NeurIPS 2022 Workshop Tackling Climate Change with Machine Learning

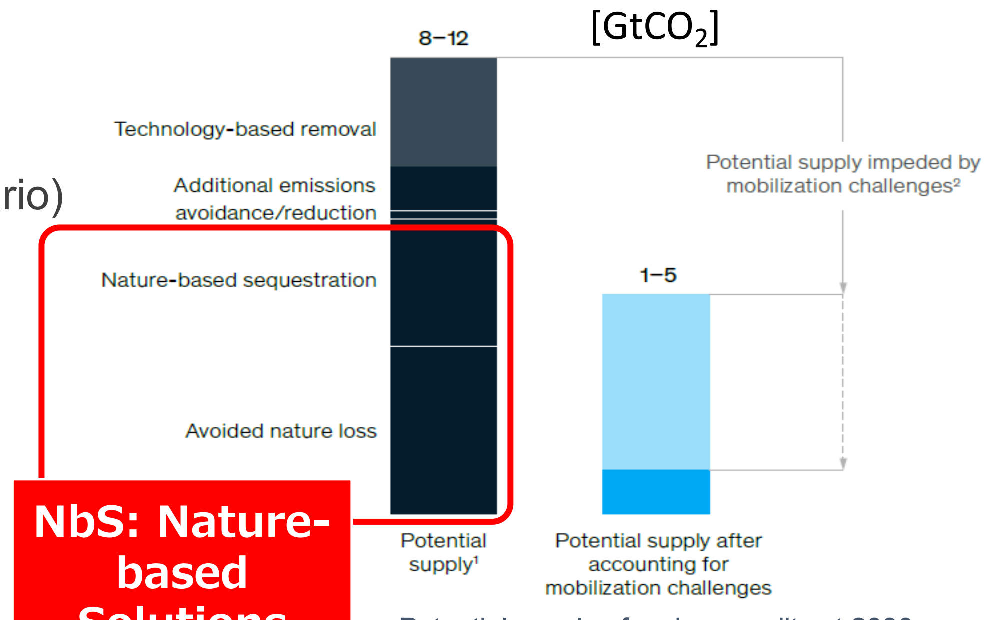
Bayesian State-Space SCM for Deforestation Baseline Estimation for Forest Carbon Credit

Keisuke Takahata*, Hiroshi Suetsugu*, Keiichi Fukaya**, Shinichiro Shirota***

* sustainacraft, Inc., Tokyo, Japan.
** National Institute for Environmental Studies, Ibaraki, Japan.
*** Center for the Promotion of Social Data Science Education and Research, Hitotsubashi University, Tokyo.

Background

- Carbon credit
  - an incentive scheme to promote projects that have additional benefits for climate change mitigation
  - expected to play an important role in offsetting the gap from net zero emission after reduction efforts
- Nature-based solutions (NbS) are important
  - GHG emission reduction from NbS will be the primal source of carbon credits supply.
- Credit calculation = Causal inference problem
  - # of credits =
    f(carbon stock in project scenario – carbon stock in baseline scenario)
  - Baseline scenario is sometime controversial



Potential supply of carbon credits at 2030

source : McKinsey & Co. " A blueprint for scaling voluntary carbon markets to meet the climate challenge" (2020)

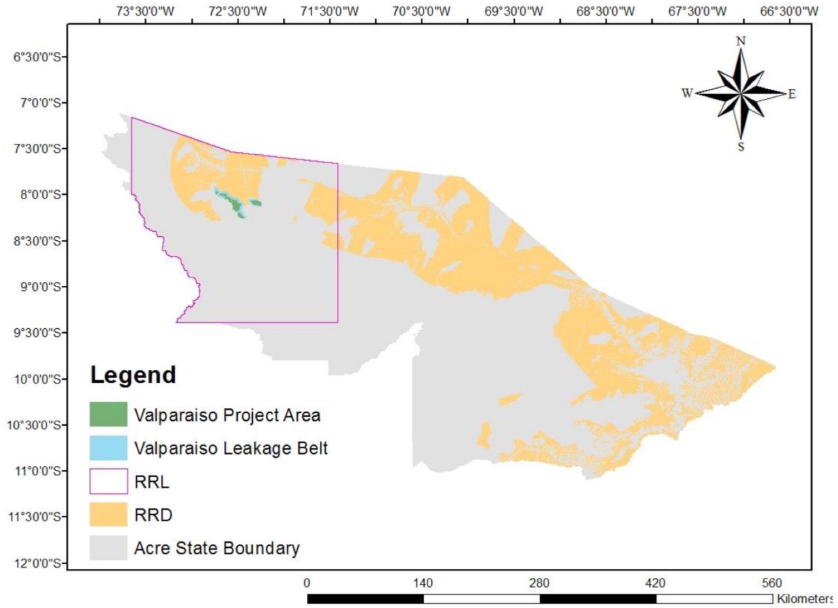
VM0007: A REDD+ methodology for emission reduction evaluation

PA:	Project Area
RRD:	Reference Region for projecting rate of Deforestation

- Reference region (RRD) is selected based on:
  - deforestation agents, landscape factors, socio-economic variables, etc.
- Baseline calculation: simple projection, with adjustment by spatial mapping (optional)
  - projection approaches: 1) historical average, 2) linear/non-linear model

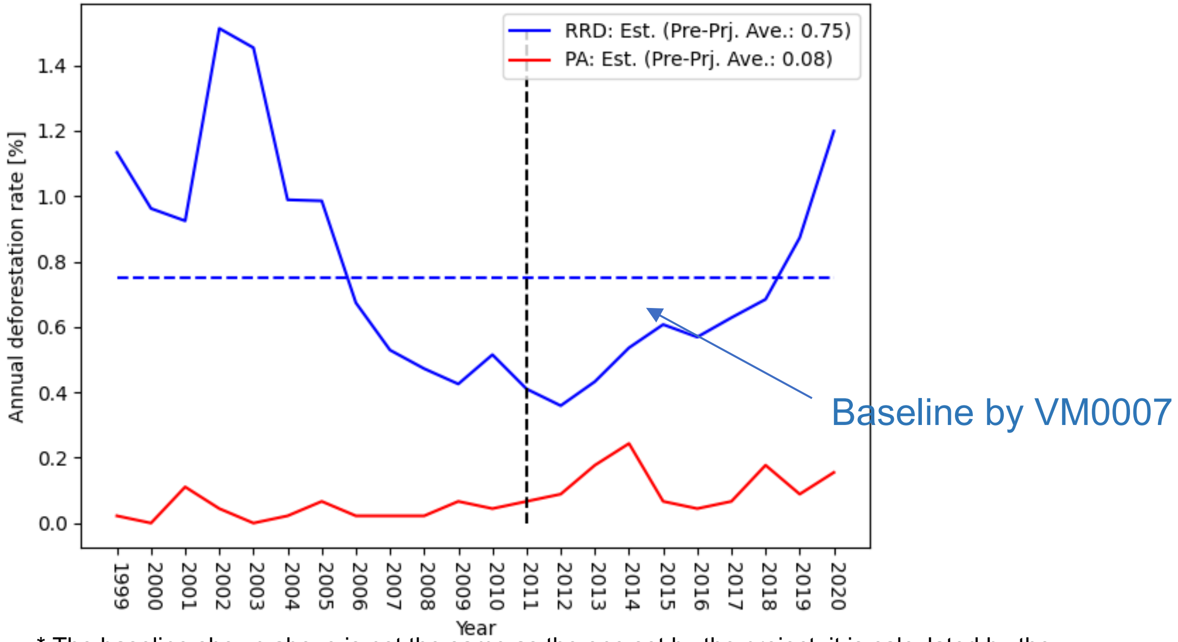
    pre-specified functional form and requirements on the fitting performance for 2)

PA and RRD



source: The Valparaiso project PDD

Annual deforestation rates



* The baseline shown above is not the same as the one set by the project; it is calculated by the authors for this research.

Issues on Carbon Credit

- Junk carbon credit
  - Unreasonable baseline setting (Bento et al, 2016; Haya et al., 2020)
  - Can’t account for external change (e.g. policy change on forest conservation)
    → The use of Synthetic Control Method (Roopsind et al., 2019; Correa et al., 2020; West et al., 2020)

- Early finance problems
  - Result-based payment => Projected Carbon Units (Verra, 2022)
  - Inaccurate projection due to too simplified methods; no uncertainty information

- No integrated methods that would solve both issues at the same time
  - In SCM-based approach baseline estimation will be available after a project starts
    → Early finance problems remain

Our approach: Bayesian State-Space SCM

- A fully Bayesian modeling for both ex-ante forecasting and ex-post evaluation
  - Ex-ante forecasting: State-space modeling
  - Ex-post evaluation: SCM (Abadie et al., 2010), CausalImpact (Brodersen et al, 2015)

- Our ex-ante/ex-post estimation can be improved in an integrated manner as a project proceeds

- Uncertainty evaluations can be done based on posteriors

Formulation

- State-space model for annual deforestation rates
  - $y_{1,t}$ (scalar) and z_t (vector): annual deforestation rates of PA and RRDs
  - $\tilde{z}_t$ (vector): latent state vector for z_t
  - β: weight applied to RRDs to get synthetic controls (i.e. baseline)

$$\begin{bmatrix} y_{1,t} \\ z_t \end{bmatrix} = \begin{bmatrix} \beta' \\ I \end{bmatrix} \tilde{z}_t + \epsilon_t, \quad \epsilon_t \sim N(0, Q_t),$$
$$\tilde{z}_{t+1} = \tilde{z}_t + v_t + \eta_t, \quad \eta_t \sim N(0, R_t),$$
$$v_{t+1} = v_t + \xi_t, \quad \xi_t \sim N(0, S_t),$$

- Covariate-dependent prior for covariate matching
  - Use the idea of general Bayesian updating (Bissiri et al., 2016)

$$p(\beta \mid \{x_j\}_{j=1}^{J+1}) \propto \exp(-wL(\beta; \{x_j\}_{j=1}^{J+1}))p(\beta)$$

  - Loss function: SCM-type quadratic loss

$$L(\beta; \{x_j\}_{j=1}^{J+1}) = 1/(2J) \cdot (x_1 - X_0\beta)'V(x_1 - X_0\beta)$$

Formulation

- State-space model for annual deforestation rates
  - $y_{1,t}$ (scalar) and z_t (vector): annual deforestation rate of PA and RRDs
  - $\tilde{z}_t$ (vector): latent state vector for z_t
  - β: weight applied to RRDs to get the synthetic control (i.e. baseline)

$$\boxed{\begin{bmatrix} y_{1,t} \\ z_t \end{bmatrix} = \begin{bmatrix} \beta' \\ I \end{bmatrix} \tilde{z}_t + \epsilon_t, \quad \epsilon_t \sim N(0, Q_t),}$$

Observation equation: Relates to SCM (Brodersen et al., 2015; Abadie et al., 2010)

$$\boxed{\begin{aligned} \tilde{z}_{t+1} &= \tilde{z}_t + v_t + \eta_t, \quad \eta_t \sim N(0, R_t), \\ v_{t+1} &= v_t + \xi_t, \quad \xi_t \sim N(0, S_t), \end{aligned}}$$

Transition equation: Local linear trend model for predicting the deforestation rates of RRDs

- Covariate-dependent prior to account for covariate matching
  - Use the idea of general Bayesian updating (Bissiri et al., 2016)

$$p(\beta \mid \{x_j\}_{j=1}^{J+1}) \propto \exp(-wL(\beta; \{x_j\}_{j=1}^{J+1}))p(\beta)$$

  - Loss function: SCM-type quadratic loss

$$L(\beta; \{x_j\}_{j=1}^{J+1}) = 1/(2J) \cdot (x_1 - X_0\beta)'V(x_1 - X_0\beta)$$

Posterior distribution and baseline updating

- The full posterior distribution of the weight β and other parameters
  - The inference of β is based on the data before a project starts $(1 \leq \mathrm{t} \leq \mathrm{T}_0)$

$$p(\beta, \{u_t\}_{t=1}^{T_0}, \{\Sigma_t\}_{t=1}^{T_0} \mid \{z_t\}_{t=1}^{T_0}, \{y_{1,t}\}_{t=1}^{T_0}, \{x_j\}_{j=1}^{J+1}, w)$$
$$\propto \prod_{t=1}^{T_0} f(y_{1,t}, z_t, u_t \mid u_{t-1}, \beta, \Sigma_t) \cdot \exp(-wL(\beta; \{x_j\}_{j=1}^{J+1}))p(\beta)p(u_0)p(\{\Sigma_t\}_{t=1}^{T_0})$$

- When the project proceeds to $\mathrm{t} = \mathrm{T}_1\ (\geq T_0)$, the ex-ante baseline prediction $(\mathrm{T}_1 < t \leq T_2)$ can be updated as the following posterior predictive distribution:

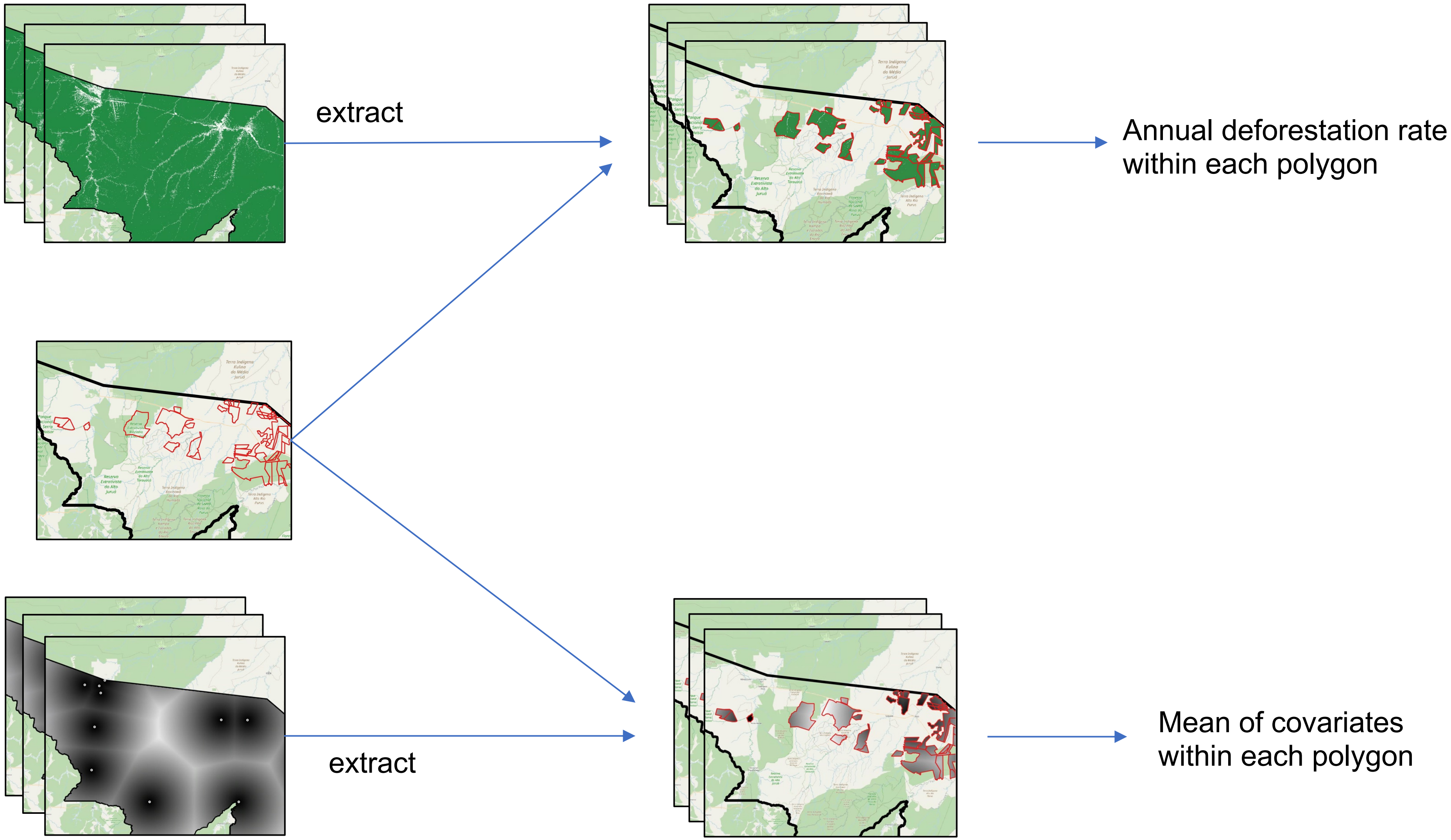
$$p(\{y_{1,t}^{\mathrm{bsl}}\}_{t=T_0+1}^{T_2} \mid \{z_t\}_{t=1}^{T_1}, \{y_{1,t}\}_{t=1}^{T_1}, \{x_j\}_{j=1}^{J+1}, w) = \int \prod_{t=T_0+1}^{T_2} f(y_{1,t}^{\mathrm{bsl}}, z_t, u_t \mid u_{t-1}, \beta, \Sigma_t)$$
$$\cdot\, p(\beta, \{u_t\}_{t=1}^{T_0}, \{\Sigma_t\}_{t=1}^{T_0} \mid \{z_t\}_{t=1}^{T_0}, \{y_{1,t}\}_{t=1}^{T_0}, \{x_j\}_{j=1}^{J+1}, w) \cdot d\beta \cdot \prod_{t=1}^{T_2} \Sigma_t \cdot \prod_{t=1}^{T_2} du_t \cdot \prod_{t=T_1+1}^{T_2} dz_t$$

Data

<u>Forest map</u>
MapBiomas

<u>Forest polygon data</u>
Project boundary
CAR (Brazil) for RRD

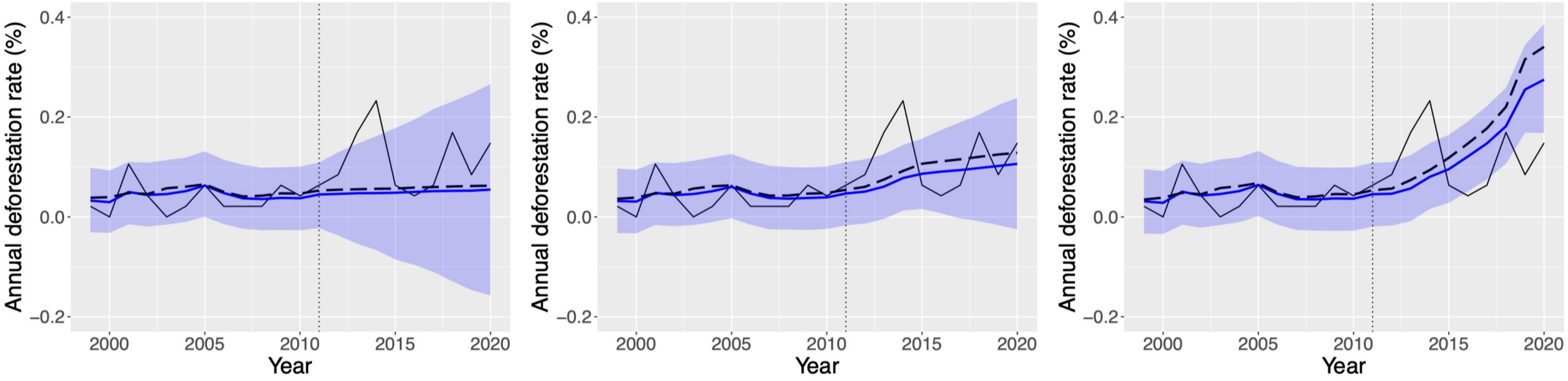
<u>Covariate data</u>
- Distance to road
- Distance to urban centers
- Elevation
- Slope



*Followed West et al. (2020) for data preprocessing

Result

- The 90% interval of the ex-ante baseline includes the posterior mean of the ex-post baseline at least up to three years forward => ex-ante prediction worked to some extent.
- The baseline according to VM0007 (0.75%) could have been overestimated, but the project may have had a small positive effect, especially after 2015
  - Cf.) There is an upward trend of deforestation rate in Brazil since 2012



(a) Pre-intervention ($T_1 = 2010$) **(b)** 5 years after intervention ($T_1 = 2015$) **(c)** 9 years after intervention ($T_1 = 2019$)

Blue solid line (—): the posterior mean of the estimated baseline **with** covariate balancing
Black dashed line (--): the posterior mean of the estimated baseline **without** covariate balancing

Discussions and Future work

- Need to include some covariates as a time-series
  - e.g. road network development is often considered to be an important deforestation driver

- Counterfactual simulations using pixel-level spatial modeling can be necessary.
  - The progress of deforestation surface is important
  - Forest district polygon may not make sense/exist

References

Alberto Abadie, Alexis Diamond, and Jens Hainmueller. Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. Journal of the American Statistical Association, 105(490):493–505, 2010.

Antonio Bento, Ravi Kanbur, and Benjamin Leard. On the importance of baseline setting in carbon offsets markets. Climatic Change, 137(3-4):625–637, 2016.

Kay H. Brodersen, Fabian Gallusser, Jim Koehler, Nicolas Remy, and Steven L. Scott. Inferring causal impact using Bayesian structural time-series models. The Annals of Applied Statistics, 9(1):247–274, 2015.

Juliano Correa, Elías Cisneros, Jan Börner, Alexander Pfaff, Marcelo Costa, and Raoni Rajão. Evaluating REDD+ at subnational level: Amazon fund impacts in Alta Floresta, Brazil. Forest Policy and Economics, 116:102178, 2020.

Barbara Haya, Danny Cullenward, Aaron L. Strong, Emily Grubert, Robert Heilmayr, Deborah A. Sivas, and Michael Wara. Managing uncertainty in carbon offsets: insights from California's standardized approach. Climate Policy, 20(9):1–15, 2020.

Anand Roopsind, Brent Sohngen, and Jodi Brandt. Evidence that a national REDD+ program reduces tree cover loss and carbon emissions in a high forest cover, low deforestation country. Proceedings of the National Academy of Sciences, 116(49):24492–24499, 2019.

Valparaiso Project. https://registry.verra.org/app/projectDetail/VCS/1113.

Verra. Public Consultation: Projected Carbon Units. https://verra.org/public-consultation-projected-carbon-units/, 3 May 2022.

Verra. VM0007 REDD+ Methodology Framework. https://verra.org/methodology/vm0007-redd-methodology-framework-redd-mf-v1-6/.

Thales A. P. West, Jan Börner, Erin O. Sills, and Andreas Kontoleon. Overstated carbon emission reductions from voluntary REDD+ projects in the Brazilian Amazon. Proceedings of the National Academy of Sciences, 117(39):24188–24194, 2020.