# MONITORING LONG-TERM FOREST DYNAMICS IN THE ANDEAN AMAZON: A COMPOSITE-BASED POST-CLASSIFICATION CHANGE DETECTION APPROACH

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## Abstract

*Monitoring long-term forest dynamics is essential to assess human-induced land cover changes and a common practice nowadays using the Landsat archive (TLA). However, in areas such as the Andean Amazon (TAA), scarce data and disturbance by noise are a challenge not yet solved by trajectory-based methods. Here, we present an approach based on image compositing and post-classification change detection called C-PCCD. Developed as an open-source software named TFDynamics (demo at:* ***https://github.com/FSantosCodes****), we applied C-PCCD to The Upper Napo Watershed (TUNW), which represents the study area in the Ecuadorian Amazon. We found that despite limited data in TLA, C-PCCD still can conduct this assessment.*

## 1. Introduction

TAA constitutes' the most diverse and carbon-rich ecosystems in the world. Deforestation is its major threat while forest-regrowth is becoming an important land cover component [1]. Unsupervised algorithms [3] to monitor long-term forest-dynamics using TLA has reported limitations in TAA since persistent cloudiness and sensors failures have diminished data quantity and quality drastically. To overcome these limitations, we implemented C-PCCD which has not yet been applied in previous research [5]. Its procedure consists in compositing Landsat derivatives and merge them with terrain parameters to train different classifiers and obtain equitemporal land cover maps. These are later harmonized and passed to a change-detection function to extract forest-loss and regrowth patterns. We applied C-PCCD to TUNW and validated our results using high-resolution imagery from different time periods. Lastly, we compared our results with other forest-dynamics studies based on a similar approach [2] but also in human-interpretation [4] for corroborate our findings.

## 2. Study Area & Research Questions

TUNW covers an area of 12.445 sq.km. and has an altitude gradient from 260 to 5.600 m a.s.l.; resulting in diverse and complex landscape mosaics and rainfall regimes (1.100-5.300 mm per year). Its name came from the Napo River, a tributary of Amazon river and a historical waterway. Land cover in 2014 [4] indicates: 88% natural vegetation, 7% pastures, 2% permanent crops and 3% other covers. Main urban centers are: Francisco de Orellana (40.730 inh.) and Tena (23.307 inh.). Our research questions are:

- Is C-PCCD a feasible approach for monitor long-term forest dynamics in TAA? Which is the workflow required?
- Which forest dynamics patterns can be found in TUNW for the period 1992-2014? Are similar to other studies?

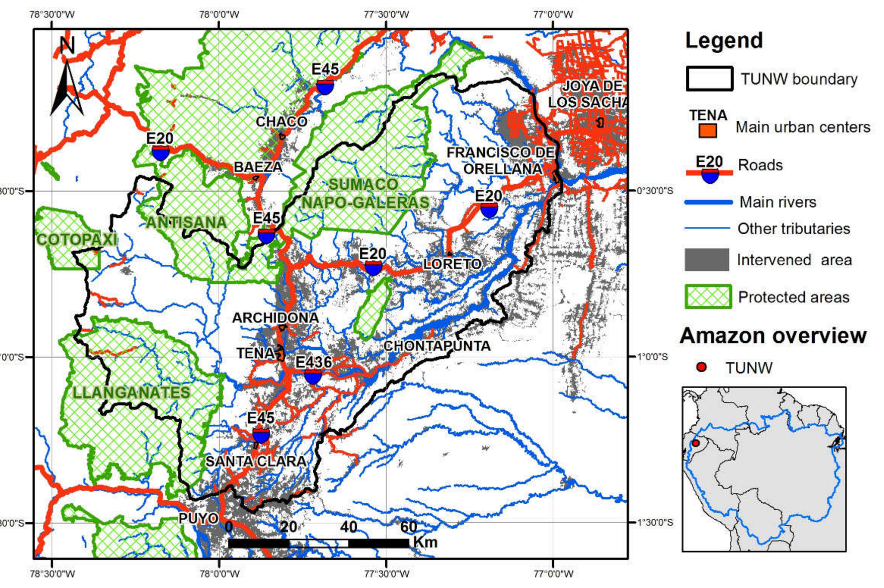


**Figure 1:** *TUNW study area*

## 3. Material & Methods

- Landsat pre-processing & other satellite imagery used
  - 288 Landsat images level L1T (72±5 for 4 footprints)
  - CFmask screening (filter <80 % no-data) + c-correction
  - Calculated derivatives: Vegetation indices, band ratios and tasseled cap transformation bands
  - SRTM terrain parameters: height, slope, aspect, etc.
  - High-resolution imagery: aerial photography, ASTER, SENTINEL-2, ALI

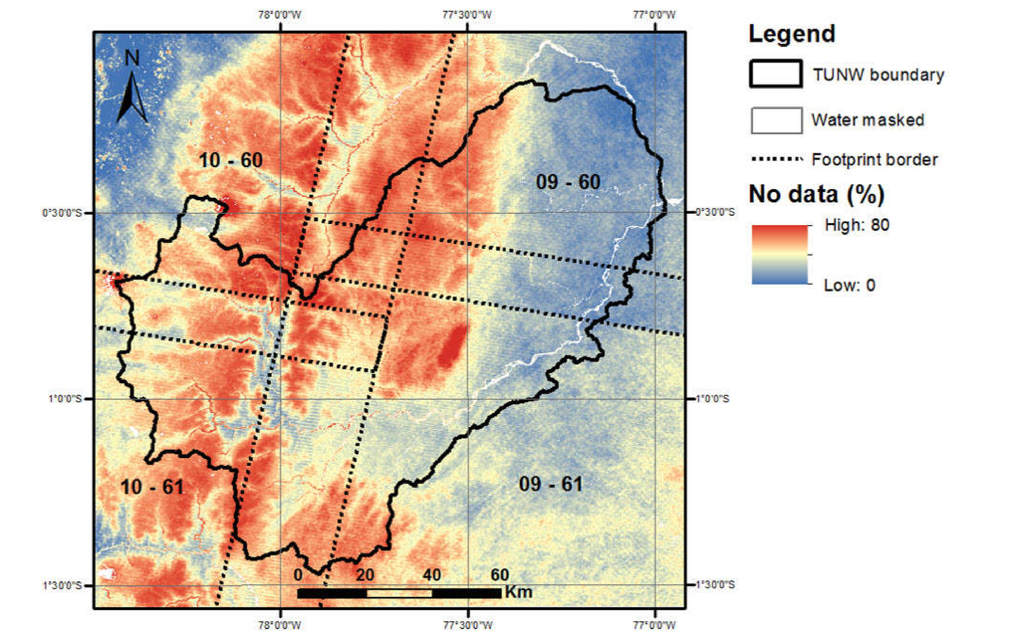


**Figure 2:** *Overall no data % in TUNW*

- Standardized biennial compositing
  - Landsat imagery reduced to 11 biennial composites (period 1992-2014)
  - Average no-data in composites: 34±14%

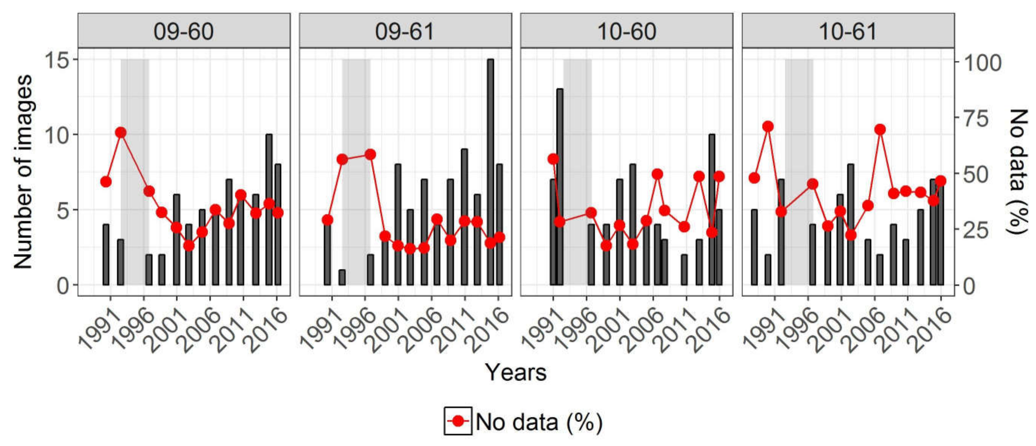
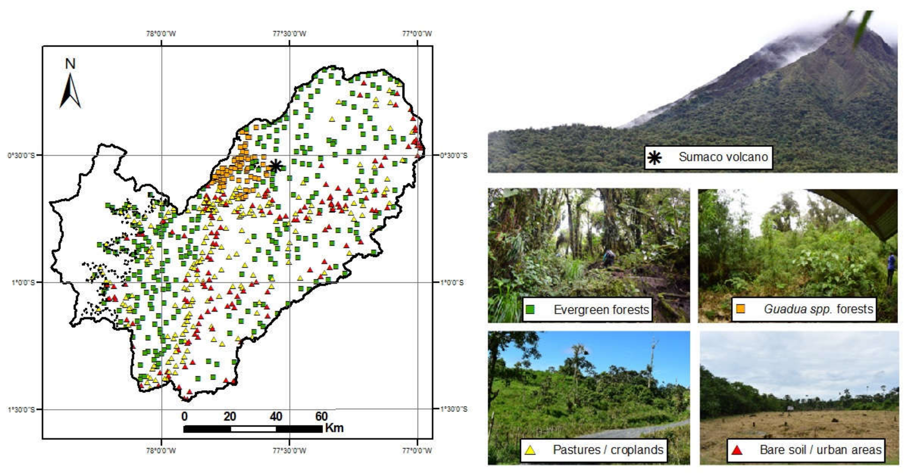


**Figure 3:** *Number of images and no data % in composites*

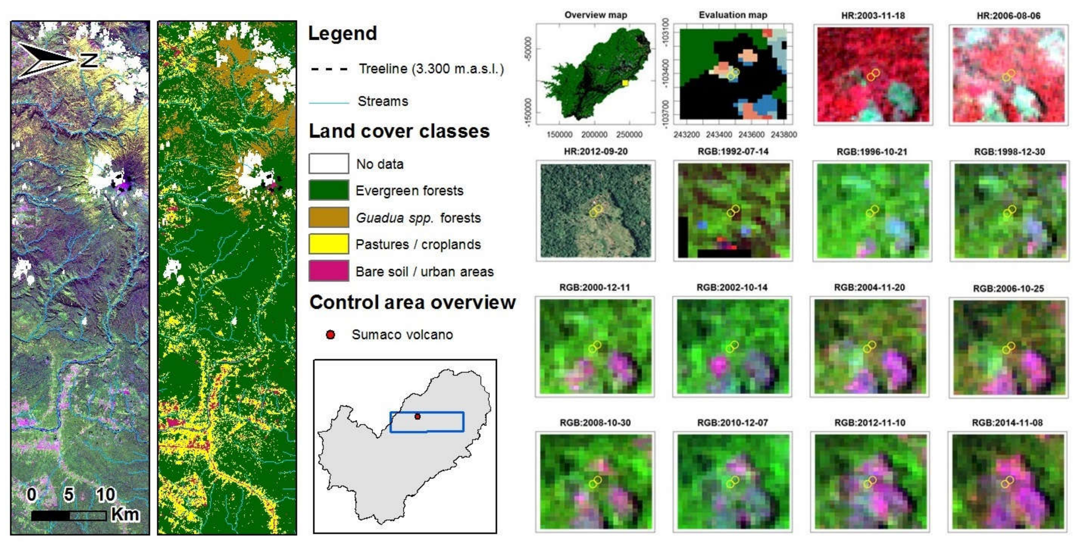
- Model training
  - 735 training samples (4 land cover classes for one composite date 2002)
  - 3016 testing samples (132-304 per composite date)
  - 15 classificators tested with 3 variables ensambles contribution (25%, 50% and 75%) but neural networks with principal component analysis (pcaNNet) outperformed



(A) (B)

**Figure 4:** *(A)Trainng samples at TUNW, (B) field-photos of the land cover classes mapped*

- Post-classification change detection
  - Trained classifier is applied to all composites biennials
  - Land cover maps harmonized using reclassification rules (34 in total)
  - Filtered results are pass to a function to extract: stable forest and intervened areas; forest loss and regrowth areas by date; land cover intensities and forest age
  - 700 validation samples (50-100 per class, >2500-3500 m. distance between samples)



(A) (B)

**Figure 5:** *(A) 743 composition and pcaNNet land cover classification test. (B) Example of a validation sample plot.*

## 4. Results

- Forest-loss and regrowth maps 1992-2014
  - Validation with high-resolution imagery indicated overall accuracies of 0.84 and 0.78 for forest loss and regrowth classes respectively
  - Comparison with other studies showed similar patterns for forest-loss and regrowth classes, specially with the one based in human-interpretation [4]. However, stable forest and intervened areas differ, affecting estimates of forest loss and regrowth areas but not trends found
  - Principal sources of error were caused by: topographic shadow, misclassification at stable-intervened class and unmasked artifacts

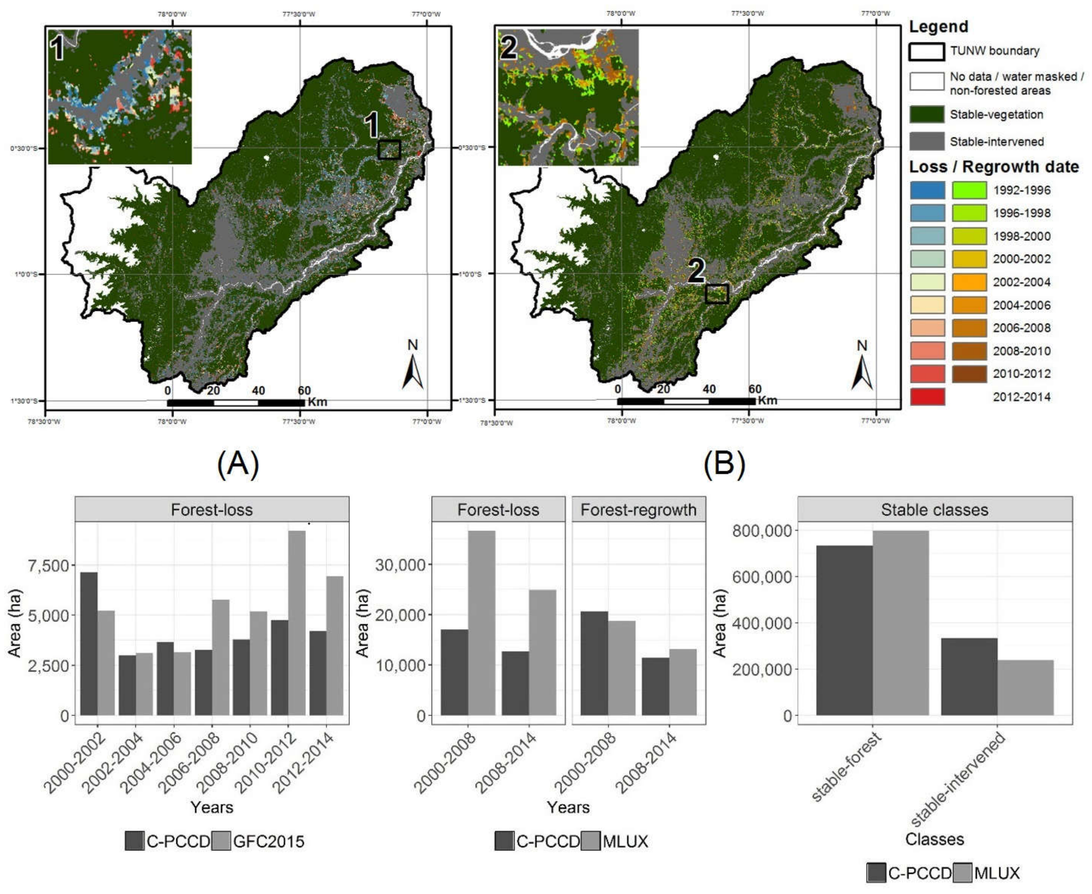


**Figure 6:** *(A) Forest-loss and regrowth maps 1992-2014 for TUNW. (B) Areas comparison between C-PCCD and other studies (GFC2015 and MLUX refers to references [2] and [4] respectively*

## 5. Discussion & Conclusions

- Despite its limitations and errors, C-PCCD demostrated to be a better (almost factible) approach for long-term forest dynamics in TAA rather than trajectory-based methods, as previous research in this project experimented in TUNW [6]
- Further development is required to solve known-errors and improve some phases (eg. reclassification rules design, interpretation of validation samples) and products (eg. implementation of more complex land cover legends, monitor other non-forested ecosystems)
- Regarding forest dynamics in TUNW, C-PCCD results match patterns found in other studies while shown more detail. Nonetheless, further research using other C-PCCD products (land cover intensities, forest age) could contribute to this objective.

## References

[1] P. M. Fearnside. Deforestation in Brazilian Amazonia: History, rates, and consequences. *Conservation Biology*, 19(3):680–688, 2005.

[2] M. C. Hansen, P. V. Potapov, R. Moore, M. Hancher, S. A. Turubanova, A. Tyukavina, D. Thau, S. V. Stehman, S. J. Goetz, T. R. Loveland, A. Kommareddy, A. Egorov, L. Chini, C. O. Justice, and J. R. G. Townshend. High-Resolution Global Maps of 21st-Century Forest Cover Change. *Science*, 342(6160):850–853, 2013.

[3] R. E. Kennedy, Z. Yang, and W. B. Cohen. Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr - Temporal segmentation algorithms. *Remote Sensing of Environment*, 114(12):2897–2910, 2010.

[4] MAE. Documentation of the information used for the establishment of Ecuador's Forest Reference Emission Level.

[5] P. V. Potapov, S. A. Turubanova, M. C. Hansen, B. Adusei, M. Broich, A. Altstatt, L. Mane, and C. O. Justice. Quantifying forest cover loss in Democratic Republic of the Congo, 2000-2010, with Landsat ETM+ data. *Remote Sensing of Environment*, 122:106–116, 2012.

[6] F. Santos, O. Dubovyk, and G. Menz. Monitoring forest dynamics in the andean amazon: The applicability of breakpoint detection methods using landsat time-series and genetic algorithms. *Remote Sensing*, 9(1), 2017.

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