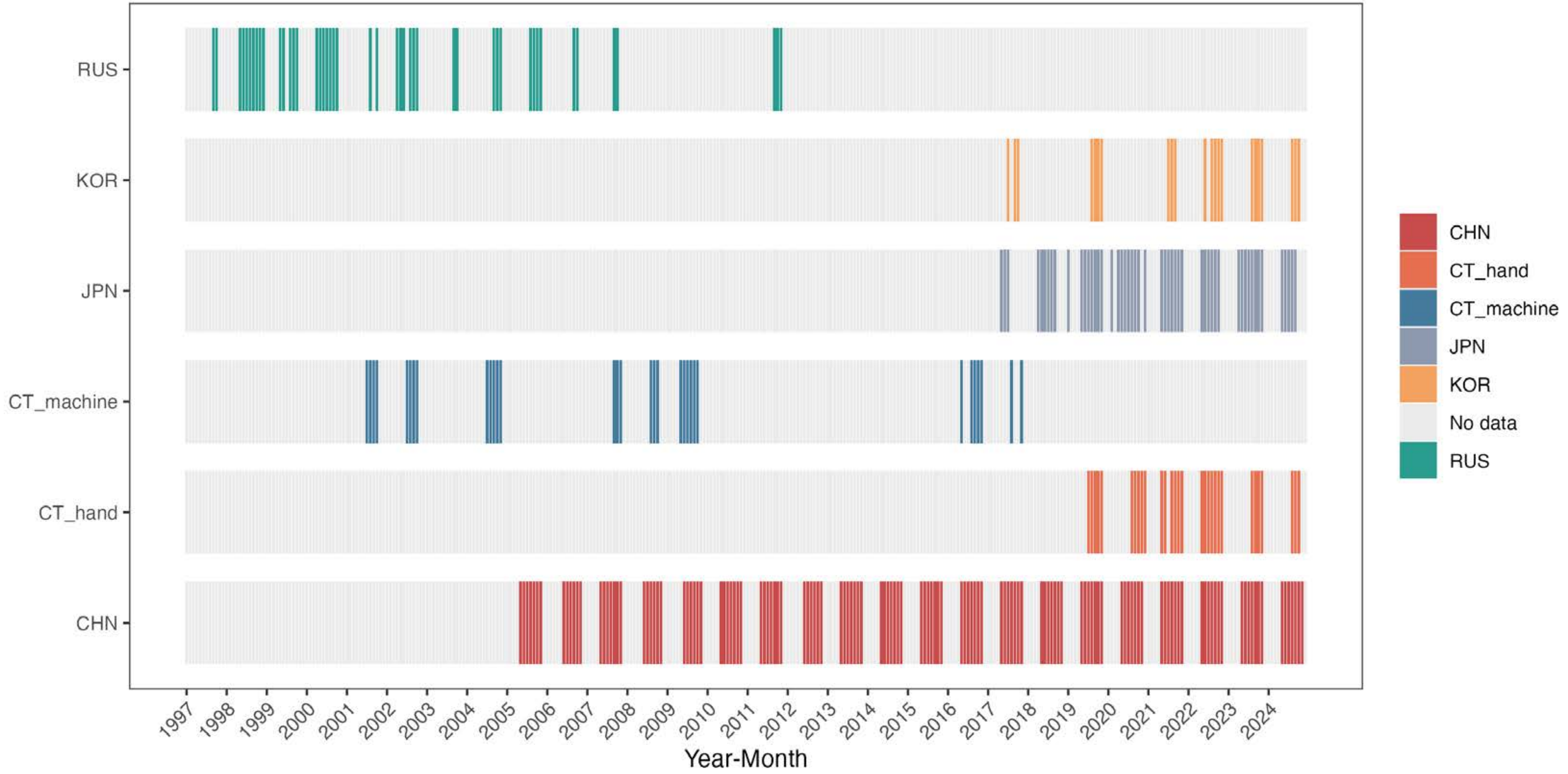
NFS Data Overview – spatial distribution



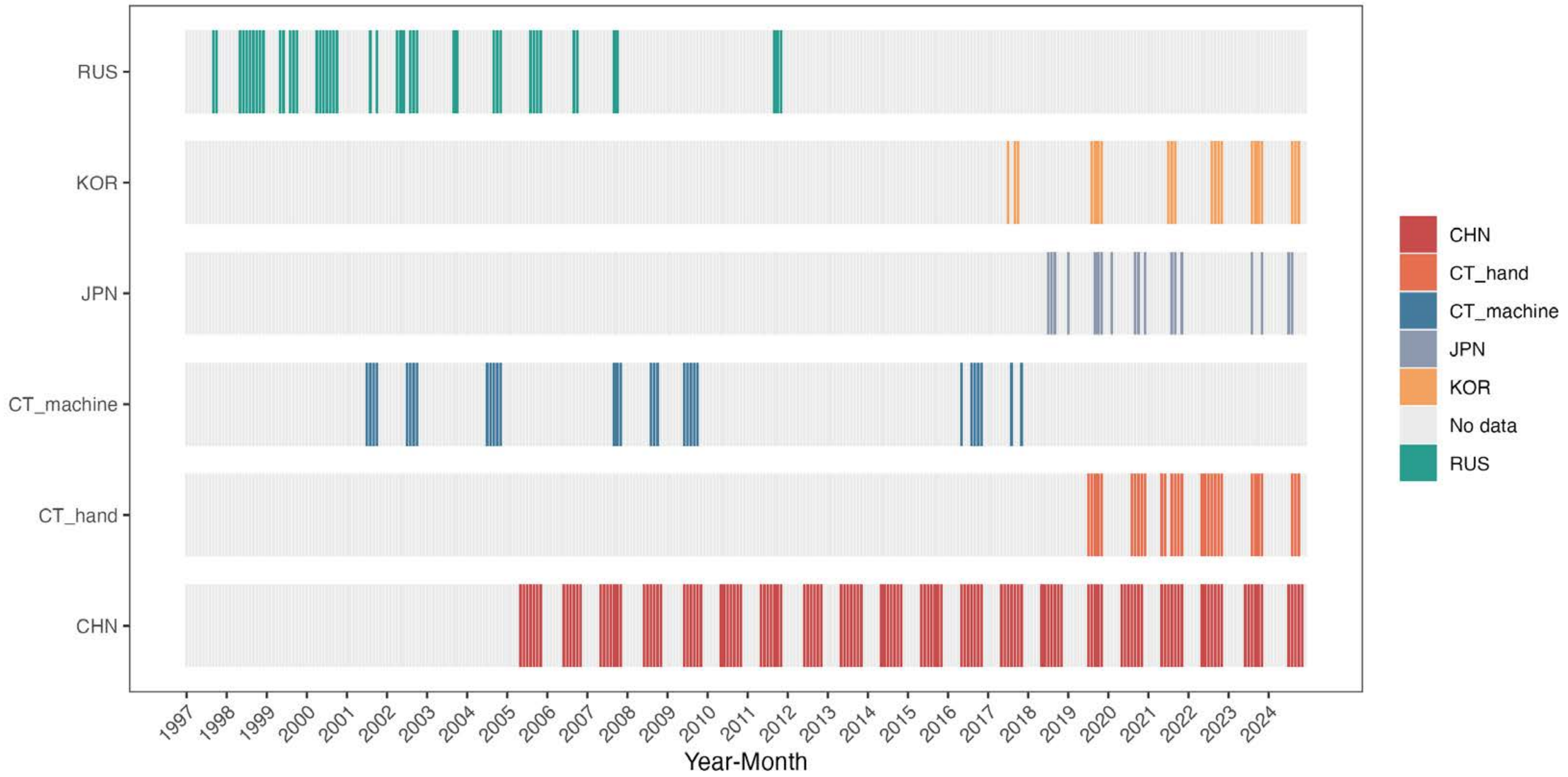
NFS Data Overview – yearly spatial distribution



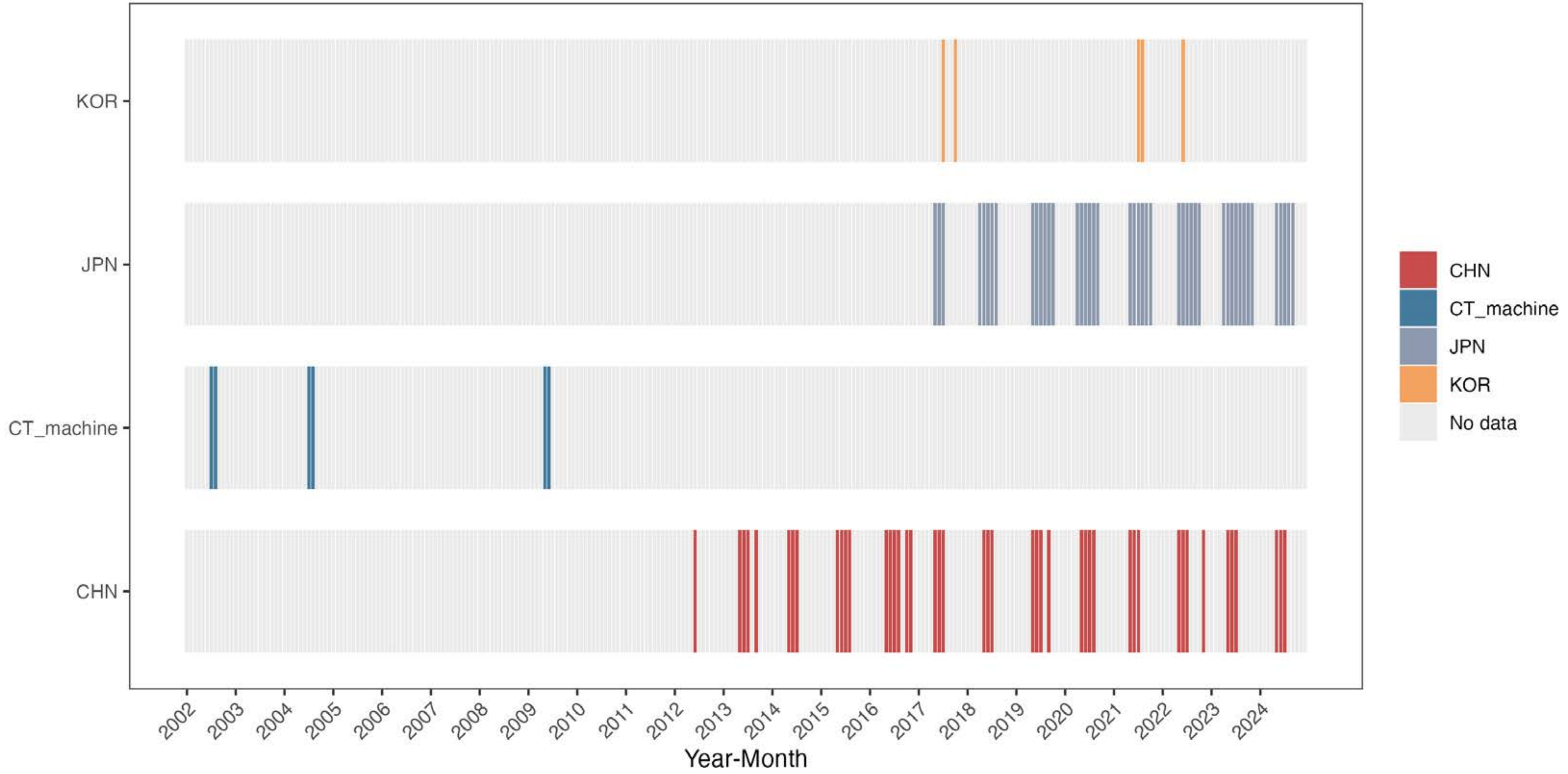
NFS Data Overview – temporal coverage



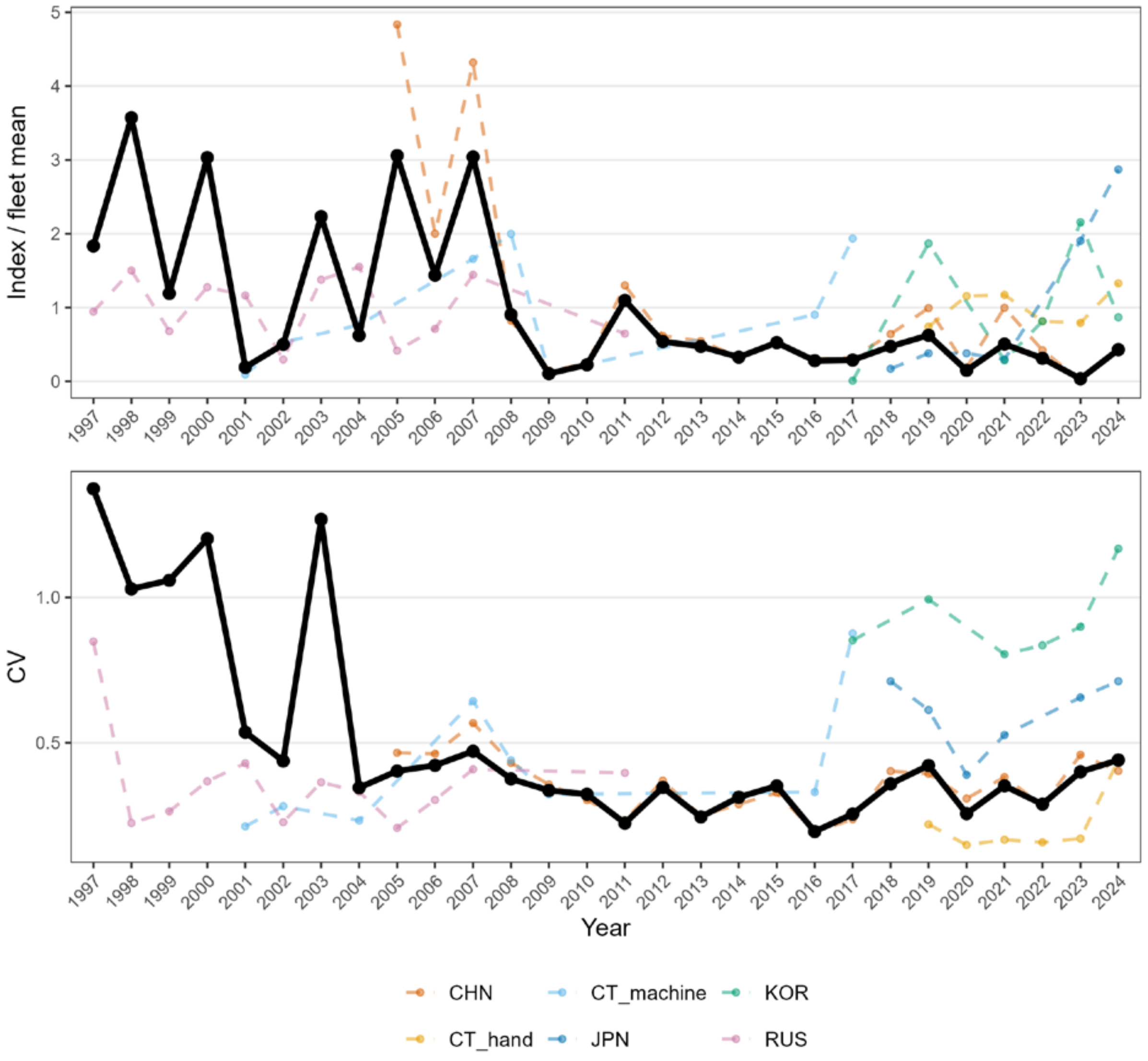
NFS Data Overview – 170° E west temporal coverage



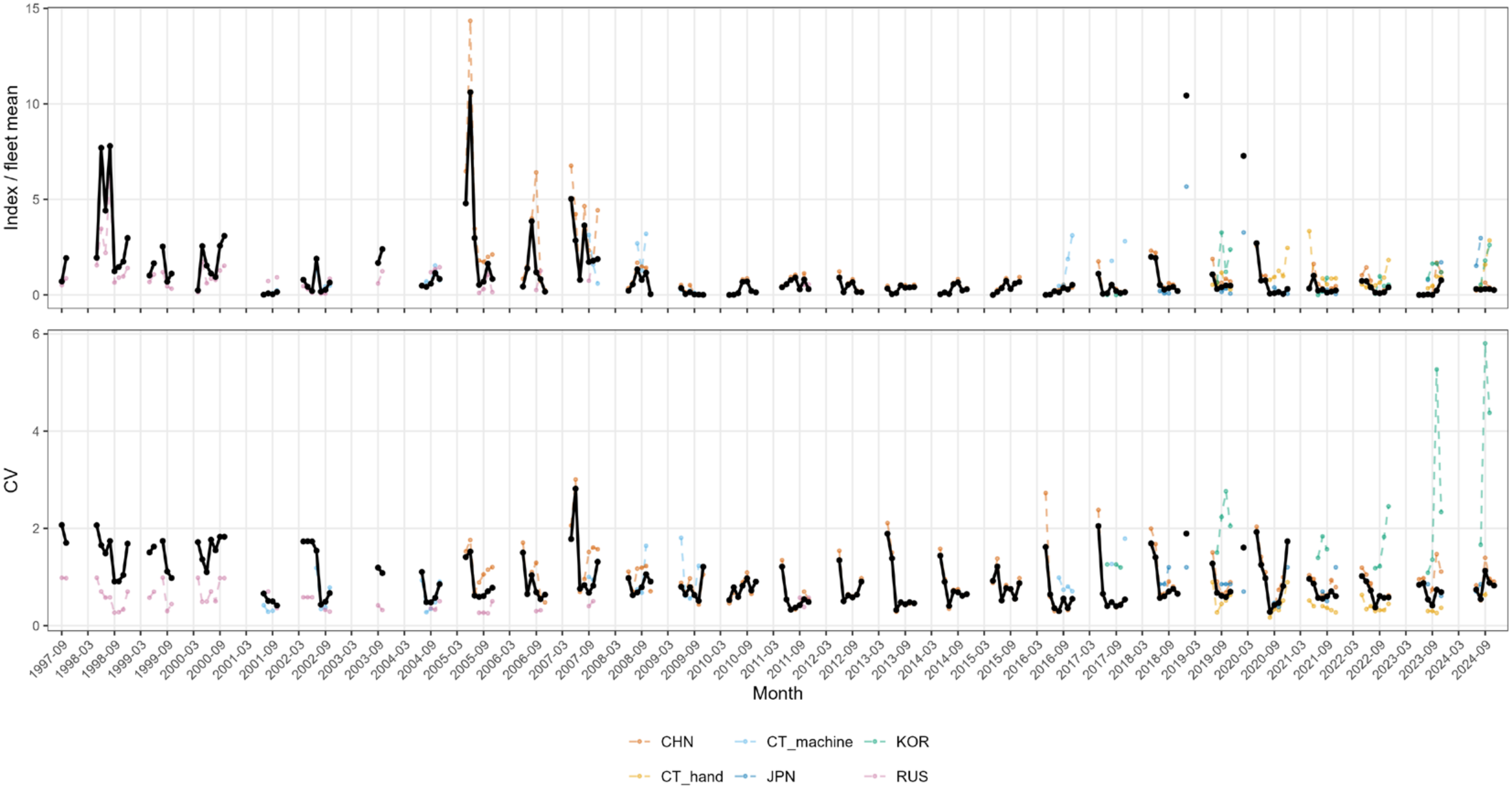
NFS Data Overview – 170° E east temporal coverage



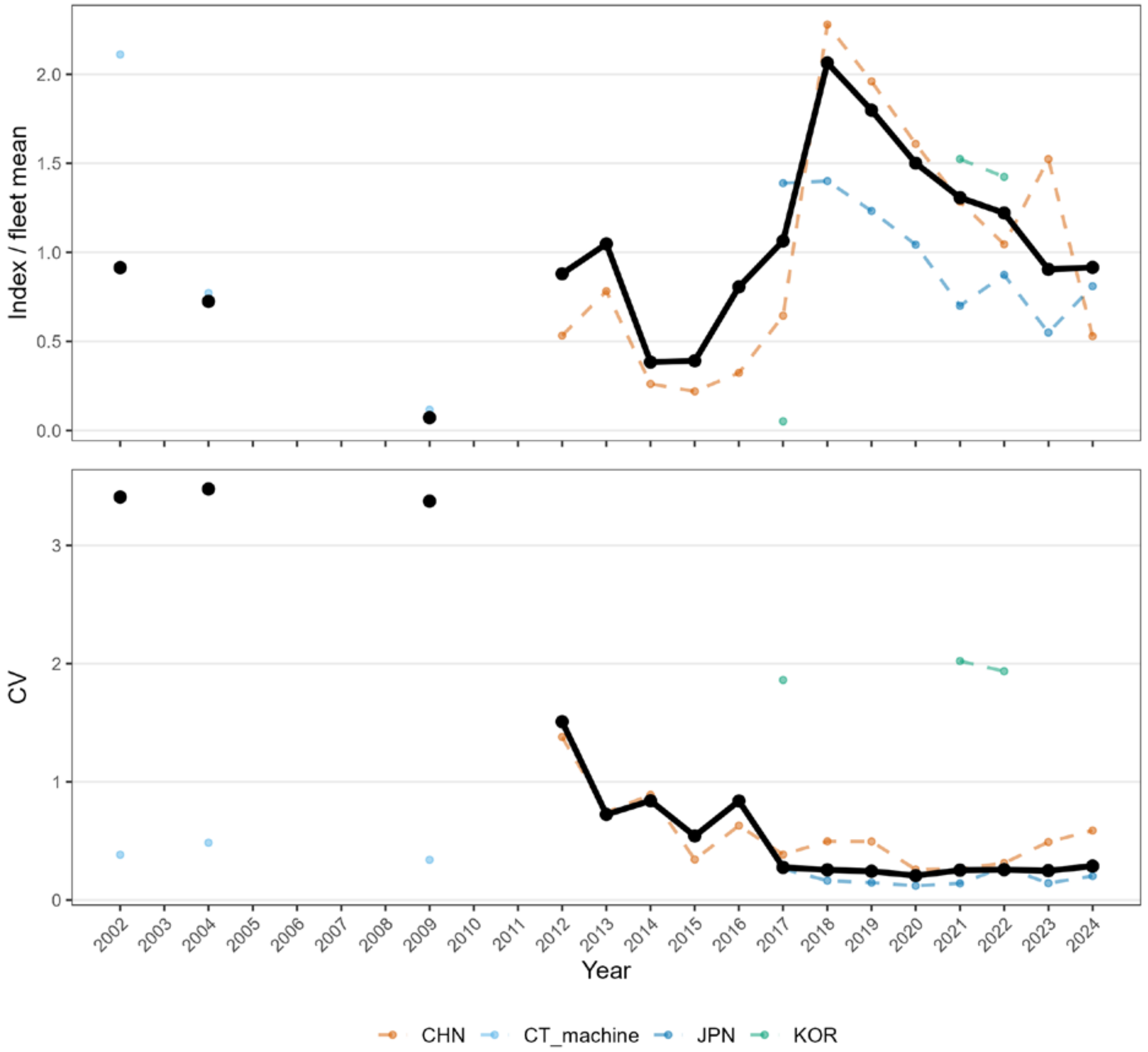
170° E West Yearly Standardized Index (CHN as Reference)



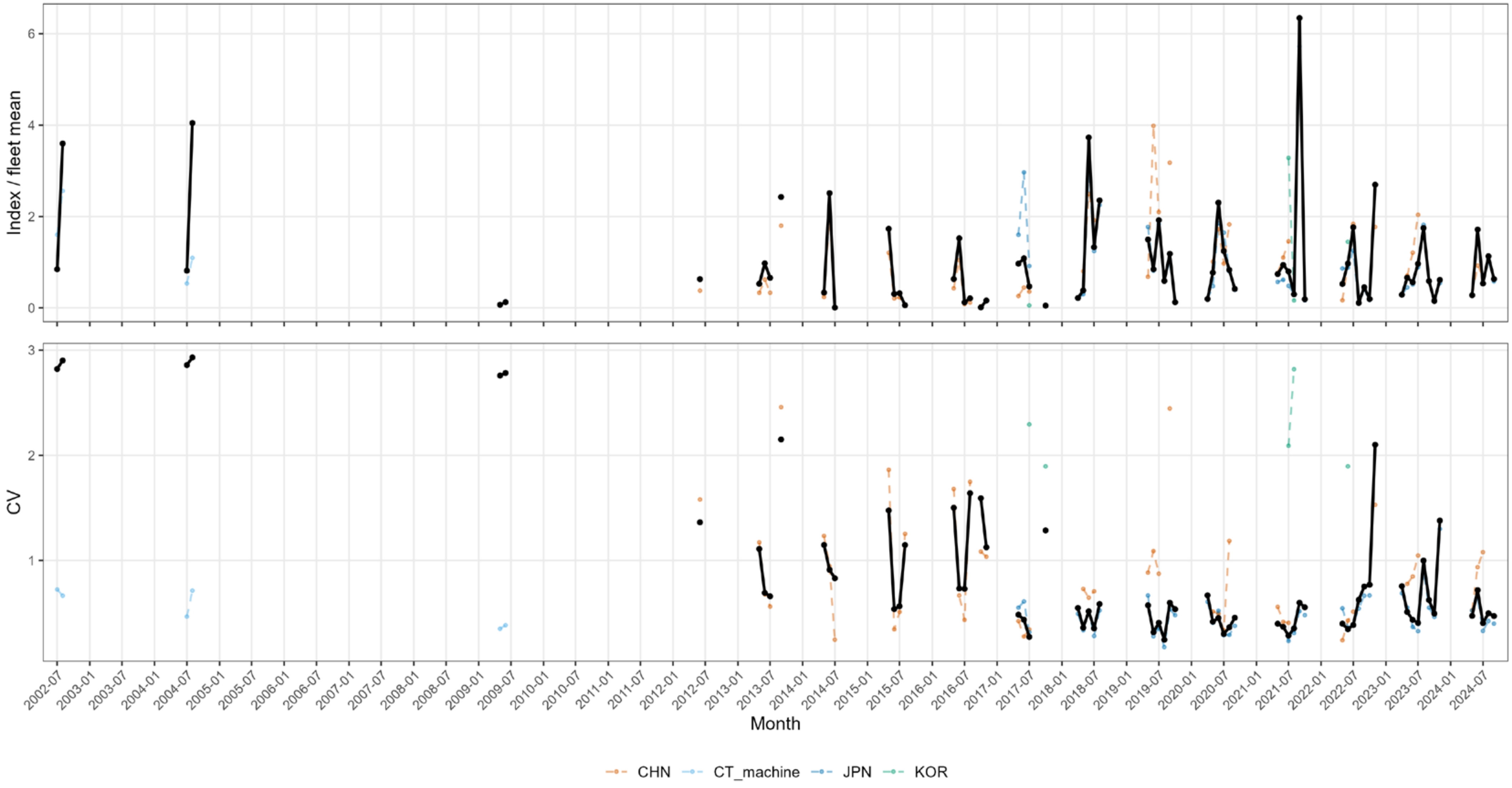
170° E West Monthly Standardized Index (CHN as Reference)



170° E East Yearly Standardized Index (CHN as Reference)



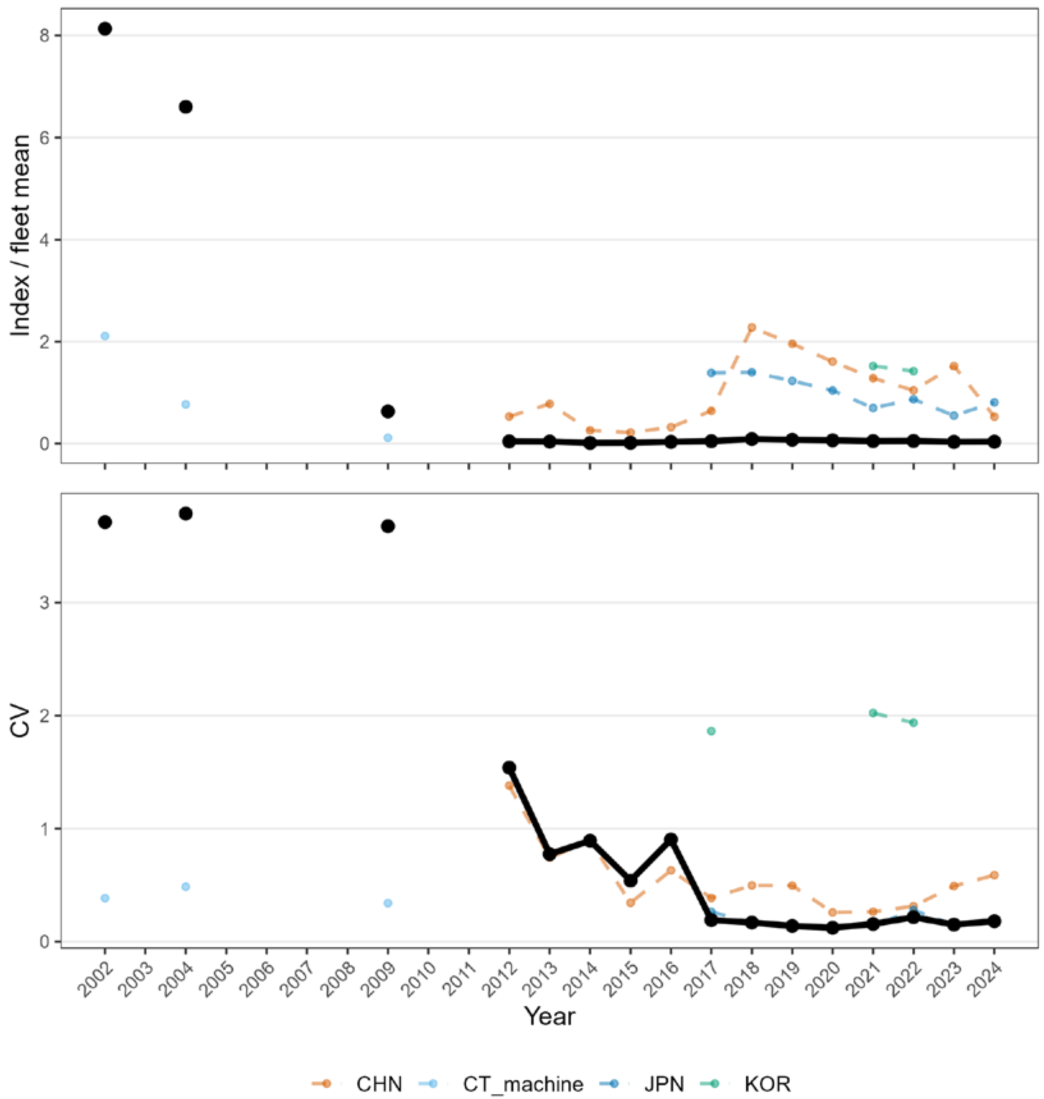
170° E East Monthly Standardized Index (CHN as Reference)

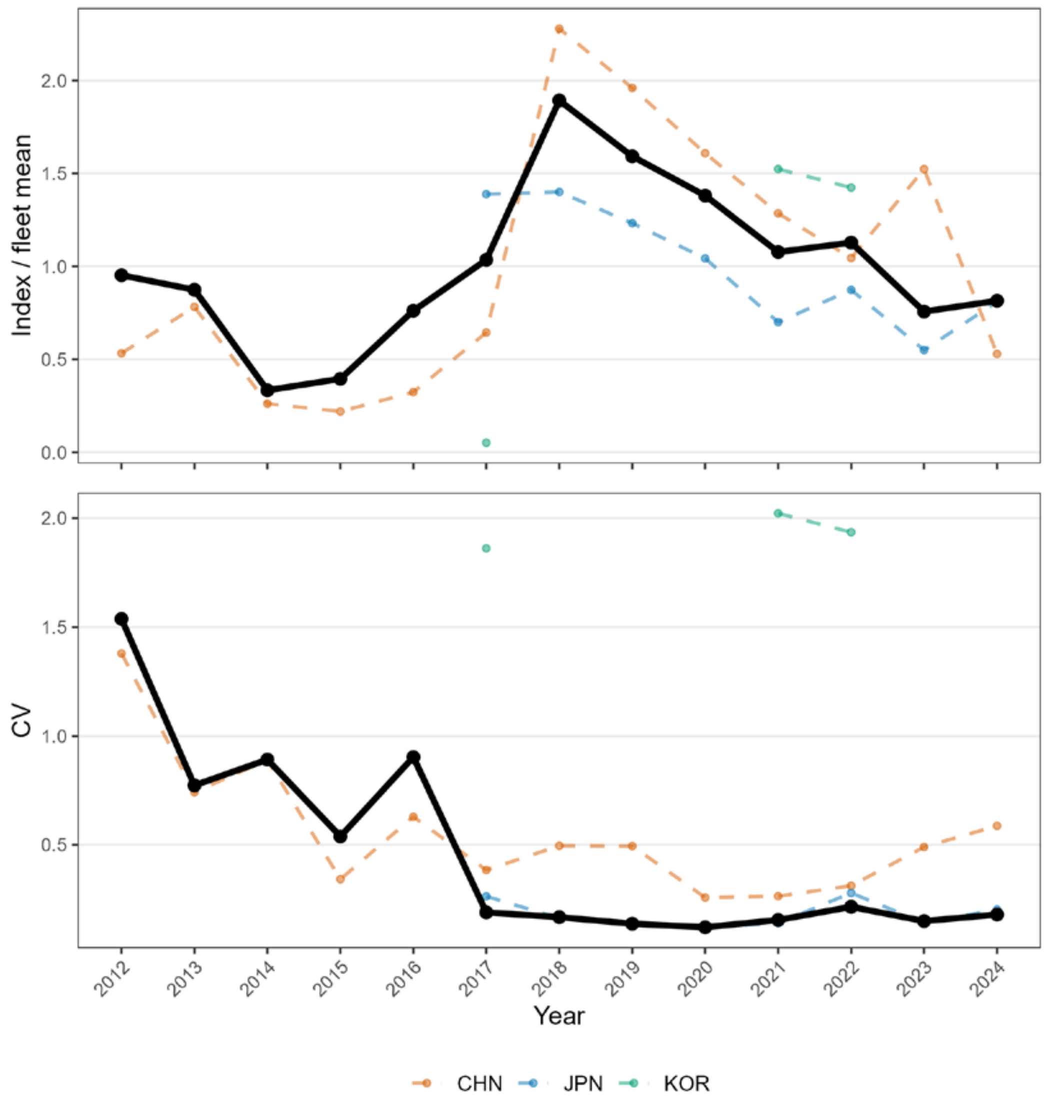


Take-Home Messages

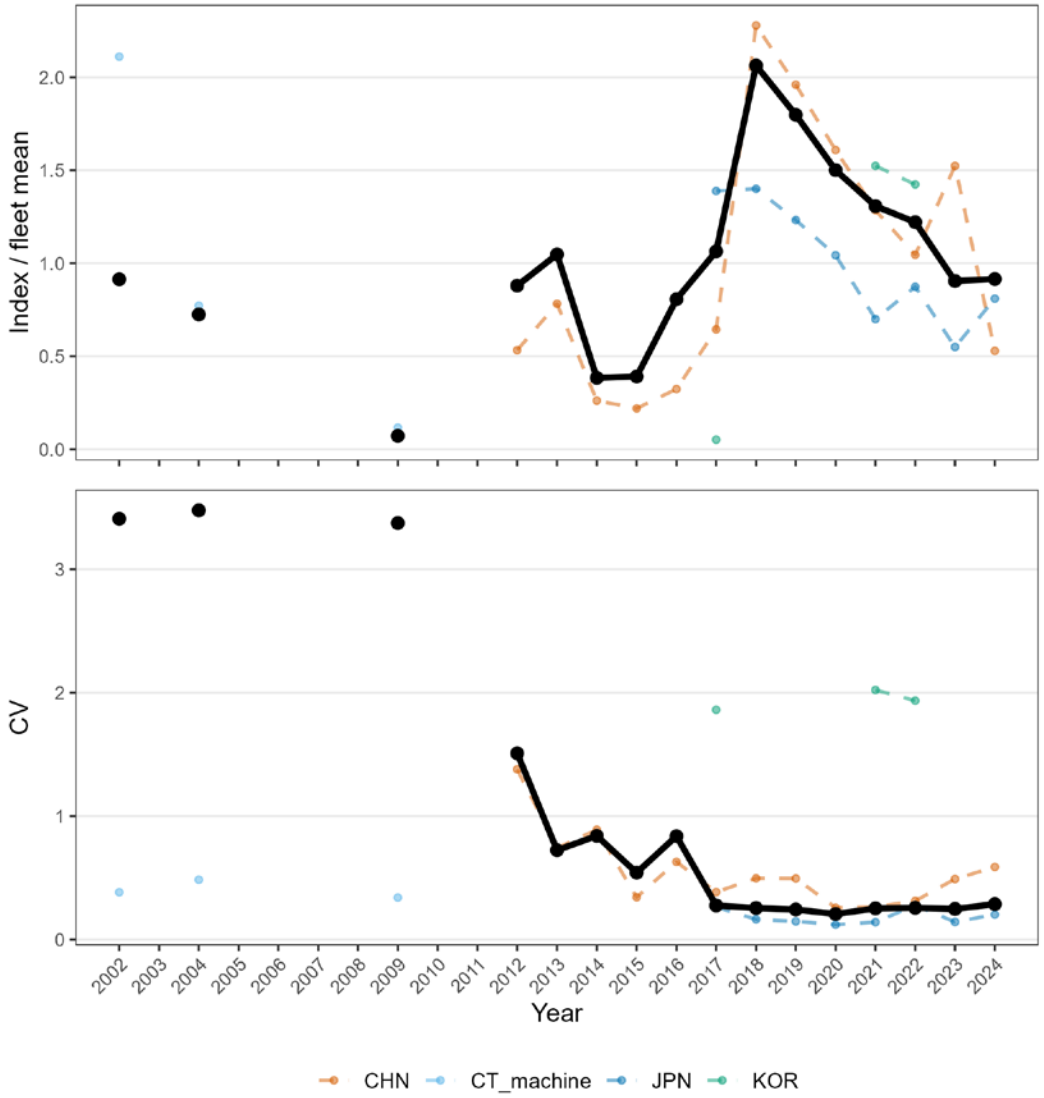
- Joint standardization is useful when multiple fleets observe the same stock with uneven overlap in space and time.
- The key modeling idea is to let fleets share a latent population surface while allowing fishery-specific catchability adjustments.
- For NFS, the approach is attractive because fleet coverage, seasonality, and spatial sampling are heterogeneous.
- The final assessment should focus not only on the index itself, but also on diagnostics, model stability, and biological plausibility.
- No environmental covariates were considered in the current analyses, but this functionality could be added to the package by allowing users to specify which covariates affect population density and which affect catchability.

170° E East Yearly Standardized Index (JPN as Reference)





170° E East Yearly Standardized Index (CHN as Reference)



JPN as Reference, index from 2012: