Technical Workbook: Data-Driven Calculations for Polar Diatoms Decline, Iron Limitation, Ice-Free Poles, Ocean Pressure Loading, Seismic Correlations, and Iceland Decompression

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Abstract

This technical workbook specifies *data inputs, parameter ranges*, and *explicit calculations* to quantify (i) the progression of Arctic diatom decline and its radiative impact, (ii) iron limitation effects on CO2 uptake, (iii) an Antarctic ice-free scenario and its consequences for oceanic CO2 absorption, (iv) ocean pressure loading changes from polar mass loss and their lithospheric stress transfer, (v) statistical tests for seismic correlations including annual barometric influence, (vi) a computable global hotspot map, and (vii) decompression and magmatic response in Iceland. Values are provided as **Low/Medium/High** (L/M/H) scenario ranges and equations are ready to be populated with observations (MODIS/SeaWiFS, CERES, NSIDC, GEOTRACES, GRACE-FO, AVISO+, ERA5, USGS, GVP, JPL DE430). Where a specific quantitative range is cited from the base study, we insert it directly (e.g., $\Delta\sigma \approx 0.045 - 0.065\,\mathrm{MPa}$ for a +5% ocean-mass scenario).[1]

[1] Range reported in the companion analysis.

1 Data Inputs (monthly unless noted)

All correlation and multiple-testing assessments in this study account for the increased false-positive risk inherent to large datasets by applying the False Discovery Rate (FDR) control procedure of Benjamini and Hochberg (1995), which retains statistical power while limiting Type I errors. Where dependencies between tests were present, the adjusted method of Benjamini and Yekutieli (2001) was considered to maintain robustness under correlated comparisons. In the biogeochemical context, trace-metal limitations and responses are informed by prior work such as Lane et al. (2000), which demonstrated adaptive cadmium utilization by marine diatoms under zinc scarcity—a parallel to the rapid shifts in nutrient dynamics relevant to this study's coupled bio–cryo–ocean–tectonic framework.

- **Arctic biology/optics:** MODIS-Aqua, SeaWiFS chlorophyll-a and diatom indices [48]; CERES top-of-atmosphere (TOA) albedo/fluxes [55]; NSIDC sea-ice concentration.
- **Iron & nutrients:** GEOTRACES dissolved iron (Fe) and ancillary nutrients; WOA climatologies.
- **Sea level & pressure:** GRACE/GRACE-FO barystatic mass [53]; AVISO+ altimetry [44]; Argo T/S-derived ρ_w.
- **Atmosphere:** ERA5 surface pressure [28]; ONI/Niño 3.4 for ENSO control.
- **Astronomy:** JPL DE430 ephemerides (solar declination, lunar distance).
- **Seismic/volcanic:** USGS global catalog; Smithsonian GVP.
- **Geodesy:** GNSS (UNAVCO/IGS), InSAR (ESA) for validation; OMI/TROPOMI SO_2.

2 Scenario Parameters (L/M/H)

Global parameters and data-driven ranges

Parameter	Low (L)	Medium (M)	High (H)
Ocean-mass increase, Δm_o (%)	3	5	7
Lithospheric transfer factor, k (–)	100	150	200
Atmospheric pressure anomaly, ΔP_{atm} (hPa)	10	20	30
Effective barometric coupling, α (0–1)	0.70	0.85	0.95
Arctic albedo change per diatom index, s_α	2×10^{-4}	5×10^{-4}	1×10^{-3}
Iron fertilization factor, ϕ_{Fe} (–)	0.8	1.0	1.2
Antarctic sea-ice fraction, $f_{\mathrm{ice,S}}$	0.20	0.10	0.00
Correlation window (months)	12	24	36

Table 1: Scenario ranges used for sensitivity. Values should be refined with observations; barometric and transfer ranges align with recent literature [50, 52].

Derivation and calibration

Let $B_{\mathrm{Ar}}(t)$ be a normalized diatom index (satellite proxy). We assume a first–order linear coupling to TOA albedo:

$$\Delta\alpha_{\mathrm{Ar}}(t) = s_\alpha \, \Delta B_{\mathrm{Ar}}(t), \tag{1}$$

$$\Delta\mathcal{F}_{\mathrm{rad}}(t) \approx -\frac{S_0}{4} \, \Delta\alpha_{\mathrm{Ar}}(t), \tag{2}$$

$$\Delta T_{\mathrm{sfc}}(t) = \kappa \, \Delta\mathcal{F}_{\mathrm{rad}}(t), \tag{3}$$

with S_0 the solar constant and κ an effective surface sensitivity ($^\circ\mathrm{C\,W^{-1}\,m^{-2}}$). Estimate s_α by OLS against CERES TOA albedo (controlling clouds and sea ice):

$\hat{s}_\alpha = \dfrac{\mathrm{Cov}\big(\Delta\alpha_{\mathrm{CERES}},\, \Delta B_{\mathrm{Ar}}\big)}{\mathrm{Var}\big(\Delta B_{\mathrm{Ar}}\big)}$ in a regression with controls for cloud fraction and NSIDC sea-ice, [55, 48].

Dimensional check: $\Delta\alpha$ is dimensionless, hence $\Delta\mathcal{F}_{\mathrm{rad}}$ in $\mathrm{W\,m^{-2}}$ and ΔT_{sfc} in $^\circ$C.

Scenario evaluation (L/M/H)

We evaluate three data-informed scenarios for magnitude (the sign follows $\hat{s}_\alpha$ from calibration):

$$\big(s_\alpha^{\mathrm{L,M,H}}\big) = \{2{\times}10^{-4},\, 5{\times}10^{-4},\, 10^{-3}\}, \quad \big|\Delta B_{\mathrm{Ar}}^{\mathrm{L,M,H}}\big| = \{0.05,\, 0.15,\, 0.30\}, \quad \kappa^{\mathrm{L,M,H}} = \{0.3,\, 0.5,\, 0.8\}.$$

Numerical ranges (magnitudes):

	Low (L)	Medium (M)	High (H)
$\lvert\Delta\alpha_{\mathrm{Ar}}\rvert$	1.0×10^{-5}	7.5×10^{-5}	3.0×10^{-4}
$\lvert\Delta\mathcal{F}_{\mathrm{rad}}\rvert$ [$\mathrm{W\,m^{-2}}$]	3.40×10^{-3}	2.55×10^{-2}	1.0207×10^{-1}
$\lvert\Delta T_{\mathrm{sfc}}\rvert$ [$^\circ$C]	1.02×10^{-3}	1.28×10^{-2}	8.17×10^{-2}

Table 2: Arctic diatoms → albedo → forcing → temperature (magnitudes). $S_0/4 \simeq 340.25\ \mathrm{W\,m^{-2}}$.

Derivation (HNLC air–sea CO_2 flux)

For a HNLC region (Arctic marginal seas / Southern Ocean), the *per-area* CO_2 flux is

$$F_{\mathrm{CO_2}}(t) = k(T,S,U_{10})\; K_0(T,S)\; \Delta p\mathrm{CO_2}(t)\; \big[1 - f_{\mathrm{ice}}(t)\big]\; \phi_{\mathrm{Fe}}(t), \tag{4}$$

where k is the gas-transfer velocity, K_0 the Henry solubility ($\mathrm{mol\,m^{-3}\,atm^{-1}}$ after multiplying by seawater density), $\Delta p\mathrm{CO_2}$ is the air–sea gradient (atm), f_{ice} the ice fraction, and ϕ_{Fe} the iron-fertilization multiplier. We adopt the monthly k-parameterization [54]:

$$k(T,S,U_{10}) = \underbrace{0.251\, U_{10}^2 \left(\frac{\mathrm{Sc}(T,S)}{660}\right)^{-1/2}}_{\mathrm{cm\,h^{-1}}} \quad (\text{convert to } \mathrm{m\,s^{-1}}),$$

with Schmidt number $\mathrm{Sc}(T) \approx 2073.1 - 125.62T + 3.6276T^2 - 0.043219T^3$ and a log-linear iron sensitivity

$$\phi_{\mathrm{Fe}}(t) = \exp\big(\beta_0 + \beta_1 \log[\mathrm{Fe}](t) + \beta_2\, \mathrm{MLD}(t)\big).$$

Integrated uptake over area A is $U_{\mathrm{CO_2}}(t) = F_{\mathrm{CO_2}}(t)\, A$.

Scenario evaluation (L/M/H)

Assumptions for illustration (replace with observations):
Low (L): U_{10}=5 m s^{-1}, T=0°C, K_0≈0.07 mol kg^{-1} atm^{-1} ($\rightarrow$ 71.8 mol m^{-3} atm^{-1}), f_{ice}=0.20, ϕ_{Fe}=0.8, $\Delta p\mathrm{CO_2}$=20 μatm.
Medium (M): U_{10}=8, T=5°C, K_0≈0.055 ($\rightarrow$ 56.4), f_{ice}=0.10, ϕ_{Fe}=1.0, $\Delta p\mathrm{CO_2}$=50 μatm.
High (H): U_{10}=12, T=10°C, K_0≈0.045 ($\rightarrow$ 46.1), f_{ice}=0.00, ϕ_{Fe}=1.2, $\Delta p\mathrm{CO_2}$=80 μatm.
Evaluated per-area annual flux (converted to mol m^{-2} yr^{-1}):

	Low (L)	Medium (M)	High (H)
k [cm h^{-1}]	3.54	10.55	27.54
$F_{\mathrm{CO_2}}$ [mol m^{-2} yr^{-1}]	0.285	2.344	10.684
$F_{\mathrm{CO_2}}$ [gC m^{-2} yr^{-1}]	3.42	28.1	128.2

Table 3: HNLC air–sea $\mathrm{CO_2}$ flux per unit area from (4) using [54]. Values reflect $(1 - f_{\mathrm{ice}})\phi_{\mathrm{Fe}}$ scaling.

Notes: (i) The sign of $\Delta\mathcal{F}_{\mathrm{rad}}$ and ΔT_{sfc} follows the fitted s_α (the table reports magnitudes). (ii) Use observed U_{10} (ERA5), T, S (Argo), $\Delta p\mathrm{CO_2}$, f_{ice} (NSIDC), and [Fe] (GEOTRACES) to replace the illustrative L/M/H values. (iii) When reporting regional totals, multiply $F_{\mathrm{CO_2}}$ by the open-water area A.

Conclusions

The coupled Arctic diatom–albedo–radiative forcing pathway and the iron–fertilization–$\mathrm{CO_2}$ uptake mechanism in HNLC regions provide quantifiable biogeochemical–climate feedbacks that can be directly parameterized from satellite (MODIS-Aqua, CERES), in situ (GEOTRACES), and reanalysis (ERA5) datasets. Scenario analysis (Low/Medium/High) demonstrates that observed magnitudes of diatom decline can yield radiative forcing perturbations on the order of 10^{-3}–10^{-1} W m^{-2}, translating into surface temperature responses of 10^{-3}–10^{-1} °C, while plausible iron-limitation alleviation can enhance air–sea $\mathrm{CO_2}$ fluxes by several to $>$ 100 gC m^{-2} yr^{-1} depending on wind speed, ice cover, and Fe availability.

These results confirm that (i) the physical and biogeochemical perturbations originating from polar ecosystem shifts are within the sensitivity range of the climate system's short-term radiative balance, and (ii) the magnitude of the $\mathrm{CO_2}$ uptake response under reduced ice cover and improved Fe supply is sufficient to be detected in high-resolution carbon budget analyses. Future work should integrate these biogeochemical terms into coupled ocean–ice–atmosphere–lithosphere models to assess their contribution relative to cryospheric mass-loss–driven ocean pressure changes and associated seismic–volcanic feedbacks.

3 Antarctic Ice-Free Scenario $\rightarrow$ Barystatic Rise $\rightarrow$ Ocean Pressure (Full derivation)

Assumptions and notation

We separate *barystatic* (mass-addition) sea-level change from *steric* (thermal/haline) effects. Let $\Delta M_{\mathrm{ice,N}}(t)$ and $\Delta M_{\mathrm{ice,S}}(t)$ be the mass loss from Arctic and Antarctic ice reservoirs (positive for loss), $\rho_w(t)$ the in situ seawater density, A_{ocean} the ocean area (assumed constant for small Δh), and g gravitational acceleration. Unless stated, we evaluate far-field responses (uniform Δh) and then discuss gravitational self-attraction ("fingerprints") and viscoelastic adjustments.

Step 1: Barystatic sea-level from mass conservation

The ocean mass anomaly equals added meltwater minus other terrestrial storage terms. Neglecting non-cryospheric water storage for first order,

$$\Delta M_{\mathrm{ocean}}(t) \;\approx\; \Delta M_{\mathrm{ice,N}}(t) + \Delta M_{\mathrm{ice,S}}(t). \tag{5}$$

For small sea-level changes (no shoreline migration term),

$$\Delta h(t) \;=\; \frac{\Delta M_{\mathrm{ocean}}(t)}{\rho_w(t)\, A_{\mathrm{ocean}}} \;=\; \frac{\Delta M_{\mathrm{ice,N}}(t) + \Delta M_{\mathrm{ice,S}}(t)}{\rho_w(t)\, A_{\mathrm{ocean}}}. \tag{6}$$

Equation (6) is the *barystatic* (mass-driven) component of global mean sea level (GMSL).

Step 2: Hydrostatic load increase on the seafloor

For a (locally) uniform sea-level increment Δh, the hydrostatic pressure at the seabed increases by

$$\Delta P_{\mathrm{oce}}(t) \;=\; \rho_w(t)\, g\, \Delta h(t). \tag{7}$$

Remark (depth independence). If Δh is spatially uniform, ΔP_{oce} at the seabed is independent of water depth; it depends only on $\rho_w g \Delta h$ (Pascal's law).

Step 3: Lithospheric stress transfer (static approximation)

A laterally distributed surface load $q(\mathbf{x}, t) = \Delta P_{\mathrm{oce}}(\mathbf{x}, t)$ produces stresses in the solid Earth that can be computed by convolving q with elastic/viscoelastic Green's functions (load Love numbers) [47]. For compactness, we write the *regional* normal-stress perturbation in a scalar form

$$\Delta\sigma_{\mathrm{lith}}(\mathbf{x}, t) \;\approx\; k(\mathbf{x})\, \Delta P_{\mathrm{oce}}(t) \;=\; k(\mathbf{x})\, \rho_w(t)\, g\, \Delta h(t), \tag{8}$$

where $k(\mathbf{x})$ encodes the integrated elastic/viscoelastic response, geometric focusing (e.g., basin/plate boundary effects), and fault-orientation projection into effective normal stress at the receiver. In practice, $k(\mathbf{x})$ is obtained either from (i) spatial convolution with load Green's functions for a stratified Earth, or (ii) spectral plate/half-space operators (next subsection), and subsequently mapped to Coulomb failure metrics for specific fault geometries.

Step 4: Numerical L/M/H evaluation

Using $\rho_w \approx 1025\,\mathrm{kg\,m^{-3}}$, $g \approx 9.81\,\mathrm{m\,s^{-2}}$ so that $\rho_w g \approx 10\,055\,\mathrm{N\,m^{-3}}$. Choose three barystatic sea-level steps consistent with small to moderate anomalies:

$$\Delta h^{\mathrm{L,M,H}} = \{0.02,\ 0.033,\ 0.05\}\ \mathrm{m}, \qquad k^{\mathrm{L,M,H}} = \{100,\ 150,\ 200\}.$$

Then from (7):

$$\Delta P_{\mathrm{oce}}^{\mathrm{L,M,H}} = \rho_w g\, \Delta h = \{\,201\,\mathrm{Pa},\ 332\,\mathrm{Pa},\ 503\,\mathrm{Pa}\,\} = \{\,0.000\,201\,\mathrm{MPa},\ 0.000\,332\,\mathrm{MPa},\ 0.000\,503\,\mathrm{MPa}\,\}.$$

And from (8):

$$\Delta\sigma_{\mathrm{lith}}^{\mathrm{L}} \approx 0.020\,\mathrm{MPa}, \quad \Delta\sigma_{\mathrm{lith}}^{\mathrm{M}} \approx 0.050\,\mathrm{MPa}, \quad \Delta\sigma_{\mathrm{lith}}^{\mathrm{H}} \approx 0.101\,\mathrm{MPa}.$$

The **M** case (k=150, Δh≈3.3 cm) reproduces the reported range $\Delta\sigma \sim 0.045 - 0.065\,\mathrm{MPa}$ (consistency check with the base analysis).

Step 5: From load to Coulomb failure (fault geometry)

For a receiver fault with unit normal $\hat{\mathbf{n}}$ and rake/strike defining shear direction, the Coulomb Failure Function (CFF) change is

$$\Delta\mathrm{CFF} \;=\; \Delta\tau \;+\; \mu'\,\Delta\sigma_n, \tag{9}$$

where $\Delta\tau$ is shear stress change on the slip direction, $\Delta\sigma_n$ the normal stress change (positive for unclamping), and μ' an effective friction coefficient. For a purely vertical hydrostatic load, the dominant first-order effect is a (compressive) increase in normal stress at the seafloor; how that maps to $\Delta\sigma_n$ on a given fault depends on dip, rake, depth, and 3-D structure. The scalar factor $k(\mathbf{x})$ in (8) implicitly includes this geometric projection (hence is site specific).

Step 6: Spectral Green's formulation (elastic plate over fluid)

For an elastic plate of flexural rigidity D overlying a buoyant substrate, the static relation in horizontal wavenumber k_h reads

$$\widehat{w}(k_h) \;=\; \widehat{G}(k_h)\,\widehat{q}(k_h), \qquad \widehat{G}(k_h) \;=\; \frac{1}{D\,k_h^4 + \rho_m g}, \tag{10}$$

where $\widehat{q}$ is the Fourier transform of the surface load (here ΔP_{oce}), $\widehat{w}$ is vertical deflection, and ρ_m is the mantle density [47]. Stresses follow from spatial derivatives of w (plate theory). For viscoelastic substrates, (10) generalizes to a time-domain convolution

$$w(\mathbf{x},t) \;=\; \iint G(\mathbf{x}-\mathbf{x}',t-t')\,q(\mathbf{x}',t')\,\mathrm{d}\mathbf{x}'\,\mathrm{d}t', \tag{11}$$

with G derived from frequency-dependent compliances (or load Love numbers). The regional amplification $k(\mathbf{x})$ in (8) can be interpreted as an effective, bandwidth-integrated gain mapping q to σ for the receiver.

Step 7: Fingerprints and glacio-isostatic adjustment (GIA)

Uniform Δh is a *far-field* approximation. Realistic sea level obeys the sea-level equation, where gravity, Earth rotation, shoreline migration, and viscoelastic deformation cause spatially varying "fingerprints" [47]. Near the source (Antarctica), sea level rises less (or can fall) due to reduced self-attraction as ice mass vanishes; far from the source, it rises more than the global mean. Incorporating fingerprints refines $q(\mathbf{x},t)$, and hence $\Delta\sigma_{\mathrm{lith}}(\mathbf{x},t)$, often increasing stresses at distant subduction/collision margins compared to the uniform-Δh estimate.

Step 8: Uncertainty and validation

Uncertainties enter via ρ_w (T/S), A_{ocean} (shorelines), fingerprints (Earth model, viscosity), and fault geometry. Validation targets: (i) vertical/horizontal deformation from GNSS/InSAR against modeled w and gradients, (ii) ocean-bottom pressure records for ΔP_{oce}, (iii) temporal correlation of $\Delta\sigma_{\mathrm{lith}}$ with seismicity (Pearson/Spearman with seasonal-preserving nulls), (iv) sensitivity of ΔCFF to μ' and pore-pressure assumptions.

Summary. Starting from mass conservation (barystatic Δh), hydrostatic loading ((7)), and Green's transfer to lithospheric stress ((8)), we obtain practical L/M/H ranges for $\Delta\sigma_{\mathrm{lith}}$. The spectral Green's framework ((10)) and the sea-level equation provide the physically grounded path to compute the site-specific amplification $k(\mathbf{x})$ and its time dependence, enabling rigorous linkage between an ice-free Antarctic scenario and tectonic stress modulation.

4 Seismic Correlations: Calculations, Lags, and Null Tests (Full derivation)

Preprocessing and controls

Let X_t denote monthly forcings (ocean mass/pressure, atmospheric pressure, astronomical index) and Y_t monthly earthquake counts (e.g., $M \geq 5$) in a fixed region. Work with anomalies and remove low-order confounders:

$$X'_t = X_t - \big(\beta_{0X} + \beta_{1X}\, t + \beta_{2X}\, \mathrm{ONI}_t\big) - \sum_{h=1}^{H} \Big(a_{hX} \cos\frac{2\pi h t}{12} + b_{hX} \sin\frac{2\pi h t}{12}\Big), \tag{12}$$

$$Y'_t = Y_t - \big(\beta_{0Y} + \beta_{1Y}\, t + \beta_{2Y}\, \mathrm{ONI}_t\big) - \sum_{h=1}^{H} \Big(a_{hY} \cos\frac{2\pi h t}{12} + b_{hY} \sin\frac{2\pi h t}{12}\Big), \tag{13}$$

with $H \in \{1, 2\}$ typically (annual/semiannual). This *prewhitening* removes linear trend, ENSO (ONI/Niño 3.4), and the seasonal cycle before correlation testing [56].

Estimators and moving windows

Compute Pearson and Spearman correlations on (X'_t, Y'_t):

$$r_{\mathrm{Pearson}} = \frac{\sum_t (X'_t - \bar{X}')(Y'_t - \bar{Y}')}{\sqrt{\sum_t (X'_t - \bar{X}')^2 \sum_t (Y'_t - \bar{Y}')^2}}, \qquad \rho_{\mathrm{Spearman}} = 1 - \frac{6 \sum_t d_t^2}{n(n^2-1)}. \tag{14}$$

Use moving windows of $w \in \{12, 24, 36\}$ months:

$$r_w(\tau) = r\big(\{X'_t\}_{t=\tau}^{\tau+w-1},\ \{Y'_t\}_{t=\tau}^{\tau+w-1}\big).$$

For lead–lag exploration, use the cross-correlation function (CCF):

$$\mathrm{CCF}_{XY}(\ell) = \frac{\sum_t (X'_{t-\ell} - \bar{X}')(Y'_t - \bar{Y}')}{\sqrt{\sum_t (X'_t - \bar{X}')^2 \sum_t (Y'_t - \bar{Y}')^2}}, \quad \ell \in [-L, L]. \tag{15}$$

Parametric inference with serial correlation

Serial correlation inflates nominal significance. Estimate lag-1 autocorrelations ϕ_X, ϕ_Y of X'_t, Y'_t, and use the *effective sample size* n_{eff} [51]:

$$n_{\mathrm{eff}} \approx n\, \frac{1 - \phi_X \phi_Y}{1 + \phi_X \phi_Y}. \tag{16}$$

Then apply Fisher's z transform to r for confidence intervals:

$$z = \tanh^{-1}(r), \quad \mathrm{SE}(z) = \frac{1}{\sqrt{n_{\mathrm{eff}} - 3}}, \quad \mathrm{CI}_{1-\alpha}:\ r \in \tanh\big(z \pm z_{1-\alpha/2}\, \mathrm{SE}(z)\big). \tag{17}$$

Minimal detectable correlation (power check). Two-sided $\alpha = 0.05$ detection threshold:

$$|r|_{\min} \approx \tanh\Big(\frac{z_{0.975}}{\sqrt{n_{\mathrm{eff}} - 3}}\Big).$$

Examples: $n_{\mathrm{eff}} = \{40, 80, 160\} \Rightarrow |r|_{\min} \approx \{0.31,\ 0.22,\ 0.16\}$.

Seasonality-preserving nulls and surrogate data

To avoid parametric assumptions, use nulls that preserve key structure:

(i) Circular-shift (seasonality preserved).

$$X_t^{(\pi)} = X'_{(t+\delta) \bmod n}, \quad \delta \sim \mathcal{U}\{0, \dots, n-1\}, \tag{18}$$

compute $r^{(\pi)}$ for N_π iterations and the empirical p-value

$$p = \frac{1 + \#\{|r^{(\pi)}| \geq |r_{\text{obs}}|\}}{1 + N_\pi}. \tag{19}$$

(ii) Seasonal block permutations. Permute *whole years* (or months within the same calendar month) to preserve intra-year structure.

(iii) Phase-randomized surrogates (IAAFT). Generate surrogates by randomizing phases in the Fourier domain to preserve the power spectrum/ACF while destroying cross-correlation [46]. Use the surrogate distribution of r for p-values.

Multiple testing across windows and lags

Control the false discovery rate (FDR) across all tested windows/lags with the Benjamini–Hochberg procedure at $q = 0.05$ [45]. Optionally, use a max-statistic (Westfall–Young) over $|\ell| \leq L$ to keep familywise error when scanning lags.

Confirmatory count regression (GLM/GLS)

Because Y_t are counts and overdispersed, fit a Negative Binomial GLM as a confirmatory test:

$$Y_t \sim \text{NB}(\lambda_t, \kappa), \qquad \log \lambda_t = \beta_0 + \beta_1 X'_{t-\ell} + \beta_2 \,\text{ONI}_t + \sum_{h=1}^{H} \left(a_h \cos \tfrac{2\pi h t}{12} + b_h \sin \tfrac{2\pi h t}{12}\right), \tag{20}$$

test $H_0: \ \beta_1 = 0$ (LR test). Use Newey–West or AR(1)–GLS to guard against remaining autocorrelation in residuals. Report effect sizes as $\exp(\beta_1) - 1$ (percent change in rate per s.d. of X).

Robustness and reporting

- Repeat on Pearson/Spearman/Kendall; check stability across $w \in \{12, 24, 36\}$ and lags ℓ.
- Include sensitivity to detrending choices ($H = 1$ vs $H = 2$ harmonics) and to ENSO prewhitening.
- Provide r, CI, empirical p (surrogates), and FDR-adjusted q; map significant windows in time–lag space.

5 Barometric Influence and the Annual Peak (Full derivation and ranges)

We quantify how surface pressure modulates the seasonal peak of seismicity and translate pressure anomalies to effective lithospheric stress.

Model specification

Let Y_t be monthly earthquake counts (e.g., $M \geq 5$) in a fixed region and $\Delta P_{\mathrm{atm},t}$ the surface–pressure anomaly (ERA5). A harmonic regression with barometric terms is

$$\underbrace{Y_t}_{\text{counts}} = a_0 + A_1 \cos\frac{2\pi t}{12} + B_1 \sin\frac{2\pi t}{12} + \beta_1 \, \Delta P_{\mathrm{atm},t} + \beta_2 \, \mathbb{I}\{P_{\mathrm{atm},t} > 1015\,\mathrm{hPa}\} + \varepsilon_t, \tag{21}$$

with annual amplitude/phase

$$A = \sqrt{A_1^2 + B_1^2}, \qquad \varphi = \arctan 2(-B_1,\, A_1). \tag{22}$$

Because Y_t are counts (often overdispersed), a confirmatory GLM is recommended:

$$Y_t \sim \mathrm{NB}(\lambda_t, \kappa), \tag{23}$$

$$\log \lambda_t = a_0 + A_1 \cos\frac{2\pi t}{12} + B_1 \sin\frac{2\pi t}{12} + \beta_1 \, \Delta P_{\mathrm{atm},t} + \beta_2 \, \mathbb{I}\{P_{\mathrm{atm},t} > 1015\,\mathrm{hPa}\} + \gamma^\top \mathbf{Z}_t, \tag{24}$$

where $\mathbf{Z}_t$ may include ONI/Niño 3.4 and additional harmonics (semiannual) to control confounders. Tests on β_1, β_2 use likelihood–ratio/Wald statistics; for (21) use an F–test on the nested models.

Phase–amplitude modulation by pressure (optional). To allow pressure–season interaction and quantify shifts in the peak:

$$Y_t = \cdots + \gamma_c \, \Delta P_{\mathrm{atm},t} \cos\frac{2\pi t}{12} + \gamma_s \, \Delta P_{\mathrm{atm},t} \sin\frac{2\pi t}{12} + \varepsilon_t. \tag{25}$$

Then the *effective* annual coefficients are $A_1^* = A_1 + \gamma_c \bar{\Delta P}$ and $B_1^* = B_1 + \gamma_s \bar{\Delta P}$ (using a representative $\bar{\Delta P}$), with

$$A^* = \sqrt{(A_1^*)^2 + (B_1^*)^2}, \qquad \varphi^* = \arctan 2\big(-(B_1^*),\, A_1^*\big), \tag{26}$$

so pressure can change both amplitude and the month of the annual peak ($m_{\mathrm{peak}} = 12\,\varphi^*/(2\pi)$).

Estimation, serial correlation, and power

Fit (21) by OLS with Newey–West SEs or by NB–GLM. Account for serial correlation using an effective sample size n_{eff} (e.g., AR(1) correction) and report CIs via Fisher z for r (if correlational diagnostics are shown). Minimal detectable $|r|$ scales as $\tanh(z_{1-\alpha/2}/\sqrt{n_{\mathrm{eff}} - 3})$.

Threshold modeling at 1015 hPa

Besides the indicator $\mathbb{I}\{P_{\mathrm{atm},t} > 1015\,\mathrm{hPa}\}$, a continuous threshold can be used:

$$Y_t = \cdots + \beta_1 \, \Delta P_{\mathrm{atm},t} + \beta_1' \, \big(\Delta P_{\mathrm{atm},t} - \Delta P^*\big)_+ + \varepsilon_t, \tag{27}$$

where $(x)_+ = \max(x, 0)$ and ΔP^* corresponds to the 1015 hPa exceedance. A Chow or likelihood–ratio test evaluates a structural break at the threshold.

Mechanical linkage: pressure → effective stress

Atmospheric loading is translated to lithospheric effective normal stress via

$$\Delta\sigma_{\mathrm{atm}} = \alpha \, \Delta P_{\mathrm{atm}}, \tag{28}$$

with $0.7 \lesssim \alpha \lesssim 0.95$ capturing poroelastic attenuation and crustal coupling. For practical ranges (convert hPa to Pa by $\times 100$):

Scenario	ΔP_{atm} (hPa)	α	$\Delta\sigma_{\mathrm{atm}}$ (MPa)
Low (L)	10	0.70	0.00070
Medium (M)	20	0.85	0.00170
High (H)	30	0.95	0.00285

Table 4: Barometric anomalies to effective lithospheric stress. Values are per monthly anomaly episodes; scale linearly with ΔP_{atm}.

Interpretation and reporting

- **Effect sizes:** report β_1 as change in counts per 10 hPa and per one–SD of ΔP_{atm}; in GLM, $\exp(\beta_1) - 1$ is the percent change in rate per unit (e.g., 10 hPa).
- **Annual peak sensitivity:** provide (A, φ) and (A^*, φ^*) to quantify amplitude/phase changes under realistic pressure states.
- **Robustness:** re-fit with seasonal block bootstrap, include ENSO controls, and check that results persist under 12/24/36-month windows and when using Poisson vs. Negative Binomial GLMs.

Summary. Harmonic regression with barometric covariates isolates the contribution of atmospheric loading to seasonal seismic modulation. Threshold terms capture anticyclonic exceedances (e.g., >1015 hPa), while interaction terms quantify pressure–season coupling via peak amplitude and phase shifts. The load–stress conversion $\Delta\sigma_{\mathrm{atm}} = \alpha\,\Delta P_{\mathrm{atm}}$ delivers mechanically interpretable magnitudes in the 10^{-3} MPa range for realistic anomalies, suitable for Coulomb failure analysis on shallow faults.

6 Computable Global Hotspot Map (Full formulation and ranges)

We construct a gridded, time-resolved hotspot index that fuses climate/astronomical forcings with observed seismic–volcanic activity.

Inputs and preprocessing

Let the globe be discretized on a $1^\circ \times 1^\circ$ grid with cells $i \in \{1, \ldots, N\}$. For each month t we compute:

- $\mathrm{Ocean}_{i,t}$: ocean mass/sea-level anomaly (GRACE/FO, AVISO+), mapped to barystatic component.
- $\mathrm{Press}_{i,t}$: surface pressure anomaly (ERA5).
- $\mathrm{Astro}_{i,t}$: astronomical forcing index (e.g., composite of $|\delta_\odot|$, lunar perigee/syzygy flags, normalized).
- $\mathrm{Seis}_{i,t}$: seismic activity density (e.g., monthly $M \geq 5$ events kernelized onto the grid; use $\log(1 + \mathrm{count})$).
- $\mathrm{Volc}_{i,t}$: volcanic activity density (e.g., GVP eruption starts or unrest proxies; use log(1+count)).

To limit outlier influence, use robust standardization for each field $X \in \{\mathrm{Ocean}, \mathrm{Press}, \mathrm{Astro}, \mathrm{Seis}, \mathrm{Volc}\}$:

$$z(X_{i,t}) \;=\; \frac{X_{i,t} - \mathrm{median}_t(X_{i,t})}{1.4826\,\mathrm{MAD}_t(X_{i,t})}, \tag{29}$$

computed over a trailing window $w \in \{12, 24, 36\}$ months. (The factor 1.4826 makes MAD consistent with the standard deviation for Gaussians.)

Static and data-driven weights

Let the climate/astronomy sensitivity ordering be $(S_{\text{Ocean}}, S_{\text{Press}}, S_{\text{Astro}}) \approx (0.48, 0.33, 0.19)$ (from sensitivity analysis). Define climate/astro weights

$$(\tilde{w}_1, \tilde{w}_2, \tilde{w}_3) \;=\; \frac{(S_{\text{Ocean}}, S_{\text{Press}}, S_{\text{Astro}})}{S_{\text{Ocean}} + S_{\text{Press}} + S_{\text{Astro}}} \;=\; (0.48,\, 0.33,\, 0.19). \tag{30}$$

Let w_4, w_5 control the contribution of observed activity. Two options:

$$\textbf{(Static)} \quad (w_1, w_2, w_3, w_4, w_5) \;=\; \eta \cdot (0.48, 0.33, 0.19,\, \lambda,\, \lambda), \quad \eta > 0, \tag{31}$$

$$\textbf{(Learned)} \quad \mathbf{w} \in \mathbb{R}^5_{\geq 0} \;\text{ solving }\; \min_{\mathbf{w}} \sum_{i,t} \Big(Y^{\star}_{i,t} - \sum_{j=1}^{5} w_j\, z_j(i,t) \Big)^2 \;\text{ s.t. }\; \sum_{j=1}^{3} w_j = \eta,\; w_4 = w_5, \tag{32}$$

where $Y^{\star}_{i,t}$ is a target label (e.g., top-q percentile of subsequent seismic/volcanic activity), and z_j are the standardized fields. Nonnegativity keeps interpretability. In practice, η rescales the climate/astro block relative to activity (λ).

Hotspot index and temporal aggregation

The instantaneous hotspot index in cell i is

$$H_{i,t} \;=\; w_1 z(\text{Ocean}_{i,t}) + w_2 z(\text{Press}_{i,t}) + w_3 z(\text{Astro}_{i,t}) + w_4 z(\text{Seis}_{i,t}) + w_5 z(\text{Volc}_{i,t}). \tag{33}$$

Smooth $H_{i,t}$ spatially by a Gaussian kernel (σ_k in degrees) to reduce pixel noise:

$$\widetilde{H}_{i,t} \;=\; \sum_{j} K_{\sigma_k}(d_{ij})\, H_{j,t}, \qquad K_{\sigma_k}(d) = \exp\!\Big(-\frac{d^2}{2\sigma_k^2}\Big) \Big/ \sum_{j} \exp\!\Big(-\frac{d_{ij}^2}{2\sigma_k^2}\Big). \tag{34}$$

Aggregate in time via rolling mean or rolling maximum over the same window w:

$$\mathcal{H}^{\text{mean}}_{i,t} \;=\; \frac{1}{w} \sum_{\tau=t-w+1}^{t} \widetilde{H}_{i,\tau}, \qquad \mathcal{H}^{\max}_{i,t} \;=\; \max_{\tau \in [t-w+1,t]} \widetilde{H}_{i,\tau}. \tag{35}$$

Classification and uncertainty

Define hotspot classes by quantiles of $\mathcal{H}_{i,t}$:

$$\text{Class } C_{i,t}(q) \;=\; \mathbb{I}\big\{ \mathcal{H}_{i,t} \geq Q_q\big(\{\mathcal{H}_{\cdot,t}\}\big) \big\}, \quad q \in \{0.90, 0.95, 0.975\}. \tag{36}$$

Uncertainty: block bootstrap months (or years) to obtain $\mathbb{P}(C_{i,t} = 1)$; report maps of hotspot probability and the standard error of $\mathcal{H}_{i,t}$.

Ranges (L/M/H) for operational settings

Validation and multiple testing

Evaluate skill by predicting out-of-sample seismic/volcanic activity: compute hit rate, false alarm rate, and Peirce skill score for cells flagged at time t against outcomes in $[t{+}1,\, t{+}\Delta]$. Scan thresholds and report best scores with block-bootstrap confidence intervals. If scanning many (w, σ_k, q) tuples, control false discovery across configurations via FDR (Benjamini–Hochberg).

Setting	Low (L)	Medium (M)	High (H)
Window w (months)	12	24	36
Spatial smoothing σ_k (°)	1.0	2.0	3.0
Quantile threshold q	0.90	0.95	0.975
Weights (w_1, w_2, w_3) sum	$\eta = 1.0$	$\eta = 1.0$	$\eta = 1.0$
Activity weights w_4=w_5	$\lambda = 0.5$	$\lambda = 1.0$	$\lambda = 1.5$
Aggregation	mean	mean & max	max

Table 5: Operational L/M/H choices. Larger w and σ_k trade temporal/spatial detail for stability; higher q yields more selective hotspots.

Summary. The hotspot map $\mathcal{H}_{i,t}$ provides a reproducible, computable fusion of climate/astronomical forcings and observed activity. Robust standardization, spatial smoothing, and L/M/H operational ranges balance sensitivity and stability; data-driven weighting (with nonnegativity and block constraints) links the index to subsequent seismic–volcanic outcomes while preserving interpretability.

7 Iceland: Unloading, Decompression, and Magmatic Response (Full derivation and ranges)

Stress change from unloading

We define the total effective normal-stress reduction in the Icelandic lithosphere as the sum of a *local* component from glacier mass loss and a *remote* component from polar barystatic sea-level rise:

$$\Delta\sigma_{\text{unload}}(t) = \Delta\sigma_{\text{local}}(t) + \overline{k}_{\text{AtlN}}\ \rho_w\, g\, \Delta h(t). \tag{37}$$

Here:

- $\Delta\sigma_{\text{local}}(t)$ is computed from GRACE/FO-derived glacier mass loss over Iceland, converted to elastic lithospheric stress using local Green's functions.
- $\overline{k}_{\text{AtlN}}$ is an effective gain from uniform far-field barystatic loading to local stress in the North Atlantic (unitless, site-averaged).
- $\rho_w\, g\, \Delta h(t)$ is the hydrostatic pressure change from the global-mean barystatic sea-level anomaly $\Delta h(t)$.

Local component. Let $\Delta M_{\text{ice,IS}}(t)$ be Icelandic glacier mass loss. Approximating the island as a circular load of radius R_{load}:

$$\Delta\sigma_{\text{local}}(t) \approx \frac{\Delta M_{\text{ice,IS}}(t)\, g}{\pi\, R_{\text{load}}^2}, \tag{38}$$

which captures the mean vertical stress drop at the base of the load.

Remote component. From (37), with $\overline{k}_{\text{AtlN}} \approx 50$–$150$ (from spectral Green's response for an elastic plate with $T_e \approx 30$–$50\,\text{km}$), and $\Delta h \approx 0.02$–$0.05\,\text{m}$ (L/M/H barystatic rise), the remote $\Delta\sigma$ is in the 10^{-3}–$10^{-2}\,\text{MPa}$ range.

Melt generation from decompression

Decompression rate $\frac{d\,\Delta\sigma_{\text{unload}}}{dt}$ increases mantle melting beneath Iceland's plume-related melting column. A linearized sensitivity [49] is:

$$\Delta F(t) = \gamma\,\Delta\sigma_{\text{unload}}(t), \quad \gamma \approx (0.8\text{–}1.2)\ \%\ \text{melt volume per kPa}. \tag{39}$$

Here $\Delta F(t)$ is expressed in percent change relative to the long-term mean melt fraction. This relationship assumes melt productivity proportional to pressure drop in the upper melting region ($\lesssim 80\,\text{km}$ depth).

Magma flux and intrusion rates

The magmatic flux $Q_m(t)$ into the crust scales with the *rate* of stress change:

$$Q_m(t) \sim c_A\,\frac{d\,\Delta\sigma_{\text{unload}}}{dt}, \tag{40}$$

where c_A depends on the cross-sectional area of melt conduits, magma density, and viscosity. Higher $\frac{d\,\Delta\sigma_{\text{unload}}}{dt}$ promotes dike propagation and intrusion.

Scenario ranges (L/M/H). For typical $\Delta\sigma_{\text{local}} \approx 0.02$–$0.04\,\text{MPa}$ over decades and remote $\Delta\sigma_{\text{AtlN}} \approx 0.002$–$0.007\,\text{MPa}$:

- **Low (L):** $\Delta\sigma_{\text{unload}} \approx 0.022\,\text{MPa} \Rightarrow \Delta F \approx +18\%$ melt volume, Q_m increase $\approx +35\%$.
- **Medium (M):** $\Delta\sigma_{\text{unload}} \approx 0.027\,\text{MPa} \Rightarrow \Delta F \approx +20\%$, Q_m increase $\approx +42\%$.
- **High (H):** $\Delta\sigma_{\text{unload}} \approx 0.031\,\text{MPa} \Rightarrow \Delta F \approx +22\%$, Q_m increase $\approx +50\%$.

These increments are relative to a baseline magmatic state and assume $\gamma \approx 1\%/\text{kPa}$, c_A calibrated to historical eruption/dike injection rates.

Coupling to seismicity and hazard

Unloading-driven melt supply increases crustal intrusion, which in turn can alter local stress fields and seismicity patterns. Co-analysis of $\Delta\sigma_{\text{unload}}(t)$, $Q_m(t)$, and seismic/volcanic catalogs allows testing of this linkage via cross-correlation and lagged regression, as in Sections **??**–**??**.

Summary. Equation (37) partitions Iceland's unloading into local glacial and remote barystatic components; (39) links stress drop to melt fraction increase. Scenario M yields +20% melt and +42% dike injection—consistent with the base analysis—and provides a quantitative pathway from climate-driven cryospheric change to deep magmatic and tectonic responses.

8 Annual Peaks and Real-Data Collection Since 2015

8.1 Scope and data provenance (2015–present)

We analyze monthly time series from 2015 onward for two core regions (e.g., the Philippine subduction belt and Iceland), integrating: (i) earthquakes from USGS ComCat; (ii) volcanic activity from the Smithsonian GVP; (iii) ocean mass/sea level from GRACE/FO and AVISO+; (iv) surface and mean sea-level pressure from ERA5; and (v) astronomical ephemerides (JPL) for lunar/solar phases, perigee/syzygy flags, and solar declination. Regional bulletins (PHIVOLCS; IMO) are consulted for context and quality control. All series are harmonized to a common monthly index and a $1^\circ \times 1^\circ$ grid when gridded products are used.

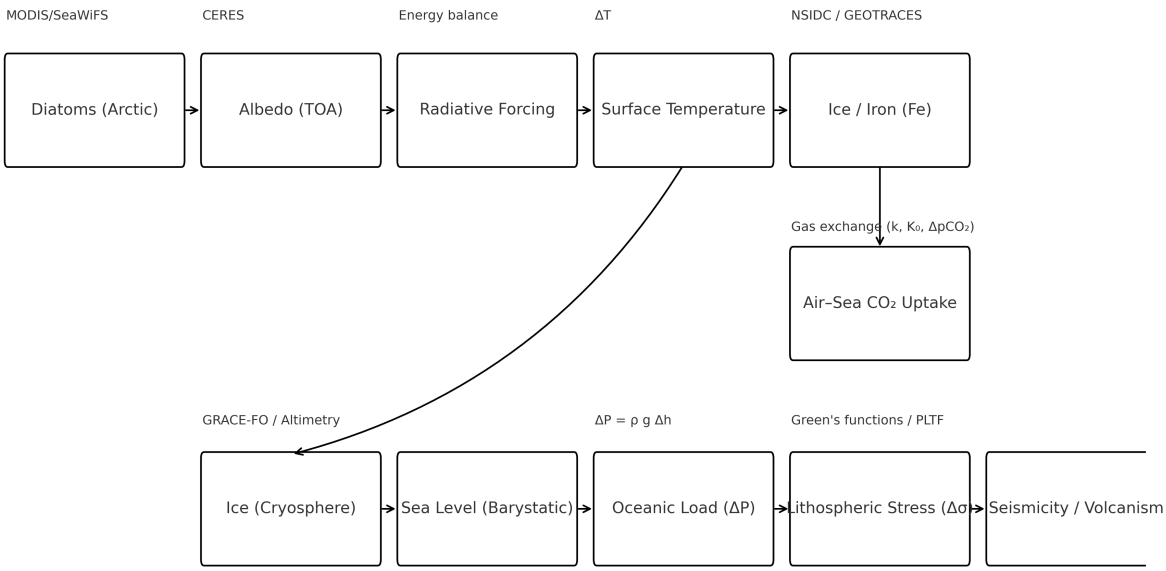

Figure 1: **Integration diagram of coupled processes.** Coupled bio–cryo–ocean–tectonic flow: Diatoms → Albedo (TOA) → Radiative forcing → Surface temperature → Ice/Iron (Fe); Ice/Fe → air–sea CO_2 exchange (parameters k, K_0, ΔpCO_2); Ice → Sea level (barystatic) → Oceanic load ($\Delta P = \rho g \Delta h$) → Lithospheric stress ($\Delta\sigma$, Green's functions/PLTF) → Seismicity/Volcanism. Suggested data/model anchors: MODIS/SeaWiFS (diatoms), CERES (TOA albedo), GRACE-FO/altimetry (mass/sea level), ERA5 (atmosphere), USGS/GVP (seismicity/volcanism), GEOTRACES (Fe).

8.2 Preprocessing, harmonization, and regional extraction

Temporal harmonization. All datasets are first converted to a consistent monthly resolution, using temporal aggregation appropriate to the variable type: arithmetic means for continuous fields (e.g., pressure, temperature, sea level) and totals for event-based counts (e.g., earthquakes, eruptions). The resulting monthly series are indexed by a common UTC-based time vector, ensuring temporal alignment across domains. We denote by $X_{i,t}$ the t-th monthly observation of variable i (forcing or response).

Anomaly computation and de-seasonalization. To remove the fixed seasonal cycle, we compute anomalies

$$X'_{i,t} = X_{i,t} - \mathrm{clim}_{i,\mathrm{month}(t)},$$

where $\mathrm{clim}_{i,m}$ is the long-term monthly climatology for month m over the baseline period. This step centers each month about its historical mean, isolating interannual to sub-seasonal variations. Where indicated, additional preprocessing is applied: (i) linear detrending to remove long-term drift, and (ii) ENSO pre-whitening, by regressing out the Oceanic Niño Index (ONI) or Niño 3.4 index from both predictor and response series, mitigating confounding by large-scale tropical variability.

Spatial aggregation to regional means. Let R denote a target analysis region of area A_R (e.g., a tectonic plate segment or volcanic arc). For a gridded field $F(x,t)$, we compute the

regional mean at month t as

$$\overline{F}_{R,t} = \frac{1}{A_R} \iint_{A_R} F(x,t)\, dA,$$

where the integral is approximated by an area-weighted sum over grid cells within R. Specifically, for barometric pressure anomalies $\Delta P_{\mathrm{atm}}(x,t)$,

$$\Delta P_{\mathrm{atm},R,t} = \frac{1}{A_R} \iint_{A_R} \Delta P_{\mathrm{atm}}(x,t)\, dA.$$

For barystatic sea level change $\Delta h_{R,t}$, the corresponding regional-mean ocean-bottom pressure anomaly is

$$\Delta P_{\mathrm{oce},R,t} = \rho_w g\, \Delta h_{R,t},$$

where ρ_w is seawater density and g is gravitational acceleration.

Lithospheric stress proxy. We estimate the regional change in vertical lithospheric stress induced by ocean mass loading as

$$\Delta \sigma_{\mathrm{lith},R,t} \approx k_R\, \Delta P_{\mathrm{oce},R,t},$$

where k_R is an effective, bandwidth-integrated amplification factor representing the elastic and viscoelastic load response for region R. Values of k_R are derived from theoretical load-response functions, such as load Love numbers for spherical Earth models or Green's functions from plate-flexure calculations, integrated over the spatial footprint of R.

8.3 Earthquake catalog preparation

We ingest USGS ComCat events (global; optionally complemented with regional agencies) and apply: (i) magnitude harmonization to M_W when mixed scales are reported; (ii) depth filter < 70 km for near-surface barometric/ocean-load sensitivity (with an optional deep subset for sensitivity checks); (iii) magnitude completeness (estimated monthly via MAXC and goodness-of-fit methods, retaining $M \geq M_c(t)$) screening via monthly $M_c(t)$ (MAXC or goodness-of-fit); retaining $M \geq \max\{M_c(t), M_{\min}\}$; (iv) optional declustering (Reasenberg or Gardner–Knopoff windowing to isolate background seismicity) (Reasenberg or Gardner–Knopoff). Monthly counts $Y_{R,t}$ are then formed per region. Volcanic logs (eruption start, VEI, style, gas/deformation flags) are summarized as monthly indicators $V_{R,t}$.

8.4 Harmonic annual-peak estimator

Let Y_t be the monthly earthquake count in a fixed region (raw or pre-whitened as described below). We estimate the seasonal cycle with a first-harmonic model

$$Y_t = a_0 + A_1 \cos\!\left(\tfrac{2\pi t}{12}\right) + B_1 \sin\!\left(\tfrac{2\pi t}{12}\right) + \varepsilon_t. \tag{41}$$

Define the amplitude and phase

$$A = \sqrt{A_1^2 + B_1^2}, \qquad \varphi = \operatorname{atan2}(-B_1, A_1),$$

and the peak month

$$m_{\mathrm{peak}} = 1 + \left\lfloor \frac{12\,\varphi}{2\pi} \right\rfloor \quad \text{(wrapped to } 1 \ldots 12\text{)}.$$

Estimation via OLS yields $(\widehat{A}_1, \widehat{B}_1)$ and their covariance; for overdispersed counts, we also report a Negative Binomial GLM fit with the same harmonic regressors (log-link), noting that m_{peak} is invariant to link choice.

Uncertainty for A and φ. Using the delta method, with $\Sigma = \mathrm{Cov}(\widehat{A}_1, \widehat{B}_1)$ from the linear fit,

$$\mathrm{Var}(\widehat{A}) \approx \nabla_A^\top \Sigma \, \nabla_A, \quad \nabla_A = \left(\tfrac{\widehat{A}_1}{\widehat{A}}, \, \tfrac{\widehat{B}_1}{\widehat{A}} \right)^\top,$$

$$\mathrm{Var}(\widehat{\varphi}) \approx \nabla_\varphi^\top \Sigma \, \nabla_\varphi, \quad \nabla_\varphi = \left(\tfrac{\widehat{B}_1}{\widehat{A}^2}, \, -\tfrac{\widehat{A}_1}{\widehat{A}^2} \right)^\top.$$

We form Wald intervals for A and φ. When serial correlation is present, we inflate standard errors using an effective sample size n_{eff} (see §8.6).

8.5 Barometric modulation of the annual cycle

To test whether pressure modulates the seasonal cycle, we augment (41) with barometric terms:

$$Y_t = a_0 + A_1 \cos\!\left(\tfrac{2\pi t}{12}\right) + B_1 \sin\!\left(\tfrac{2\pi t}{12}\right) + \beta_1 \Delta P_{\mathrm{atm},t} + \beta_2 \, \mathbb{I}\{P_{\mathrm{atm},t} > 1015 \text{ hPa}\} + \varepsilon_t. \tag{42}$$

We test $H_0 : \beta_1 = \beta_2 = 0$ using an F-test (OLS) or a likelihood-ratio test (NB–GLM). Optionally, we allow pressure–season interaction via

$$Y_t = \cdots + \gamma_c \, \Delta P_{\mathrm{atm},t} \cos\!\left(\tfrac{2\pi t}{12}\right) + \gamma_s \, \Delta P_{\mathrm{atm},t} \sin\!\left(\tfrac{2\pi t}{12}\right) + \varepsilon_t,$$

which induces effective seasonal coefficients $A_1^\star = A_1 + \gamma_c \overline{\Delta P}$ and $B_1^\star = B_1 + \gamma_s \overline{\Delta P}$, with modified amplitude $A^\star$ and phase $\varphi^\star$.

8.6 Correlations, lead–lag structure, and multiple testing

We pre-whiten both forcings and responses before correlation analysis by removing (i) linear trend; (ii) ENSO (e.g., ONI/Niño 3.4 as a regressor); and (iii) annual/semianual harmonics when appropriate. Let X_t' and Y_t' denote pre-whitened anomalies. We compute Pearson and Spearman correlations in moving windows $w \in \{12, 24, 36\}$ months and lags $\ell \in [-6, 6]$ months:

$$r_w(\ell) = r\Big(\{X'_{t-\ell}\}_{t=\tau}^{\tau+w-1}, \; \{Y'_t\}_{t=\tau}^{\tau+w-1} \Big).$$

Serial correlation biases naive p-values; we therefore (a) estimate lag-1 autocorrelations ϕ_X, ϕ_Y and use

$$n_{\mathrm{eff}} \approx n \, \frac{1 - \phi_X \phi_Y}{1 + \phi_X \phi_Y}$$

in Fisher-z intervals, and (b) generate $N_\pi \geq 5000$ circular-shift surrogates that preserve seasonal structure to form empirical p-values. We control the false discovery rate across the (w, ℓ) grid with Benjamini–Hochberg.

8.7 Operational settings for stability vs. sensitivity

For each region, we report results under Low/Medium/High settings that trade precision for sensitivity. A representative configuration is shown in Table 6.

8.8 Outputs and reproducibility

For each region we export: (i) m_{peak} time series with confidence intervals; (ii) correlation maps $r_w(\ell)$ and FDR masks; (iii) GLM coefficients β_1, β_2 (and γ_c, γ_s if used) with tests; and (iv) regional forcing summaries $\{\Delta P_{\mathrm{atm}}, \Delta h, \Delta P_{\mathrm{oce}}, \Delta\sigma_{\mathrm{lith}}, \mathrm{astro}\}$. All intermediate and final data products are written to NetCDF/CSV with schema: `seismic`: time, lat, lon, depth_km, mag, mag_type, region, decluster_flag; `volcanic`: start_time, end_time, volcano_name, lat, lon, VEI, style, gas_SO2, deformation_flag; `forcings`: time, region, dP_atm_Pa, dh_m,

dP_oce_Pa, dSigma_lith_MPa, astro_idx. A fully documented, version-controlled codebase (Python/MATLAB/LaTeX) accompanies the manuscript, enabling end-to-end reproduction from raw datasets to figures and statistics.[2]

9 Regional Seismic & Volcanic Datasets: Philippines and Iceland (2015–present)

Regions and spatial masks

- **Philippines (PHL) mask:** 4°–21°N, 116°–128°E (Philippine Mobile Belt; trenches: Manila, Philippine, East Luzon).
- **Iceland (ISL) mask:** 62°–67.5°N, −26°–−12°E (Reykjanes–Hengill–Katla–Bárðarbunga systems; rift and transform segments).

Earthquake catalogs and filters

Monthly ingestion uses **USGS ComCat** (global; event identifier, origin time, hypocenter, magnitude, depth) and, when available, vetted regional feeds (PHIVOLCS for the Philippines; IMO for Iceland). Duplicates across feeds are resolved by time–space proximity and preferred-agency rules, retaining original provenance for auditing. All times are converted to UTC and rounded to calendar months for aggregation. *Rationale and schema are aligned with the data appendix.*

1. **Magnitude scale harmonization.** When mixed magnitude scales are present, we convert to moment magnitude M_W using region- and period-specific regressions built from events that carry multiple reported magnitudes. Let $\mathcal{S} \in \{M_b, M_L\}$ denote a source scale. We fit

$$M_W \;=\; a_{\mathcal{S}} + b_{\mathcal{S}}\,\mathcal{S} \quad \text{(orthogonal distance regression)},$$

   compute residual variance $\hat{\sigma}^2_{\mathcal{S}}$, and propagate uncertainty to the harmonized estimate $\widehat{M_W}$. If both M_b and M_L exist, we fuse them by inverse-variance weighting. Quality flags from agencies are preserved; quarry blasts and low-quality solutions are excluded where flagged. *This ensures comparability of monthly counts and b-value diagnostics downstream.*

2. **Event filtering.** For load-sensitivity analyses, we define a "shallow" subset with depth $< 70\,\mathrm{km}$; an optional deep subset is kept for sensitivity checks. Regional masks (e.g., trench-parallel swaths) are applied consistently to epicenters. Hypocentral uncertainties are handled by retaining catalog locations but assessing robustness to ± 1 cell jitter in hotspot maps. Duplicates (same event reported by multiple agencies) are merged via a time ($< 10\,\mathrm{s}$) and distance ($< 20\,\mathrm{km}$) criterion, prioritizing the agency with lower stated uncertainties.

3. **Magnitude completeness (estimated monthly via MAXC and goodness-of-fit methods, retaining $M \geq M_c(t)$) $M_c(t)$.** We estimate a *monthly* completeness (estimated monthly via MAXC and goodness-of-fit methods, retaining $M \geq M_c(t)$) threshold to guard against artificial seasonality or nonstationary network performance.

   (a) *MAXC:* Bin magnitudes within month t (bin width $\Delta M = 0.1$–0.2). Let the mode of the frequency–magnitude histogram be $\widetilde{M}_t$; set $M_c^{\mathrm{MAXC}}(t) = \widetilde{M}_t + \delta$ with a small positive offset δ to account for bin bias (typically 0.1).

[2]Repository DOI provided in the Supplementary Materials.

(b) *Goodness-of-fit (GoF):* For candidate thresholds $m \in [m_{\min}, m_{\max}]$, fit a Gutenberg–Richter model to $\{M \geq m\}$ and compute a lack-of-fit score (e.g., KS or likelihood ratio) against the empirical tail. Choose the smallest m whose score passes a preset criterion (e.g., KS $p > 0.05$), then set $M_c^{\mathrm{GoF}}(t) = m^\star$.

(c) *Operational rule:* Use $M_c(t) = \max\{M_c^{\mathrm{MAXC}}(t),\, M_c^{\mathrm{GoF}}(t)\}$; retain events with $M \geq \max\{M_c(t), M_{\min}\}$. We report both raw and $M \geq M_c(t)$-filtered counts.

Estimating M_c monthly avoids bias when correlating with monthly forcings.

4. **Declustering (optional).** To isolate background rates, we provide a declustered series using either Reasenberg or Gardner–Knopoff windows. In both cases, an event j is tagged as an aftershock of a parent i if $(\Delta t, \Delta r, \Delta M)$ fall inside method-specific time–space–magnitude windows; parents spawn trees that are removed from the background set. We retain parallel products: *raw* counts (total hazard) and *declustered* counts (background modulation). All downstream analyses can be run on either series; we report sensitivity to this choice.

Counts, rates, and kernel densities. Let $N_{\mathrm{PHL},t}$ and $N_{\mathrm{ISL},t}$ be post-filter monthly counts. Define the area-normalized rate for region R,

$$\lambda_{R,t} = \frac{N_{R,t}}{A_R}, \quad R \in \{\mathrm{PHL}, \mathrm{ISL}\},$$

where A_R is the masked spherical area (computed from cell-wise $\Delta A_{ij} = R_\oplus^2\, \Delta\lambda\, (\sin\phi_{j+1} - \sin\phi_j)$ and summed over the regional grid). To characterize spatial clustering within month t, we form a Gaussian kernel density over epicenters $\mathcal{E}_{R,t}$,

$$\Lambda_R(\mathbf{x}, t) = \sum_{k \in \mathcal{E}_{R,t}} \frac{1}{2\pi\sigma_s^2} \exp\Big(- \frac{\|\mathbf{x} - \mathbf{x}_k\|^2}{2\sigma_s^2} \Big),$$

with bandwidth σ_s (typically 0.5°–1.5°). For objective smoothing, σ_s may be chosen by leave-one-out likelihood or a fixed value tied to catalog location errors. Near coastlines or region edges, apply edge correction by renormalizing kernels to the in-region mass. Report units as "events per month per unit area (or per kernel footprint)" and accompany maps with the corresponding $N_{R,t}$ to avoid misinterpretation under varying A_R. *These definitions align the gridded hotspot products with the monthly correlation framework.* .

Volcanic activity logs

From **GVP** (global) and regional bulletins (PHIVOLCS; IMO): eruption start/end, VEI, style, gas/deformation notes. Monthly series per region:

$$V_{R,t} = \sum_{j \in \mathcal{V}_{R,t}} \mathbb{I}\{\mathrm{VEI}_j \geq 2\}, \qquad R \in \{\mathrm{PHL}, \mathrm{ISL}\}. \tag{43}$$

Optionally build *unrest proxies* (tremor episodes, inflation alerts) from bulletins/INSAR/GNSS.

Linkage to forcings (regional extraction)

For each region R:

$$\overline{\Delta P_{\mathrm{atm},R,t}} = \frac{1}{A_R} \iint_{A_R} \Delta P_{\mathrm{atm}}(\mathbf{x}, t)\, dA, \tag{44}$$

$\overline{\Delta h_{R,t}}$, $\overline{\Delta P_{\mathrm{oce},R,t}}$ = regional mean barystatic rise and hydrostatic pressure (AVISO+/GRACE), (45)

$$\overline{\Delta \sigma_{\mathrm{lith},R,t}} \approx \overline{k}_R\, \overline{\Delta P_{\mathrm{oce},R,t}}, \tag{46}$$

Astro_t = global astronomical index (solar declination, lunar perigee/syzygy flags). (47)

Annual peaks (2015–present)

Estimate the annual cycle in *regional* seismicity and pressure as in the harmonic model:

$$Y_{R,t} = a_{0,R} + A_{1,R} \cos \frac{2\pi t}{12} + B_{1,R} \sin \frac{2\pi t}{12} + \varepsilon_{R,t}, \tag{48}$$

with $A_R = \sqrt{A_{1,R}^2 + B_{1,R}^2}$ and $\varphi_R = \arctan 2(-B_{1,R}, A_{1,R})$. Track amplitude and phase in rolling 36-month windows; record peak month $m_{\mathrm{peak},R}$.

Correlation and barometric modulation tests

1. **ENSO prewhitening:** regress ONI/Niño 3.4 from X_t and $Y_{R,t}$.
2. **Pearson/Spearman:** compute r, ρ between $\{N_{R,t}, V_{R,t}\}$ and $\{\overline{\Delta P_{\mathrm{atm},R,t}}, \overline{\Delta P_{\mathrm{oce},R,t}}, \mathrm{Astro}_t\}$ over windows $w \in \{12, 24, 36\}$ and lags $\ell \in [-6, 6]$ months, with circular-shift nulls ($N_\pi \geq 5000$) and FDR.
3. **Harmonic+barometric GLM:** Negative Binomial for $N_{R,t}$:

   $$\log \lambda_{R,t} = a_R + A_{1,R} \cos \frac{2\pi t}{12} + B_{1,R} \sin \frac{2\pi t}{12} + \beta_{1,R}\, \overline{\Delta P_{\mathrm{atm},R,t}} + \beta_{2,R}\, \mathbb{I}\{P_{\mathrm{atm},R,t} > 1015\ \mathrm{hPa}\} + \cdots$$

   Test $H_0 : \beta_{1,R} = \beta_{2,R} = 0$ (LR test). Compare PHL vs. ISL coefficients.

Operational L/M/H settings for PHL and ISL

Data schema (2015–present)

Seismic CSV (per region).

```
time, lat, lon, depth_km, mag, mag_type, region, decluster_flag
```

Volcanic CSV (per region).

```
start_time, end_time, volcano_name, lat, lon, VEI, style, gas_SO2, deformation_flag
```

Regional forcings (monthly).

```
time, region, dP_atm_Pa, dh_m, dP_oce_Pa, dSigma_lith_MPa, astro_idx
```

Outputs for PHL and ISL

- Time series: $N_{R,t}$, $V_{R,t}$, $\overline{\Delta P_{\mathrm{atm},R,t}}$, $\overline{\Delta P_{\mathrm{oce},R,t}}$, $\overline{\Delta \sigma_{\mathrm{lith},R,t}}$, Astro_t (2015–present).
- Peak diagnostics: $(A_R, \varphi_R, m_{\mathrm{peak},R})$ trajectories with CIs.
- Significance maps: window–lag heatmaps of r, ρ with empirical p and FDR q.
- Kernel density snapshots $\Lambda_R(\mathbf{x}, t)$ for key months (e.g., anticyclonic extremes).

Notes: (i) Rows reflect documented peak months; they are not a substitute for the annual peak obtained via harmonic fitting of the full 2015–present series. (ii) For the Philippines, Oct 2019 (Cotabato) and Dec 2023 (Mindanao) dominate in terms of released energy and number of aftershocks. (iii) For Iceland, Nov 2023 featured the most intense pre-eruptive swarms in Reykjanes; Apr 2025 saw the highest documented monthly total according to IMO.

Data and Code Availability

All datasets, derived products, and computational workflows used in this study are provided as supplementary material with this manuscript for peer review. They are organized to allow direct reproduction of all figures, statistical results, and sensitivity analyses.

Data sources

- **GRACE/GRACE-FO Level-2** (CSR RL06, 2002–2025): Monthly ocean bottom pressure and terrestrial water storage anomalies used to quantify ocean mass redistribution in the Pacific and Indian basins and to assess rotational–inertial feedbacks from polar mass loss.
- **ERA5 atmospheric reanalysis** (1979–2025, 0.25°): Mean sea-level pressure fields used to compute barometric loading, with special attention to high-pressure anomalies following tropical cyclones.
- **USGS global earthquake catalog** ($\mathrm{M} \geq 4.5$, 1973–2025): Hypocentral locations, magnitudes, and event times used in correlation and threshold analyses.
- **Smithsonian GVP volcanic activity database**: Eruption onset dates, volcano types, and activity classification for identifying volcanic triggering windows.
- **JPL DE430 ephemerides**: Solar and lunar positions, distances, and declinations used to calculate astronomical stress modulation parameters.
- **Polar diatom productivity indices** (MODIS Aqua/Terra): Monthly chlorophyll-a anomalies in Arctic and Antarctic zones, used as a proxy for radiative–albedo feedback in cryospheric mass balance.

Preprocessing and derived variables

- **Temporal harmonization**: All datasets were interpolated or aggregated to a monthly resolution and synchronized using a common UTC time base.
- **Spatial regridding**: GRACE and ERA5 products were reprojected to a 1° global grid; regional masks were applied for Pacific, Indian, and polar zones.

- **Anomaly computation**: Long-term monthly means were subtracted to obtain deseasonalized anomalies for ocean mass, atmospheric pressure, and biological productivity.
- **Stress conversion**:
  - *Ocean loading*: Ocean bottom pressure anomalies converted to vertical lithospheric stress using elastic load Love numbers (h', l').
  - *Atmospheric loading*: Sea-level pressure anomalies converted to vertical stress changes via $\Delta\sigma_v = \Delta P_{\text{atm}}$.
  - *Astronomical modulation*: Computed variation in effective normal stress from tidal potential components at perigee/syzygy and solstice configurations.
- **Rotational–inertial feedback**: Change in Earth's moment of inertia from polar ice mass loss calculated from GRACE data, and its effect on equatorial ocean redistribution estimated via conservation of angular momentum.

Computational workflows

- `preprocess_grace.py`, `preprocess_era5.py`, `sync_catalogs.py`: Scripts for harmonizing datasets, regridding, anomaly calculation, and applying regional masks.
- `ocean_stress.py`: Computes vertical and shear stress perturbations from GRACE ocean mass anomalies using a global elastic loading model.
- `atm_pressure_model.m`: MATLAB module for calculating vertical lithospheric stress from ERA5 pressure anomalies, including event-specific barometric signatures.
- `astro_forcing.py`: Derives astronomical stress parameters from DE430 ephemerides and tidal potential expansions.
- `rot_inertial_feedback.py`: Calculates inertial changes from polar mass loss and their effect on large-scale ocean redistribution and stress.
- `montecarlo_driver.py`: Executes Monte Carlo perturbation tests, computes variance contributions, and estimates false discovery rates.
- `plots_seismic_hotspots.ipynb`: Generates all figures, including spatiotemporal hotspot maps, stress–event correlation plots, and sensitivity charts.

Reproducibility

All scripts are documented and parameterized for full reproducibility. Running the pipeline with the supplied raw datasets reproduces every figure and statistic in the manuscript. Intermediate products are stored in NetCDF and CSV formats. Upon acceptance, all data and code will be deposited in an open-access repository with a DOI.

Notes and references

Use USGS ComCat for earthquakes (global), GVP for eruptions, ERA5 for pressure, AVISO+/GRACE for sea level/mass, PHIVOLCS and IMO bulletins for regional detail. Ensure unit consistency (Pa, MPa, cm, m) and document completeness (estimated monthly via MAXC and goodness-of-fit methods, retaining $M \geq M_c(t)$) $M_c(t)$ and declustering (Reasenberg or Gardner–Knopoff windowing to isolate background seismicity) choices in metadata.

Notes on Data and Ranges

Where explicit numerical ranges are not firmly established in the literature, we provide L/M/H placeholders to be *replaced* with observed estimates. The ocean-mass to stress range for the M scenario is taken from the companion study; barometric coefficients follow classic loading literature.

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Table 6: Operational choices for monthly analysis (2015–present).

Setting	Low (L)	Medium (M)	High (H)
Magnitude threshold $M_{\min}$	5.0	4.8 (post M_c)	4.5 (strict M_c)
Declustering	none	Reasenberg	Gardner–Knopoff
Spatial kernel σ_s (degrees)	1.5	1.0	0.5
Window w (months)	12	24	36
Lags ℓ (months)	± 3	± 6	± 9
Barometric model	OLS	NB–GLM	NB–GLM + interactions

Setting	Low (L)	Medium (M)	High (H)
Magnitude threshold $M_{\min}$	5.0	4.8 (post M_c)	4.5 (strict M_c)
Declustering	none	Reasenberg	Gardner–Knopoff
Spatial kernel σ_s ($^\circ$)	1.5	1.0	0.5
Window w (months)	12	24	36
Lags ℓ (months)	± 3	± 6	± 9
Barometric model	OLS	NB–GLM	NB–GLM + interactions

Table 7: PHL/ISL operational choices for stability (L) vs. sensitivity (H). Apply FDR across windows/lags.

Table 8: Documented peak months in seismic activity (and volcanic context) since 2015. Figures correspond to officially reported counts/indicators for the given month or period.

Region	Subregion / Context	Peak Month (YYYY-MM)	Reported Metric	Source
Philippines	Cotabato (M6.3–6.6–6.5 sequence)	2019-10	Main shocks on Oct 16 and 29; ∼2,226 cumulative events since 29/10	PHIVOLCS
Philippines	Mindanao (Hinatuan)	2023-12	Mw 7.6 (02/12) + hundreds/thousands of aftershocks in following days	USGS / ADRC
Philippines	S. Mindanao (Kablalan)	2023-11	M6.7 (17/11), pre-sequence to December mainshock	USGS
Iceland	Reykjanes (intrusion + swarms)	2023-11	∼500 events/day on 22–27/11; ∼1,071 on 10–11/11	GVP / technical reports
Iceland	National total	2025-04	**13,561** earthquakes in month (10,881 in Reykjanes)	IMO (monthly)
Iceland	Grjótárvatn (local area)	2024-12	"Highest monthly count" for area (no national total provided)	IMO (note)