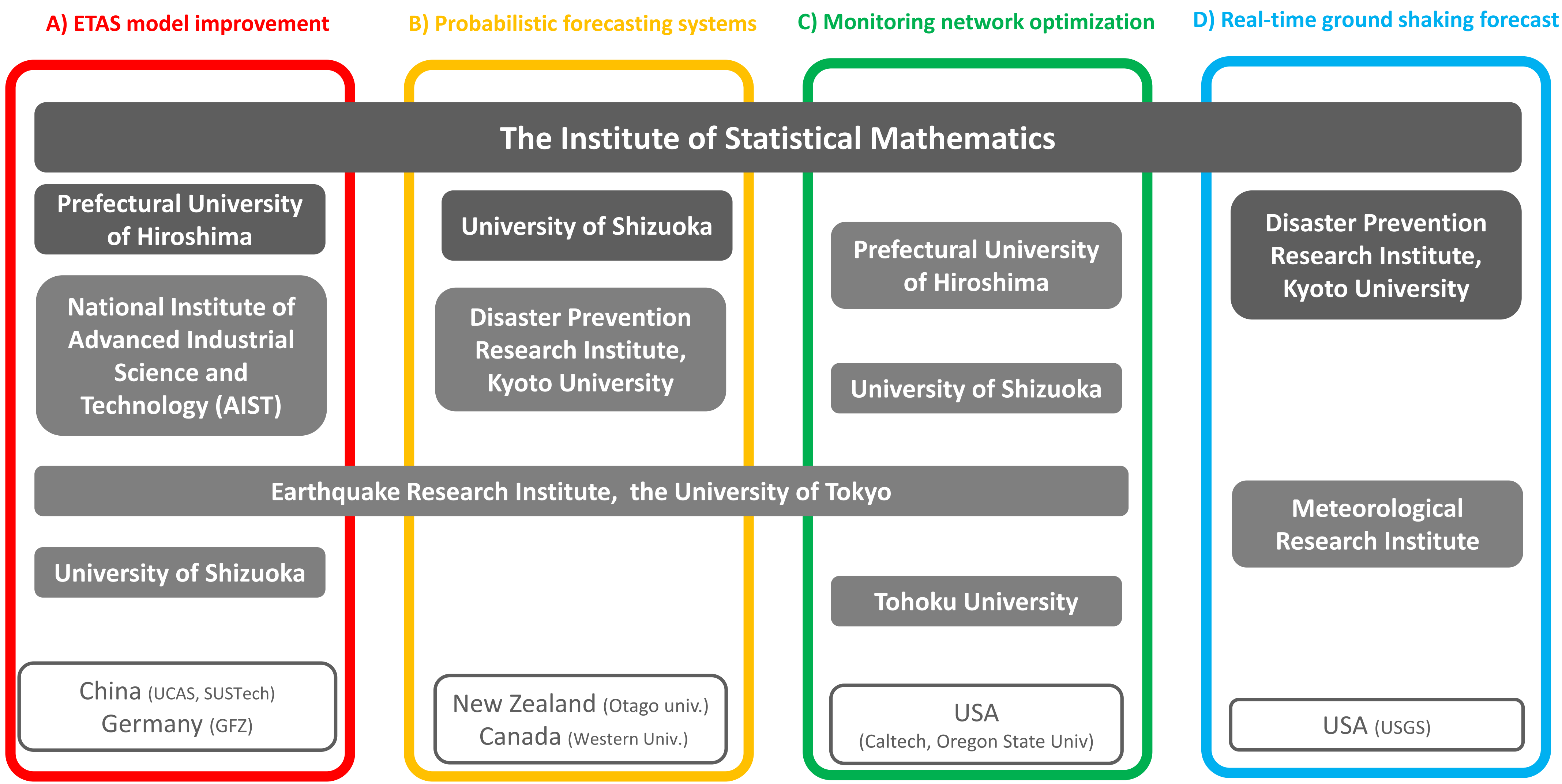
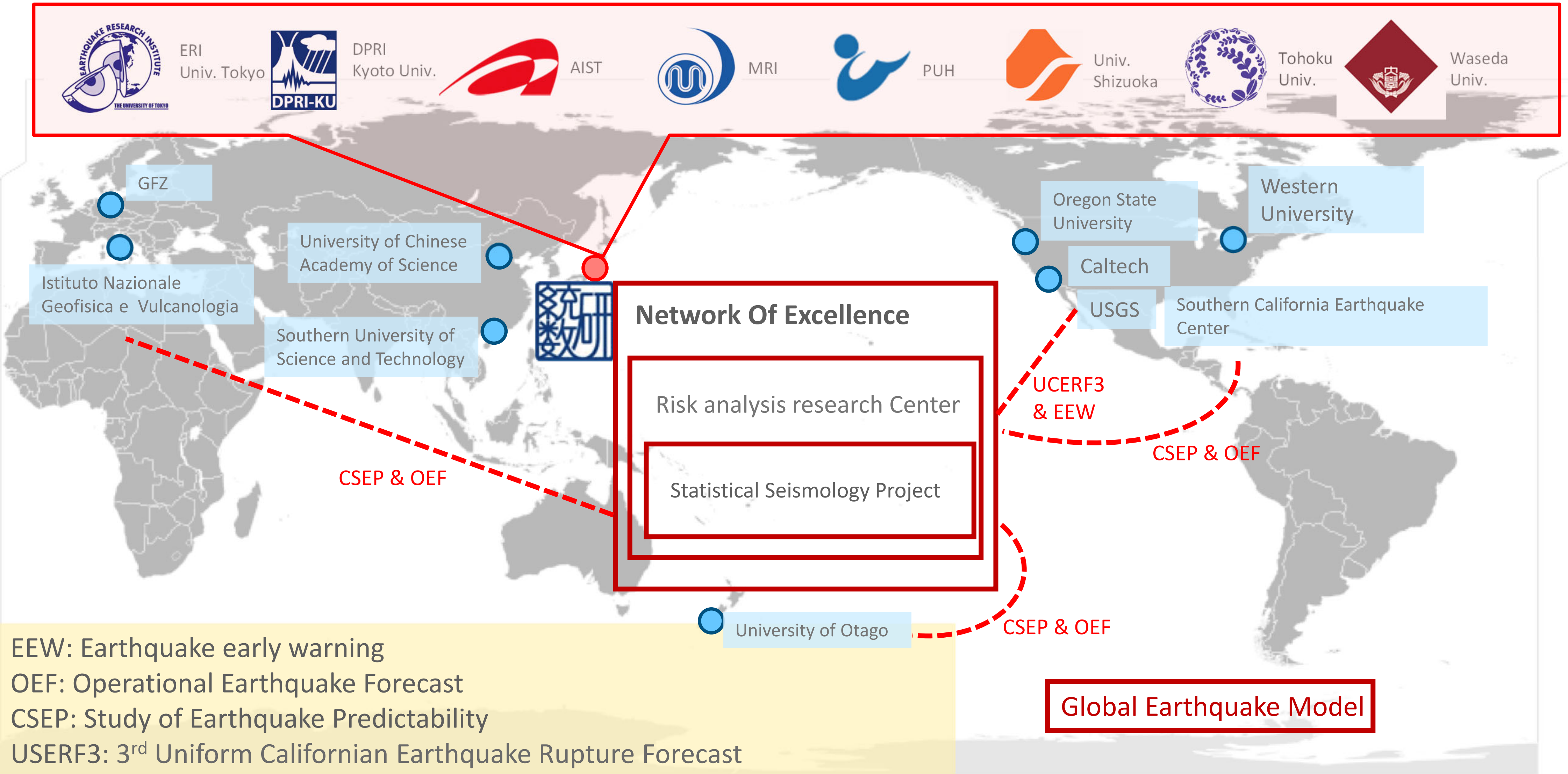
Research Organization



Domestic / International collaborations



EEW: Earthquake early warning
OEF: Operational Earthquake Forecast
CSEP: Study of Earthquake Predictability
USERF3: 3rd Uniform Californian Earthquake Rupture Forecast

Theme A : Developing Seismicity Modeling and Data Analysis Methods Based on Japanese Regional Data

Spatiotemporal ETAS model

$$\lambda(t,x,y) = P\{\,N(dtdxdy) = 1 \mid \text{obs. history before } t\,\}$$
$$= \mu(x,y) + \sum_{i:t_i<t} \kappa(m_i)g(t-t_i)f(x-x_i, y-y_i; m_i)$$

$$\lambda\,(t,x,y,\ldots) = \mu(x,y)\cdots + \sum_{i:t_i<t} \kappa(m_i)g(t-t_i)f(x-x_i, y-y_i;\, m_i,\cdots)\cdots + \sum_{j:u_j<t} \cdots$$

- Hypocenter depth, focal Mechanism, …
- Seasonality (daily, monthly, annually) , long-term trend : GNSS observation, strain, …
- Source rupture geometry, Coulomb stress
- Observations on external anomalous phenomena

Hierarchical modelling to investigate spatiotemporal non-stationarity and non-uniformity

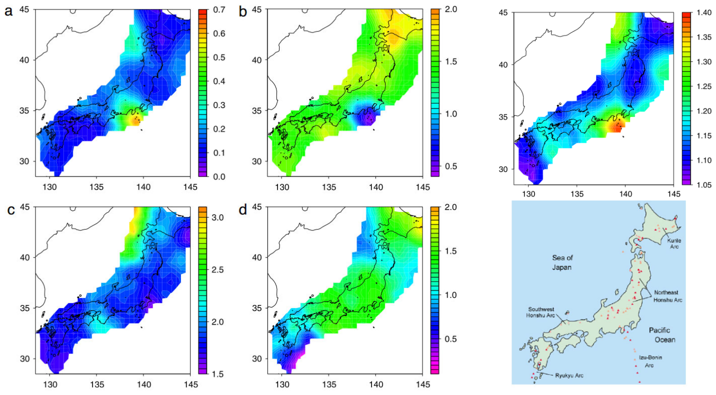
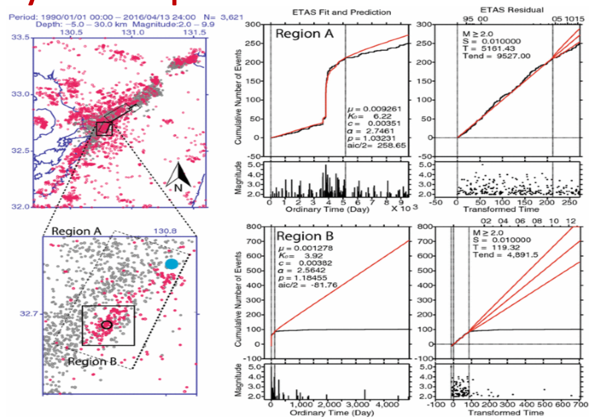


Fig. 5. Spatial variation of ETAS parameters estimated using the MWLE: (a) A (unit: events), (b) α, (c) q, (d) γ.

(Zhuang, 2015)

Anomalous deviations of seismic activity from the ETAS model and physical interpretation



(Kumazawa, Ogata, and Tsuruoka 2017)

Theme B ： Constructing on-line probability forecasting systems

Various predictors

Retrospective tests
Database accumulation
Spatiotemporal scaling

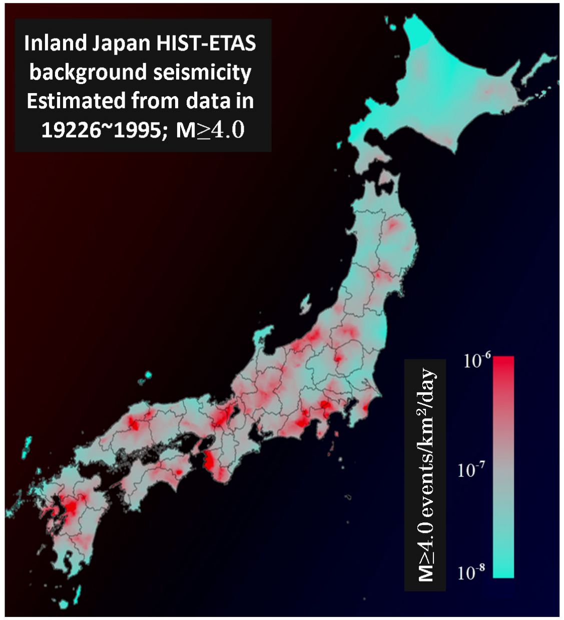
Candidate forecasting models： Logistic/Product/Additive: Combined (hybrid) models

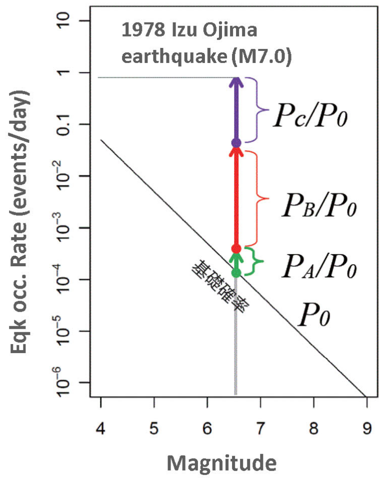
$$\lambda(t,x,y,M\,|\,H_t,F_t^1,\cdots,F_t^K) = \mu(x,y,M)\underbrace{\frac{\lambda_{ETAS}(t,x,y,M\,|\,H_t)}{\mu(x,y,M)}}\prod_{k=1}^{K}\underbrace{\frac{\lambda_k(t,x,y,M\,|\,F_t^k)}{\mu(x,y,M)}}$$

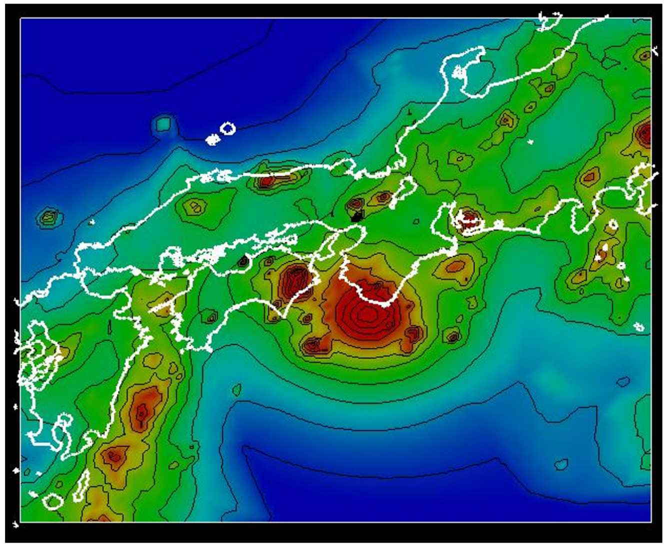
Point-process version of the multi-predictor forecasting equation

Risk enhancement factors

Probability gain/Information gain

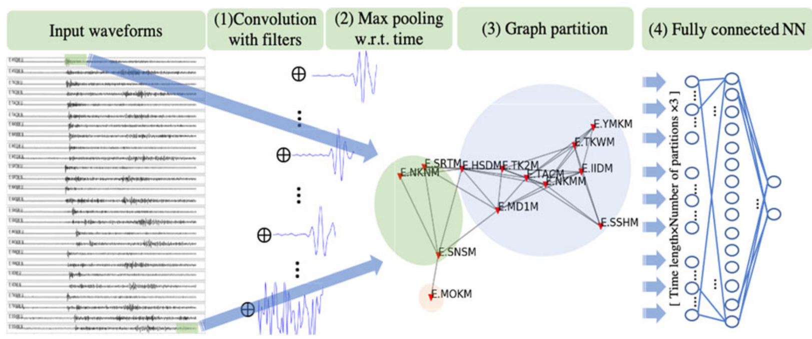




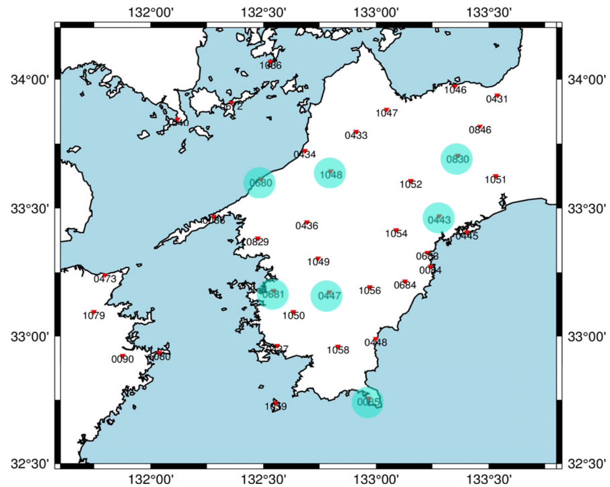


Theme C： Optimization of Network Information Integration for Prediction and Monitoring

- Dynamic observation point integration method using noise information and prediction information
    - Improving the accuracy of earthquake discrimination deep learning models by integrating observation points (Findings from Yano et al., 2021)
    - Further enhancement by utilizing dynamic noise information for each observation point and prediction information from Theme B

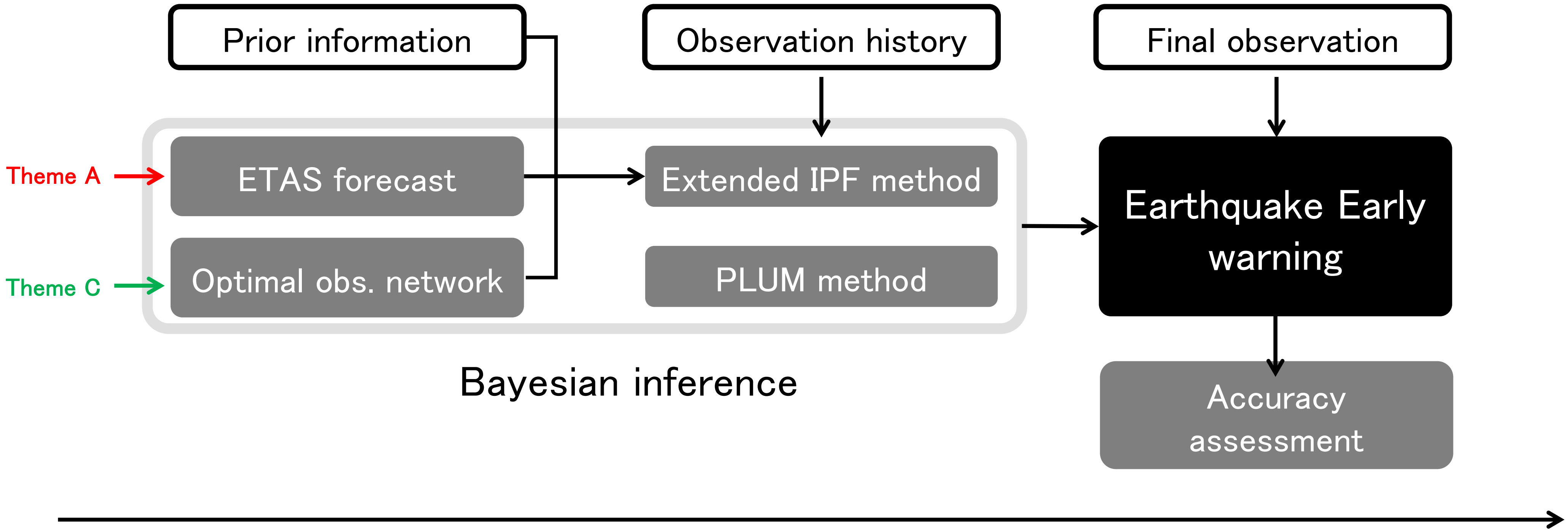


- Development of observation point integration and selection methods for inverse analysis
    - Increase reliance on observation points with “good fit” in inverse analysis → Improving accuracy of inverse analysis (for Theme D)
    - Conduct out-of-sample evaluation using information criteria



- Optimal design based on seismicity and earthquake forecast information
    - Maximize utility in long-term monitoring
    - Apply to temporary observation network placement / new observation technologies (DAS)

Theme D : Real-time forecast of ground shaking



D-1. Using ETAS forecasts as prior information

D-2. Development of extended IPF methods based on observations from optimal monitoring network

D-3. Hybridization of the extended IPF method and the PLUM method

D-4. Visualization of earthquake early warning outputs