Defining and Analyzing Temporal Stationarity in Roraima, Brazil

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Defining Temporal Stationarity

References: Stationarity in time series analysis | by Shay Palachy | Towards Data Science
Detecting stationarity in time series data I by Shay Palachy I Towards Data Science

Temporal Stationarity is when the statistical properties of the metrics of difference describing a time series do not change over time.

Typically **variance** and **covariance** are used to determine whether something is stationary or nonstationary in a time series. Here, we are interested in the fluctuation of metrics of difference above/below the gain/loss line, and we develop new metrics to assess stationarity.

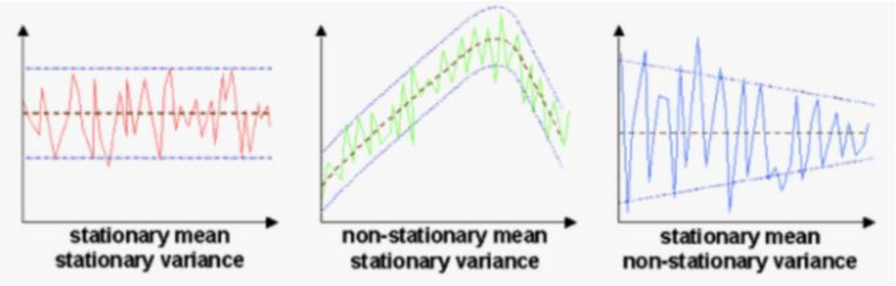
If a bar is above the gain line or below the loss line, then the change is **fast**. If a bar is below the gain line or above the loss line, then the change is **slow**.

Once a process is identified as **stationary**, literature in other fields use the behavior of variance in the data as independent variable changes to further define the process.

Types of Stationarity

<u>Strong stationarity</u> assumes no distributive properties in the data, only that the probability distribution should be the same through time.

<u>Weak stationarity</u> is when the mean and covariance do not vary through time.

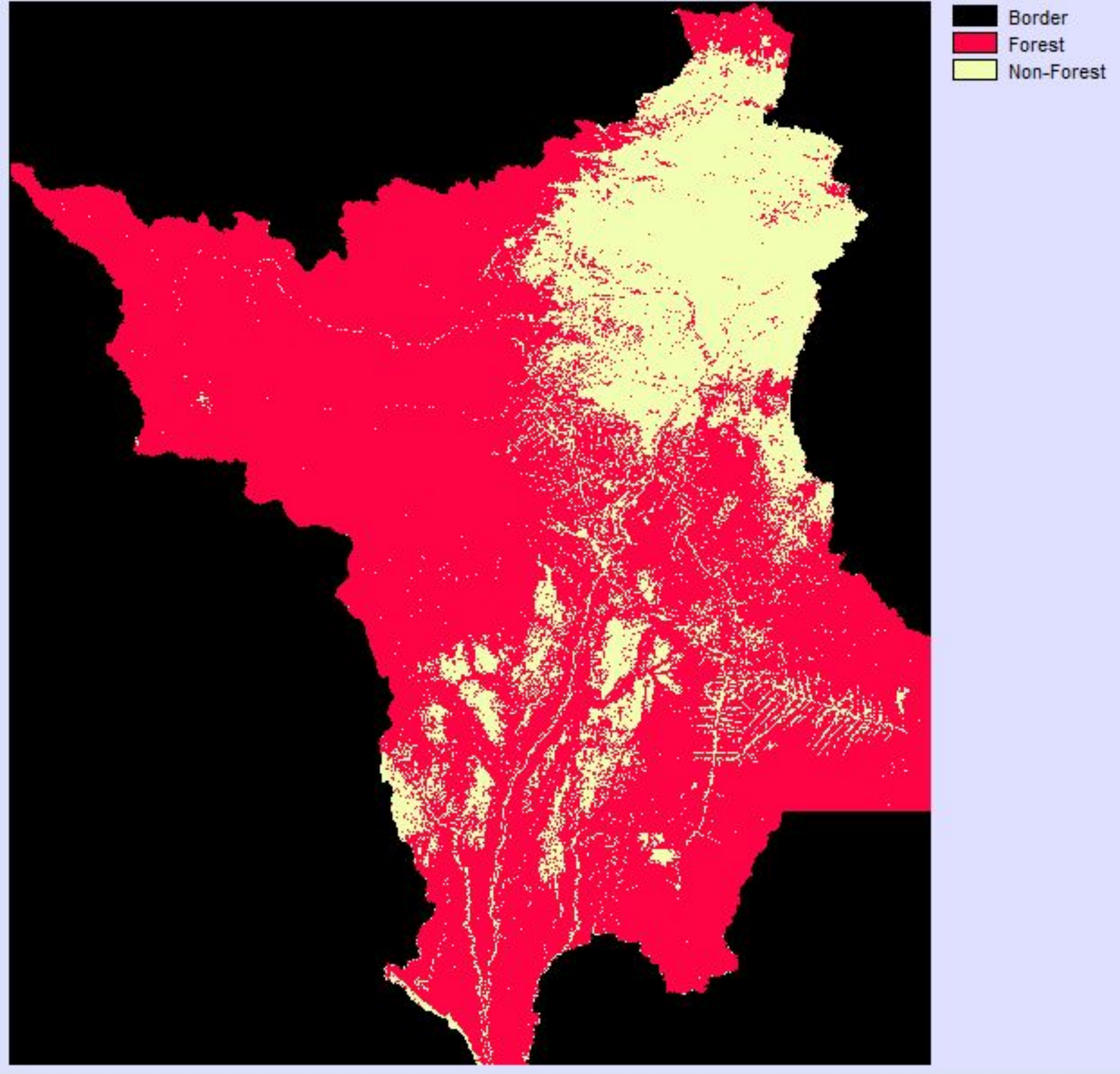


Methods Update

Issue: Uniform gross line defines slow and fast uniformly throughout the time interval, whereas time-specific definitions of slow and fast could provide new insights.

We have narrowed our project down to **comparing two approaches:**

1. Gain Line / Loss Line subsetting
2. Moving Window Gain / Loss Line



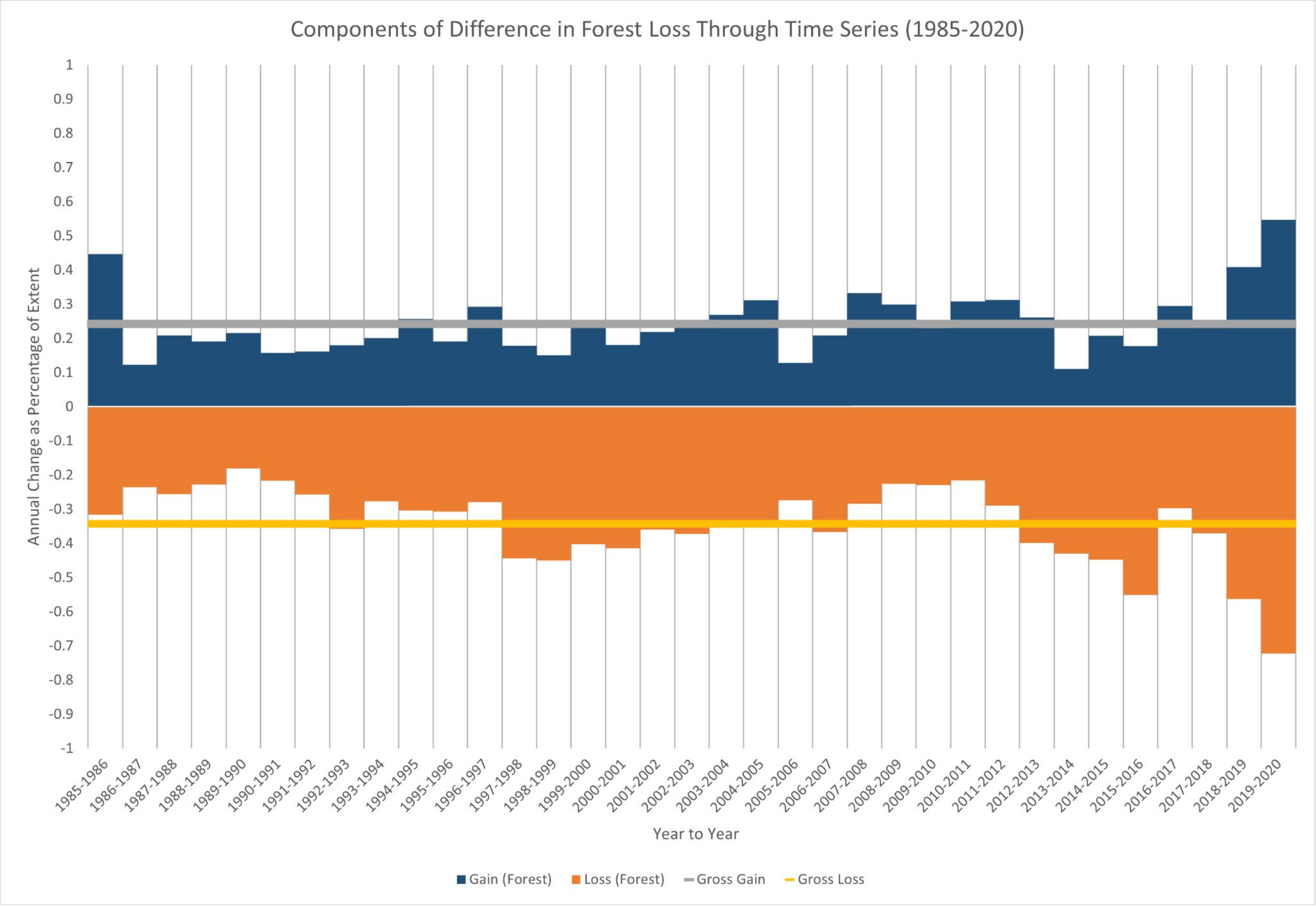
Data Formatting

1. Retrieved all data from MapBiomas GEE portal.
2. Clipped data to Roraima State political boundary.
3. Reclassed all 36 time points (1985-2020) to Forest and Non-Forest categories.
4. Computed Crosstabs at 1 year, 5, year, 7 year, and 35 year temporal resolution to record Persistence, Loss, and Gains.
5. Produced graphics that represent the different temporal resolutions and gross line methods.
6. The extent of the data is 86,350 mi^2, or 250,331,408 pixels, so .1% of the extent is equal to 250,331 pixels.

Equations

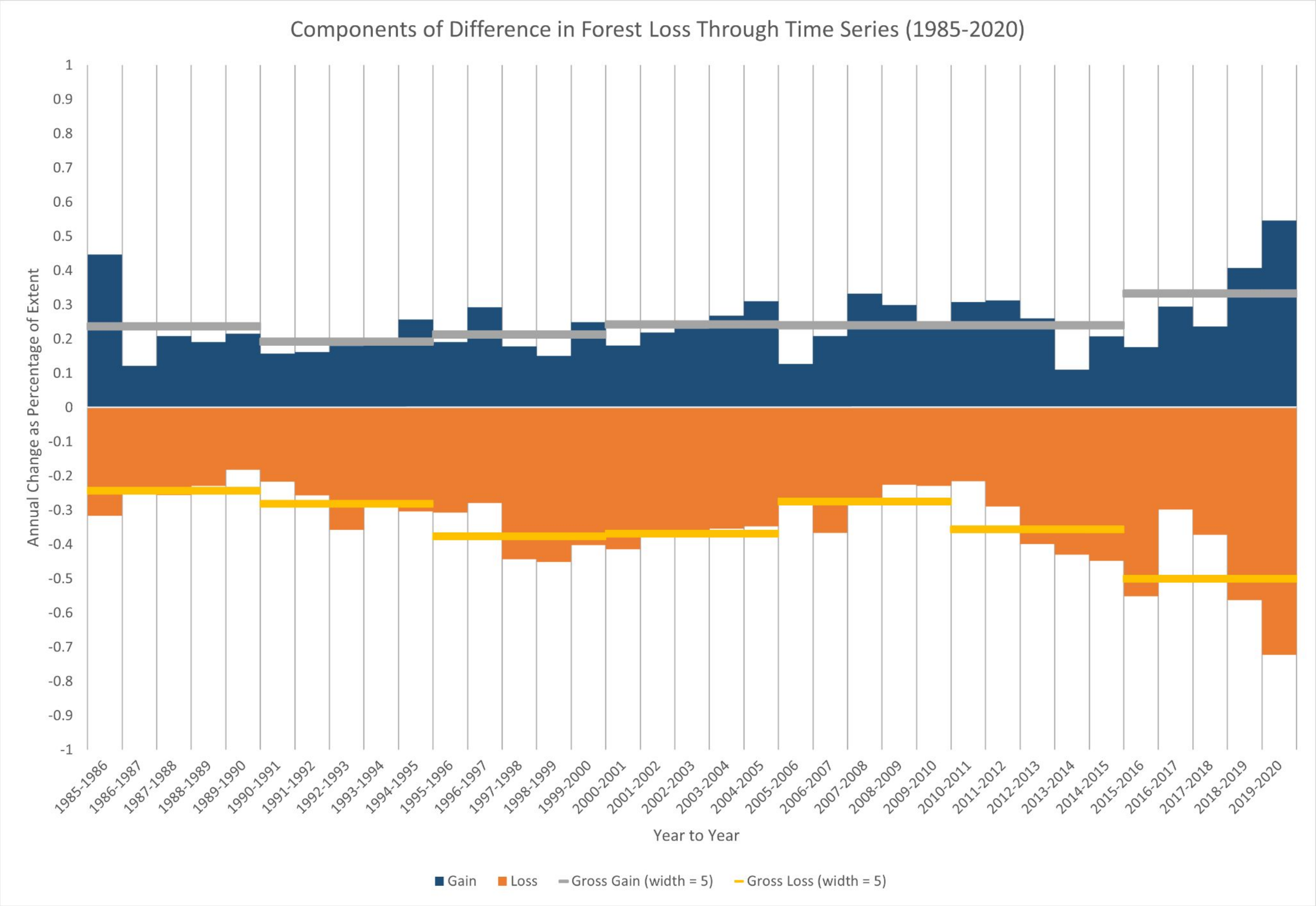
Notation	Meaning
s	index for a time subset where $s = 1, 2, \ldots S$
S	number of time subsets in s
$Time\ Subset\ Gain\ Gross\ Line$	$\sum_{m=1}^{M}\sum_{t=1}^{T} G_{smt}/D$
w	index for a moving window where $w = 1, 2, \ldots W$
$\hat{w}$	collection of windows present at t.
W	number of windows present at t.
$Moving\ Windows\ Mean\ Line$	$\sum_{m=1}^{M}\sum_{t=1}^{T} G_{\hat{w}mt}/DW$

Uniform for Comparison:



Approach #1: Gain/Loss Line Subsetting

1. Gain/Loss gross lines are contextualized in time, relative to surrounding data.
2. *S* must be a factor of *D* (temporal extent). This ensures that the number of windows fits into the extent.
3. Very sensitive to large gains and losses within a subset, could artificially inflate/deflate gain line.
4. Lets the user decide the temporal resolution and window width appropriate for their Gain Line
   a. Introduces flexibility in multi-resolution temporal analysis.



Findings of Subset Approach with MapBiomas Data:

1. More change emphasized in subset #7 with subset approach compared to Uniform Gross line.
    a. Moving to a smaller Gross Line width illuminates new patterns. Shows more non-stationarity in the data as opposed to the uniform line (see the red boxes in Table 1.)

2. While the first and last subset are more sensitive to the outlier data, the inner subsets are not affected by the outlier data.
   a. Last subset has the most difference between Subset Gross Line and Uniform Gross Line (0.09% difference as a percentage of the total extent)
   b. 2nd subset has the 2nd most difference between Subset Gross Line and Uniform Gross Line (0.03% difference as a percentage of the total extent)

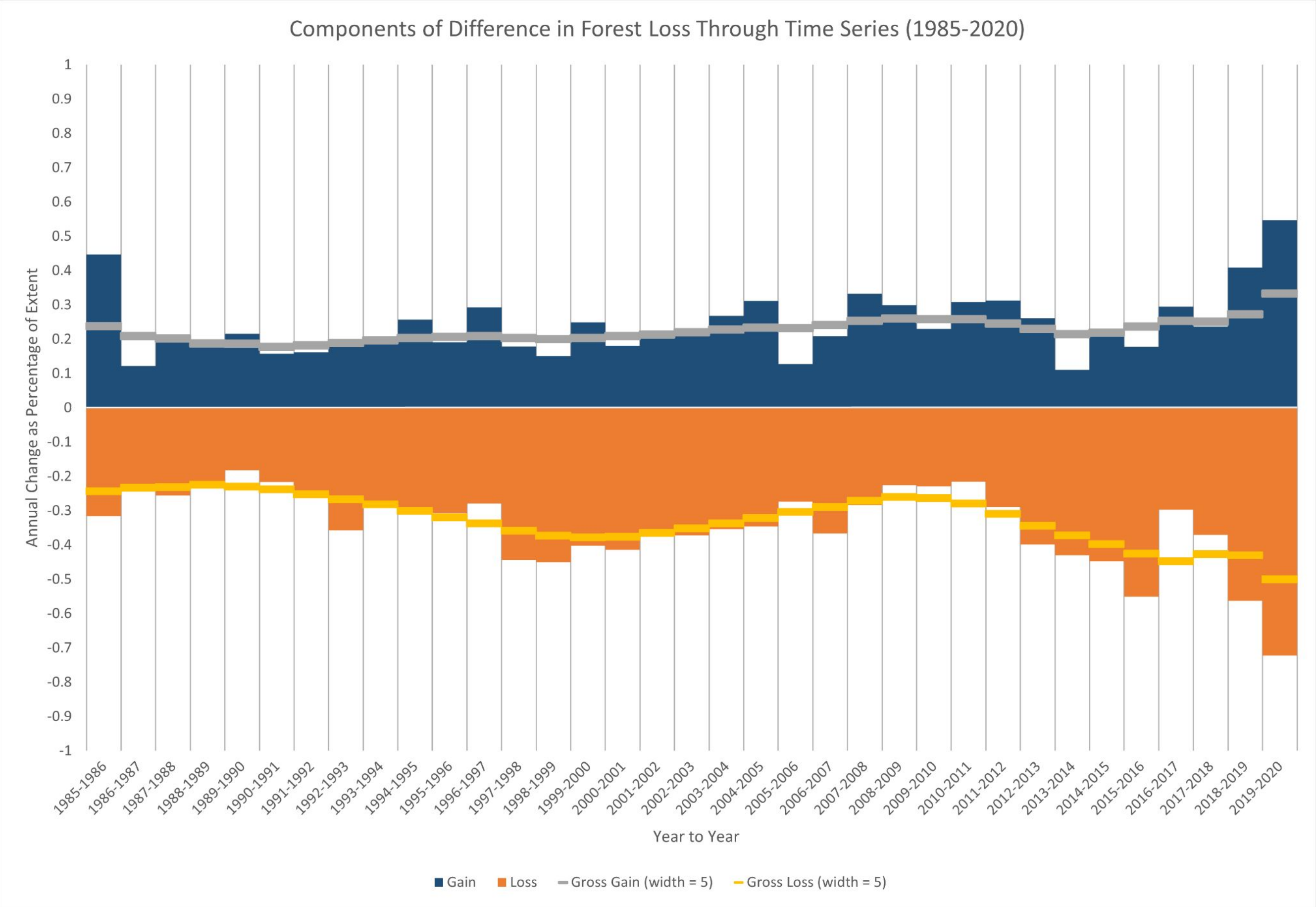
3. While these numbers may seem small, **1** change of Gain/Loss to slow or fast influences whether or not a researcher detects stationarity in the time series.

GAIN SPEED IN SUBSET VS UNIFORM APPROACH (2015-2020)	
Gain Speed (width=5)	**Gain Speed (width=35)**
Slow	Slow
Slow	Fast
Slow	Slow
Fast	Fast
Fast	Fast

Approach #2: Moving Windows

Features of moving window:

1. Resolves sensitivity issues of Approach 1.
2. Computationally and theoretically complex.
3. Finer resolution window size introduces room for error with so many gross lines to average. Could lead to overfitting.
4. Time points before the time point equal to the window width (e.g. width of 5 and w=5) will have less values to compute the gross line.
5. The moving windows mean line operates similarly to a moving average but can account for peripheral data at the beginning and end of the time series.



Findings of Moving Window Approach with Biomas Data:

1. Smoothing of the data, more dynamic slow and fast thresholds.
2. Overall less stationarity in the data with a moving window definition of the gross line (less instances of consecutive slows or fasts).
3. Effects of outliers at first and last time point are further diminished.
4. Gross line minimum and maximum are greater than those in the subset approaches.
5. Fasts that were lost in the Uniform / Subsetting approaches, particularly in Gross Loss, are now present with the moving windows method.
6. Moving windows should be used in tandem with Uniform and Subset approaches. The moving window method is dynamic but may also be overfitting the data (future gross lines might be over-influenced by surrounding data). We would need to conduct more analysis with this data to make that determination, but there is value in all 3 of these Gross line approaches.

Next Steps

1. Finalize report for MapBiomas researchers on the findings of our new approaches (more quantitative analysis).
2. Create an Excel sheet similar PontiusMatrix42 for users to reproduce our findings.
3. Present to MapBiomas

Availability to Present to Map Biomas

We are available December 10th and 17th but would prefer to present the 17th.

References

Aldrich, S. P., Walker, R. T., Arima, E. Y., Caldas, M. M., Browder, J. O., & Perz, S. (2006). Land-Cover and Land-Use Change in the Brazilian Amazon: Smallholders, Ranchers, and Frontier Stratification. *Economic Geography*, *82*(3), 265–288. https://doi.org/10.1111/j.1944-8287.2006.tb00311.x

Barni, P. E., Manzi, A. O., Condé, T. M., Barbosa, R. I., & Fearnside, P. M. (2016). Spatial distribution of forest biomass in Brazil's state of Roraima, northern Amazonia. *Forest Ecology and Management*, *377*, 170–181. https://doi.org/10.1016/j.foreco.2016.07.010

Carreiras, J. M. B., Jones, J., Lucas, R. M., & Gabriel, C. (2014). Land Use and Land Cover Change Dynamics across the Brazilian Amazon: Insights from Extensive Time-Series Analysis of Remote Sensing Data. *PLOS ONE*, *9*(8), e104144. https://doi.org/10.1371/journal.pone.0104144

Pontius, R. G. (2018). Criteria to Confirm Models that Simulate Deforestation and Carbon Disturbance. *Land*, *7*(3), 105. https://doi.org/10.3390/land7030105

Souza, C. M., Z. Shimbo, J., Rosa, M. R., Parente, L. L., A. Alencar, A., Rudorff, B. F. T., Hasenack, H., Matsumoto, M., G. Ferreira, L., Souza-Filho, P. W. M., de Oliveira, S. W., Rocha, W. F., Fonseca, A. V., Marques, C. B., Diniz, C. G., Costa, D., Monteiro, D., Rosa, E. R., Vélez-Martin, E., … Azevedo, T. (2020). Reconstructing Three Decades of Land Use and Land Cover Changes in Brazilian Biomes with Landsat Archive and Earth Engine. *Remote Sensing*, *12*(17), 2735. https://doi.org/10.3390/rs12172735