Seasonal mixing in forest-cover maps for humid tropics and impact of fluctuations in spectral properties of low vegetation

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Abstract: *With advances in satellite data, computer storage capacities and processing technologies, it is increasingly feasible to map forest cover over large areas at high spatial resolutions that are relevant for most decision-makers. For outputs to be informative, however, they must be accurate. The finer spatial resolution of recent large-scale forest products comes at a cost of lower temporal resolution. With few input images available for a given year, appropriate image selection in the creation of forest cover and forest-cover change maps is critical. This work highlights the need for more careful consideration of seasonality in mapping forest cover in the tropics. While most studies of seasonality on forest mapping focus on deciduousness and potential errors of omission, this study highlights seasonal fluctuations in non-forested vegetation and likely errors of comission. Vegetation indices provided good separability between tropical forests and low vegetation including commercial crops, pasture and young fallow, in the dry season, but not in the wet season. Forest-cover maps and change analyses that combine wet- and dry-season images without accounting for seasonality risk overestimating initial forest cover and subsequent deforestation. Likewise, analyses that do not distinguish between truly aseasonal wet equatorial regions and seasonal regions of the tropics risk overestimating forest cover in the former.*

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24 **Key words:** Forest cover; land-cover mapping; low vegetation; Landsat; seasonality; spectral
25 indices; NDVI; Accumulated Wetness index; soil moisture; humid tropics; Panama

26

27 **1. Introduction**

28 The capacity to quantify and monitor tropical forest cover is critical for balancing the
29 global carbon budget, mitigating climate change, motivating sustainable resource management
30 and conserving important and increasingly rare habitat. With advances in satellite data,
31 computer storage capacities and processing technologies, it is increasingly feasible to map
32 forest cover over large areas at small spatial and temporal resolutions that are relevant for
33 most decision-makers (Ban et al. 2015; Boyle et al. 2014; Nelson and Robertson 2007). In the
34 past few years, several global forest-cover products with 30 m pixel resolution have been made
35 readily available to the public via the internet (e.g. Chen et al. 2015; Gong et al. 2013; Hansen
36 2013; Kim et al. 2014; Sexton et al. 2013; Yu et al. 2013). The combination of global
37 contextualization, high spatial resolution and highly automated procedures allowing for
38 continued monitoring offers great potential to expand the reach of remote sensing data and
39 facilitate its impact on decision-making for resource management. However, wide
40 disagreement between available products at local levels currently obscures their usefulness and
41 motivates examination of the methodology used to produce global maps.

42 One area that warrants more attention in large-area, high-resolution tropical forest
43 mapping is seasonality and selection of input images. Intra-annual fluctuation in spectral
44 signatures of vegetation has long been recognized as an important factor in land-cover mapping

and is directly incorporated into algorithms used to generate many land-cover products of coarser spatial resolution (e.g. Arino et al. 2008; DiMiceli et al. 2011; Friedl et al. 2010; Ganguly et al. 2010; Hansen et al. 2003; Hansen et al. 2000; Tateishi et al. 2014). With recent Landsat-based products, however, the benefit of higher spatial resolution comes at a cost of decreased temporal resolution. While coarser AVHRR and MODIS images are available on a daily basis, Landsat images are only available for a given location every 16 days. This small data stack is further reduced by persistent cloud cover in much of the tropics (Ju and Roy 2008), precluding the intrinsic modeling of seasonality that is common with AVHRR- and MODIS-based products.

When intra-annual variation cannot be directly incorporated into the model, appropriate selection of input imagery becomes critical. For forest mapping in temperate zones, it is common practice to target images from the growing season to avoid underestimation of forest cover due to deciduousness (Townshend et al. 2012; Tucker et al. 2004). Targeting of greenest periods is also sometimes recommended for tropical-forest mapping to avoid underestimating seasonal forests during leaf-off periods (Tucker and Sellers 1986) and help reduce noise from clouds (DeFries et al. 1995). In many cases, seasonality is simply ignored for tropical regions of global forest-cover maps (Kim et al. 2011; Tucker et al. 2004). In commonly used global products, target acquisition dates for tropical regions generally correspond to those of adjacent temperate regions (e.g. Latifovic et al. 2004), use all available images (e.g. Hansen 2013; Mayaux et al. 1998), or use the least cloudy image from any season (e.g. Gutman et al. 2013). Given that over 70% of the tropics experience some degree of seasonality (Kottek et al. 2006), ignoring seasonality in tropical regions seems unadvisable. Inclusion of seasonality in the tropics, however, merits different considerations than for temperate zones. While some

deciduousness occurs in most tropical forests and seasonal variation has been noted even in tropical evergreen forests (Asner et al. 2000; Moreau and Defourny 2012; Ponzoni et al. 2014), strong seasonal fluctuations in non-forest vegetation (You et al. 2013; Soudani et al. 2012; Ferreira et al. 2003) may be of more importance in the humid tropics. Given the high productivity of even low vegetation during the growing season in tropical regions, maps that emphasize growing-season images could result in overestimation of tropical forests.

This work highlights the occurrence and potential effects of intra-seasonal mixing of images in global forest-cover mapping by focusing on a humid tropical region in Western Panama. The first section presents a preliminary assessment of existing global Landsat-based land-cover products in discriminating between forests and low vegetation in the study area. Next, to elucidate the impact of seasonality in potential overestimation of forests in the study area, seasonal fluctuations in spectral indices commonly used to discriminate forests from low vegetation are explored. Various spectral indices are evaluated to assess the length of the temporal window that would most likely result in acceptable accuracy for forest cover mapping in the region, with a secondary goal to determine the best indices for distinguishing forests from low vegetation in Panama.

This work illustrates the usefulness of a Wetness Index to measure and evaluate seasonality. Existence of a correlation between spectral indices such as NDVI and rainfall has been well established for low vegetation (French and Sauer 1974) with observed lags that suggests that the response is related to soil moisture content rather than direct precipitation (Nicholson et al. 1990; Richard and Pocard 1998). The use of a Wetness Index, as a proxy of stored soil moisture, is used to help identify the conditions under which low vegetation can be

reasonably discriminated from forest in the humid tropics.

2. Materials and methods

2.1. Study site

The study area is a heterogeneous landscape of western Panama (Fig 1) with areas representative of much of the tropics. Based on a Köppen-Geiger climate classification, approximately a third of the study area has a wet equatorial climate with no true dry season (Af) while the remaining area has a tropical seasonal climate (Aw or Am) with three to four months of drought-like conditions between mid December and mid April (UNESCO 2008). The land cover is a mosaic of approximately 36% upland forest, 3% wetland forest, 16% commercial crops or pastures, 43% swidden agriculture in various stages of fallow and productivity, and less than 1% built area along the Pan-American highway (ANAM 2000).

Fig. 1: Study site and location of weather stations for data from Panamanian Empresa de Transmisión Eléctrica (ETESA). Climatic zones digitized from UNESCO 2008. Black square frame shows approximate coverage of Landsat scene (actual coverage varies slightly by date).

2.2. Class comparisons

For the purposes of this study, only the following distinct land-cover classes were included:

- **FOREST:** Mature trees (at least 25 years) with at least 80% canopy cover, within a patch at least 5 ha in size. Excludes monoculture plantations such as oil palm and teak.
- **NO VEGETATION:** More than 80% created material (e.g. concrete, asphalt, metal or clay) or bare substrate (rock, sand or dirt) that remains without vegetation for 12 months.

- LOW VEGETATION: Any of the following, or any direct observation of very low vegetation with less than 20% tree canopy where land use cannot be further distinguished
 - COMMERCIAL CROP: herbaceous crops maintained for at least two years prior without a period of woody fallow, but with an observable harvest cycle.
 - PASTURE: herbaceous cover with less than 20% tree-canopy, maintained for at least two years prior with no apparent harvest cycle (although may be burnt periodically).
 - YOUNG REGROWTH: One to three-year growth following clearing, harvesting, or burning. Requires a later observation confirming that it is in a transitional state of growth.

All other types of landcover, including four to 24-year growth and vegetation with 20-79% tree cover were excluded from this study so as to focus on obvious misclassification due to seasonality rather than fuzzy class boundaries and varying definitions of forest.

2.3. Landsat data and preparation

To study the effect of seasonality on the ability to distinguish between low vegetation and forest in the study region, 64 individual Land-Surface Reflectance Products from Landsat TM and ETM images for path 13 row 54 were also obtained from the U.S. Geological Survey Earth Resources Observation and Science Center. All available images acquired between 1997 and 2012 with a cloud-cover estimate in the metadata of less than 75% were included except for two that were largely misaligned. These Land Surface Reflectance Products are pre-processed to correct for positional and atmospheric conditions (Masek et al. 2006). Geographic

alignment of images was verified with a set of control points identified from a core set of clear base images. Images with resulting RMSEs of greater than 30 m were rectified using these points. Two images for which a 30 m RMSE could not be achieved with linear georectification were excluded from the dataset. Cloud and shadow contamination was removed from each image based on a mask produced with Fmask version 3.2 (Zhu et al. 2015) that was manually retouched to remove an estimated 3% of clouds and 25% of shadows not identified by the Fmask algorithm.

2.4. Reference data:

Reference land-cover data was interpreted from high-resolution satellite imagery available on Google Earth. Individual Landsat pixels were selected using a stratified random sampling scheme based on probable land cover from maps provided by Panama's environmental ministry (ANAM 2000) within the constrained boundaries of available Google Earth imagery. Because geolocation differences of over half a pixel are common between Landsat images and can cause large validation errors in homogeneous landscapes (Foody 2002; Beauchemin 2012; Shi and Hao 2013), only cases where the pixel and its eight surrounding neighbors are covered by the same land cover type were included. In cases of heterogeneity at the original location, randomly selected coordinates were shifted by up to 150 m to the nearest homogenous 9-pixel block best matching the primary land cover of the original point. Although this deviation from pure probability sampling (Olofsson 2014; Stehman 2009) could result in inflated accuracy estimates, this tradeoff was preferred over the substantial deflation of accuracy observed to be a direct result of misalignment in heterogeneous areas.

Each Landsat image was assigned a unique reference data set based on the observations available for the corresponding date. When possible, land cover observations were interpolated across time. Pixels observed to be forest at a given date were assumed to be forest on all prior dates, but this assumption of static state could not be applied to non-forested pixels. Commercial crops and pastures were considered static if observed to be in the same state on two dates within five years of each other. Regrowth was assumed to follow a linear trajectory between the time of observed clearing and observed older growth.

Sample sizes varied between dates due to available Google Earth imagery and cloud cover and averaged 180 clear pixel blocks for forests and 150 clear pixel blocks for low vegetation (50 for crops, 47 for pastures, 40 for young regrowth and 13 for unspecified low vegetation) in Humid Seasonal zones and 98 clear pixel blocks for forests and 22 clear pixel blocks for low vegetation in the Wet Equatorial zone. Sampling of low vegetation in the Wet Equatorial zone was inhibited by persistent cloud cover, rapid rate of regeneration and small sizes of cleared swidden patches (often smaller than the 0.81 ha required for a valid sample in this study). Images where sample size for a given class was less than 25 were omitted from separability and regression analyses for that class.

2.5. *Assessment of global forest-cover products for western Panama*

Six Landsat-based global maps and several coarser-resolution products were obtained from the internet to evaluate accuracy in discriminating between low vegetation and forest in the study region. Because forest definitions differ substantially between map producers (Magdon et al. 2014; Putz and Redford 2010), two classification systems were used to evaluate

the maps, one strict and one looser. With the strict system, forests were correctly mapped if labeled with the word "forest," "wetland," or "mangrove" or if percent tree cover was at least 80%; low vegetation was correctly mapped if it was given a label indicative of low herbaceous cover or assigned less than 20% tree cover. Pixels assigned other labels or 20-79% tree cover in the map products were reclassified as no data for the accuracy assessment; error values reflect pixels that are determined to be low vegetation in the reference sample but classified with one of the above forest definitions in the map product and vice-versa.

Because the validation set only contained pixels with tree cover less than 20% or greater than 80%, these strict rules could be considered accurate. However, a pixel with slightly less than 80% tree cover would still be considered forest by most definitions and is closer to the observed state than it is to low vegetation. A looser validation system was therefore also tested, where a forest pixel was correctly mapped if it was assigned at least 40% tree cover or classified as something like "closed shrubland," "open trees," "forest," "wetland," or "mangrove", and low vegetation was considered correctly mapped if assigned up to 40% tree cover or given a label indicating herbaceous cover or low or open shrubs.

Samples used to evaluate the land cover products averaged 360 pixel blocks for forests (230 for upland forest and 130 for wetland forests) and 618 pixel blocks for low vegetation (283 for pasture, 137 for commercial crops, 130 for young regrowth, and 68 for unspecified low vegetation). In addition to the underrepresentation of heterogeneous areas discussed in section 2.4, other deviations from pure probabilistic sampling occurred as a result of large missing data categories, different data being available in Google Earth for different years and different classes in the map products than the original validation strata (Stehman 2014). The

purpose of this validation exercise is only to provide a preliminary assessment of the performance of map products for the sample area in discriminating between distinct categories of low vegetation and forest. It is worth noting that the deviations from probabilistic sampling are likely to overestimate rather than underestimate accuracy.

2.6. Vegetation indices & selection

Sixteen vegetation indices were selected for initial assessment of ability to separate forest from low vegetation spectrally (Table 1), including the seven spectral indices provided by the U.S. Geological Survey Earth Resources Observation and Science Center (USGS 2014). These indices include the NDVI, the most commonly used index for vegetative mapping; three variants, EVI, SAVI and MSAVI, intended to reduce noise from soil and atmospheric conditions; two burn indices, NBR and NBR2; and NDMI, developed to detect drought stress in temperate forests (Hardisky et al. 1983). In addition to these seven indices, nine additional indices were selected based on literature suggesting better performance in discriminating between vegetation classes in tropical forests. These include BYD1, an index based on thermal and mid-infrared bands (Boyd et al. 1996; Southworth 2004) and a variant, BYD2 (Hartter et al. 2008), MTVI, a chlorophyll-independent leaf-area index which may be less prone to saturation at high canopy densities (Haboudane et al. 2004), the first three components of the Tasseled Cap transformation TC1, TC2 and TC3 (Crist 1985) and the three components of a fractional coverage index produced by CLASlite version 3.0 representing soil (CL1), photosynthetic vegetation (CL2) and non-photosynthetic vegetation (CL3) (Asner et al. 2009).

TABLE 1: Spectral Indices evaluated

Index	Label	Formula using Landsat TM/ETM bands*
Normalized Difference Vegetation Index	NDVI	$(B4-B3)/(B4+B3)$
Enhanced Vegetation Index	EVI	$(B4-B3) / ((B4+B6)*(B3-7.5)*(B1+1))$
Soil Adjusted Vegetation Index	SAVI	$((B4-B3)*1.5) / (B4+B3+.5)$
Modified Soil Adjusted Vegetation Index	MSAVI	$((2 * B4 + 1) - \sqrt{(2 * B4 + 1)^2 - 8(B4 - B3)})/2$
Normalized Difference Moisture Index	NDMI	$(B4-B5)/(B4+B5)$
Normalized Burn Ratio	NBR	$(B4-B7)/(B4+B7)$
Normalized Burn Ratio2	NBR2	$(B5-B7)/(B5+B7)$
Tasseled Cap - Brightness	TC1	$.2043*B1+.4158*B2+.5524*B3+.5741*B4+.3124*B5+.2303*B7$
Tasseled Cap - Greeness	TC2	$-.1603*B1-.2819*B2-.4934*B3+.7940*B4-.0002*B5-.1446*B7$
Tasseled Cap - Wetness	TC3	$.0315*B1+.2021*B2+.3102*B3+.1594*B4-.6806*B5-.6109*B7$
Boyd Ratio	BYD1	$(B2*B6)/(B7)$
Boyd Ratio2	BYD2	$(B6)/(B3+B5)$
Modified Triangular Vegetation Index	MTVI	$1.2[1.2(B4 - B2) - 2.5(B3 - B2)]$
CLASlite - Soil	CL1	Respective bands of fractional coverage image produced from spectral unmixing using CLASlite 3.0 software
CLASlite - Photosynthetic Vegetation	CL2	
CLASlite - Non-Photosynthetic Vegetation	CL3	

* BX refers to the surface reflectance value for corresponding band 1-7 of Landsat image

Index performance in terms of ability to discriminate between forests and no or low vegetation was evaluated for each image using Divergence (D) and transformed divergence (TD) (Swain and King 1973):

$$D_{fi} = .5\text{tr}[(C_f - C_i)(C_f^{-1} - C_i^{-1})] + .5\text{tr}[(C_f^{-1} + C_i^{-1})(M_f - M_i)(M_f - M_i)^T]$$

where C_f is the covariance matrix for forest pixels, C_i is the covariance matrix for the class being compared to forest (e.g. no vegetation, low vegetation, crops)

C^{-1} is the inverse of the covariance matrix, M is the mean vector, T is the

transpose function of the matrices and tr is the trace function of the matrices.

$$TD_{fi} = 2000[1 - \exp(-D_{fi}/8)]$$

While D is useful in ranking indices and images, it increases infinitely and thus does not provide a clear measure of whether two classes can be separated adequately. The use of TD , which saturates at 2.0, helps overcome this. As a rule of thumb, an index is esteemed to provide good

separability between two classes if TD is greater than 1.9, mediocre to poor separability as TD declines to 1.0, and very poor separability if TD is less than 1.0 (Forestier et al. 2013).

2.7. Accumulated Wetness Index

Accumulated soil wetness was used as a proxy for vegetation wetness. The Wetness Index was calculated as: $W = W_{\max} + (\text{Date} - \text{StartDry}) * (P_{\text{Dry}} - \text{ETP}_{\text{Dry}})$ for images acquired during the dry season and $W_{\max} + (\text{EndDry} - \text{StartDry}) * (P_{\text{Dry}} - \text{ETP}_{\text{Dry}}) + (\text{Date} - \text{EndDry}) * (P_{\text{Wet}} - \text{ETP}_{\text{Wet}})$ for images acquired during the wet season, where StartDry and EndDry are the beginning and ending dry season dates for the corresponding year provided by the Panama Canal Authority, P_{Dry} and P_{Wet} are generalized estimates of precipitation (mm/day) in the dry and wet season, respectively, and ETP_{Dry} and ETP_{Wet} are generalized estimates of evapotranspiration (mm/day) in the dry and wet season, respectively. $W_{\max}$ corresponds to the maximum field capacity (in mm), such that the wetness is at its maximum on the first day of the dry season. Maximum field capacity varies widely depending on land cover (Hendrickx et al. 2005); forests have much deeper roots and can access water at greater soil depths than grasses and other low vegetation. Because the objective of this work is to determine conditions under which forests can best be distinguished from low vegetation, it makes sense to use a low field capacity corresponding to croplands and pastures. Here, $W_{\max}$ was set to 150 mm, the field capacity estimate used by Panama's agricultural ministry (MIDA) for assessment of water stress in croplands and pastures. ETP_{Dry} and ETP_{Wet} were set to 4.7 mm and 3.5 mm respectively and P_{Dry} and P_{Wet} was set to 1.2 mm and 8 mm, respectively. These values are the averages of daily data from 2010-2014 provided by the Panamanian Electrical Transmission Company (ETESA 2015) from five weather

stations spread across the humid tropical region of western Panama (Fig 1). Images with a negative accumulated wetness value are considered "dry", those with a value of zero to 149 mm are considered "transitional", and those with a value of 150 mm or greater are considered "wet". For regression analyses, the wetness index was capped at 150 mm because it does not make sense for soils to be wetter than the saturation point. Values greater than 150 mm have been retained for visualization purposes only.

Although each Landsat image was assigned a single Wetness Index based on its acquisition date, sample points within the aseasonal Wet Equatorial region were considered as a separate data set from those within the two drier regions. Data from the Bocas de Torro weather station in the northwest corner of the study site indicate that soil wetness never drops below 150 mm, thus this Wetness Index is likely inappropriate for the Wet Equatorial region.

3. Results and discussion:

3.1. Image acquisition dates and performance of global land cover products

In the methodology literature for all of the Landsat-based forest-cover products evaluated, it is mentioned that greenest or wettest acquisition dates are targeted (Table 2). Likewise, greenest periods are targeted in the Global Land Survey (GLS) dataset from which some of these datasets draw (Tucker et al. 2004). Due to persistent cloud cover, images are not always available from the targeted period and dry-season images are sometimes included. The GLS dataset for Panama thus includes images from different seasons both across the country at any given date and across time (Table 3).

Table 2: Performance of global forest-cover products at 30m resolution for P13R54 (Panama)

Dataset	Year	# ^a	scene Season	Accuracy ^b				$\hat{K}$	Notes	Primary Ref
				Users		Producers				
				LV	For	LV	For			
FROM-GLC (original)	2010	S	Dry	95	64	68	94	57	Targets wettest period but Panama images are from mixed seasons; P13R54 is dry (Feb).	Gong et al. 2013
				95	65	69	94	58		
FROM-GLC segmentation	2010	S +	Dry	90	64	68	88	53	Uses same base images as original model. Incorporates 16-day EVI and WorldClim Data.	Yu et al. 2013
				90	65	69	88	54		
GLOBLand30	2010	S	Dry	98	61	59	98	53	Targets "local vegetation growing season" but most Panama scenes are from dry season (Feb)	Chen et al. 2015
				98	64	64	98	57		
Percent Tree Cover	2000	M	All	38	92	33	94	35	Targets "growing season", but appears to include year-round data for Panama.	Hansen 2013
				80	93	35	99	45		
Landsat-based VCF	2005	S	Wet	22	13	24	12	9	MODIS VCF data used to train model based on Landsat reflectance. Landsat image from GLS (mixed seasons, P13R54 is wet for 2000 & 2005 (Aug-01 & Dec-04)).	Sexton et al. 2013
				80	72	67	83	50		
	2000	S	Wet	2	60	13	17	2		
				16	91	46	69	9		
Landsat Forest Cover Change	2005	S	Wet	79	62	45	88	35	Targets "leaf-on"; Panama uses original GLS images (For P13R54: 1990, 2000 & 2005 images are wet (Nov-88, Aug-01 & Dec-04)).	Kim et al. 2014
				86	63	46	93	39		
	2000	S	Wet	17	91	34	81	10		
				17	91	34	81	10		
Pantropical Forest Height	2007	S		43	55	25	73	30	30 m resolution, but based on ALOS PALSAR radar data trained with lidar data, not Landsat.	Kellndorfer et al. 2014
				87	76	64	92	58		
MODIS Land Cover Type	2005	M	All	69	78	84	61	50	500 m resolution. Incorporates monthly EVI & Land Surface Temperature data from MODIS.	Friedl et al. 2010
				76	88	91	71	62		
GLC_NMO	2008	M	All	44	49	38	55	26	500 m resolution. Uses 16-day MODIS NBAR composites plus derived NDVI.	Tateishi et al. 2014
				67	75	77	65	41		
GlobCover / CCI-LC 2000	2000	M	All	4	59	34	11	4	300 m resolution ENVISAT_MERIS with phenology data from SPOT_VGT. Images from 1998-2002. Each pixel has at least 16 viewings.	Arino et al. 2008
				33	95	57	86	33		
MODIS VCF	2010	M	All	5	42	24	10	4	250 m resolution, annual MODIS product (sample year). Phenology not directly included.	DiMiceli et al. 2011
				46	92	60	87	41		

278 *Bolded/shaded information regards 30 m-resolution Landsat-based products. One 30 m non-*

279 *Landsat-based product and four coarser-resolution products are noted for comparison.*

280 ^a *Number of input images: M=Multiple, S=Single, S+ = Single image with ancillary information.*

281 ^b *Top values are based on strict classification rules corresponding to validation set (e.g. LowVeg*

282 *<20% tree cover, Forest >=80% tree cover); bottom values are based on looser rules (see text).*

283 *LV=LowVeg, For=Forest; $\hat{K}$ = Cohen's Kappa * 100*

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**Table 3: Seasonal variation of Global Land Survey dataset²⁸⁵
for Panama across time and space**

GLS year	scene P14R54	scene P13R54	scene P12R54	scene ²⁸⁶ P11R54
1975	22-Jan-79	30-Jan-79	23-Feb-74	9-Jan-79
1990	17-Jan-87	4-Nov-88	31-Oct-86	18-Apr-93
2000	14-Feb-00	20-Aug-01	28-May-02	28-Mar-00 ²⁸⁸
2005	15-Mar-05	18-Dec-04	30-Dec-05	19-Jan-04
	13-Jan-06	6-Sep-07	16-Dec-06	05-Jan-05 ²⁸⁹
2010	29-Mar-10	10-Feb-10	17-Dec-09	12-Feb-10 ²⁹⁰
	16-Mar-11			

Bolded dates indicate dry images; shaded dates indicate wet

images; remainder are transitional

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Two of the Landsat-based forest-cover products evaluated (and one variation) are based on dry-season images because a suitable wet-season image was not available for that year. These products were found to perform considerably better in mapping low vegetation as the products based wholly or partially on wet-season images. Most products evaluated suggest a general problem of over-mapping of forests. Although the validation set was not designed to evaluate products with resolution lower than 30 m and likely underestimates accuracy of coarser products due to heterogeneity within larger pixels, higher accuracy was observed with some coarser products such as the MODIS Land Cover Type. This higher accuracy might be attributed to the higher temporal resolution and direct accounting of phenology in the input data.

3.2. Performance of Vegetation Indices with seasons

The NDVI outperformed all other indices in ability to distinguish forests from no vegetation and crops, and performed second best to CL2 in ability to distinguish forests from pastures (Table 4). The NDVI did not perform particularly well in distinguishing between forest and young regrowth, where BYD2 and CL2 were stronger. In all cases and for both wet- and dry-

season images, the NDVI outperformed the modified versions SAVI, EVI and MSAVI. Likewise, BYD2 always outperformed its counterpart, BYD1, and NBR always outperformed its counterpart, NBR2. For simplicity, SAVI, EVI, MSAVI, BYD1 and NBR2 are therefore dropped from the results. TC1 and CL1 were never useful in separating any of the classes during any season. The performance of the remaining indices (NDVI, NBR, TC2, TC3, CL2, CL3, NDMI, MTVI) is shown in Table 4. As NDVI, CL2 and BYD2 were strongest in separating forest and all types of low vegetation, they are the focus of the remaining analysis.

Table 4: Transformed divergence (TD) between Forest and low vegetation classes for top indices

FOREST Vs.	season	CL2	NDVI	BYD2	NBR	CL3	TC2	NDMI	MTVI	TC3
LOW VEGETATION (all)	All	1.61	1.57	1.47	1.40	1.37	0.84	1.28	0.6	1.22
	Dry	1.75	1.90	1.76	1.84	1.75	1.33	1.71	0.97	1.55
	Wet	1.32	0.88	1.11	0.73	0.75	0.22	0.72	0.22	0.79
Commercial Crop	All	1.63	1.75	1.65	1.50	1.44	1.04	1.33	0.75	1.23
	Dry	1.78	1.97	1.80	1.91	1.78	1.58	1.78	1.25	1.62
	Wet	1.31	1.17	1.30	0.79	0.74	0.33	0.65	0.19	0.60
Pasture	All	1.96	1.79	1.76	1.69	1.64	1.01	1.60	0.73	1.61
	Dry	1.99	1.92	1.88	1.94	1.92	1.45	1.91	1.11	1.84
	Wet	1.69	1.23	1.62	1.05	0.79	0.29	0.99	0.18	1.10
1-3 yr Regrowth	All	1.57	1.02	1.53	1.20	1.15	0.46	1.29	0.37	1.24
	Dry	1.81	1.49	1.75	1.66	1.68	0.80	1.62	0.49	1.48
	Wet	1.20	0.47	1.31	0.72	0.36	0.21	0.96	0.22	0.98
NO VEGETATION	All	1.91	2.00	1.04	1.90	1.53	1.91	1.52	1.74	1.15
	Dry	1.90	2.00	0.95	1.94	1.70	1.95	1.69	1.84	1.28
	Wet	1.86	2.00	0.91	1.92	1.26	1.88	1.41	1.66	1.04

Shaded boxes indicate the best (darkest) and second best (lighter) index performance in separating each class from forest within tropical seasonal climatic zones. Bolded values indicate good separability (TD>1.9), italicized values indicate very poor separability (TD<1)

Observations that NDVI values can be affected by background scatter from the underlying soil have led to the development of modified indices EVI, SAVI and MSAVI. In this

study, however, none of these three indices performed better than the NDVI in any situation comparing low vegetation to forest. No attempt was made to compare low vegetation classes to one another, however, a purpose for which reducing noise from soil would likely be more critical. Another commonly noted limitation of the NDVI is its tendency to saturate and therefore not discriminate well between classes of closed vegetation when leaf-area index (LAI) exceeds two (Boyd et al. 1996; Haboudane et al. 2004; Kalacska et al. 2004). This limitation is supported by the results of this study; even in dry-season images, the NDVI did not provide the best separability between forests and young regeneration. Even low vegetation often has a LAI greater than two in the tropics (McWilliam et al. 1993; Xavier and Vettorazzi 2003). Indices that incorporate data from the mid-infrared portion of the spectrum, which is most sensitive to moisture absorption, can better highlight the distinction between dense low vegetation and moist forests in the dry season, explaining the better performance of BYD2. It should be noted, however, that the range of the thermal band reflectance is relatively small across the study area, thus BYD2 is driven almost entirely by the denominator and is highly sensitive to terrain shadows and noise that ratio-band indices are designed to reduce. The high performance of the CLASlite product (CL2) supports observations that unmixed PV and NPV products can perform superior to NDVI in distinguishing vegetation structure (Asner and Heidebrecht 2002; Higgins et al. 2014; Huang et al. 2002). The soil component of the CLASlite product (CL1) provided almost no information, suggesting that the spectral libraries are not well suited for the study area and performance of the combined product could be further improved with local calibration.

3.3. Seasonality and Wetness Index

In the Humid Seasonal zones, classified as Tropical Trade Wind (Am) and Tropical Wet-Dry (Aw) by the Köppen-Geiger system, class separability was always higher for dry-season images than for wet-season images. No index provided good separability ($TD > 1.9$) between forest and any type of low vegetation in wet-season images. Most of the indices that provided good separability in the dry season provided very poor separability in the wet season ($TD < 1$). The poor separability between low vegetation and forests in the wet season can be attributed to a general increase in index values for low vegetation with accumulated wetness (Fig 2).

Fig. 2: Effect of seasonality on three vegetation indices in Humid Seasonal climatic zone

Observations support literature that spectral measures of greenness and moisture content of moist forests vary little by season (Morton et al. 2014). On the other hand, lower vegetation, especially pasture grasses and non-irrigated crops, experiences considerable browning in the dry season. Red reflectance decreases and near- and mid-infrared reflectance increases as leaf water content decreases (Tucker 1979). Thus, it is not surprising that indices based on MIR or the ratio of NIR/Red better distinguish vegetation types in the dry season than in the wet

season. What is striking is the degree to which these measures approach those of forests once wetness reaches the soil saturation point (Fig 3).

Fig. 3. Separability of forest and all low vegetation by season using NDVI in Humid Seasonal zone

Error bars indicate one standard deviation

Herbaceous and pioneer growth recover productivity and accumulate biomass much more rapidly than mature forests in the tropics (Potvin et al. 2004; Silver et al. 2000; Steininger 2000). Tropical grass, such as the wild sugarcane (*Saccharum spontaneum*) often found in regenerating pastures in Panama, can exceed a LAI of three in the first 100 days of growth (Robertson et al. 1996). Likewise, sugarcane and corn grown in the tropics can surpass a LAI of two within one month of planting (Xavier and Vettorazzi 2003). As a measure of chlorophyll density, NDVI strongly reflects this greening of vegetation regardless of structure. Inclusion of the mid-infrared information, such as with the BYD2 index, can help reduce seasonal effects,

but relatively large fluctuations observed between images likely reflect sensitivity to more immediate fluctuations in atmospheric conditions and direct surface wetness (Burns and Joyce 1981). Short-term variation in BYD2 is especially evident with the non-vegetated class, likely due to the different water-retention properties of the diverse substrates included in this category.

3.3.1. Seasonality in Wet Equatorial zones

In contrast to the Humid Seasonal zones, separability between forest and low vegetation is always poor at the studied resolution in the Wet Equatorial zone (Figure 4). Lower observed NDVI values during the middle of the dry season for the seasonal zone suggests that at least part of this Wet Equatorial zone is influenced by a short dry season. This is confirmed by other precipitation and ground data from Panama (Condit et al. 2000).

To determine best input images for this zone, it would be necessary to estimate a Wetness Index at a sub-regional level. Preliminary analysis of the 30 m-resolution WorldClim global precipitation and evapotranspiration (Hijmans et al. 2005) suggests that these data are useful for mapping the climate gradient that is known to exist across the study site (Condit et al. 2004) and could inform better wetness estimates for pixels in the transitional zone between seasonal forests and truly aseasonal forests. The shorter the dry season, the smaller the window of appropriate acquisition dates and the more precise wetness estimates need to be. For the areas that truly have no dry season, ability to discriminate low vegetation from forests based on spectral characteristics will always be poor.

Fig. 4: Separability of forest and all low vegetation by season using NDVI in Wet Equatorial zone

Error bars indicate one standard deviation

3.3.2. Combined effect of clouds and seasonality

One strategy to reduce error caused by fluctuations in spectral signatures due to seasonality or other noise is to average the values from multiple dates or use metrics or trajectory-based methods (Hansen 2013; Huang et al. 2010; Kennedy et al. 2007; Kennedy et al. 2010). While these methods can effectively reduce noise in some cases, they are unlikely to overcome the issue of seasonality in large-area mapping of the tropics. In Panama, as in many tropical locations (Asner 2001; Ju and Roy 2008), persistent cloud cover results in only a few clear viewings per year. For this study site, for example, an average of 70% of land area had to be masked out of each image due to clouds or shadows. Although dry-season images tend to have less cloud cover than wet-season images in Panama, one cannot assume that most clear viewings occur in the dry season. This is evidenced by the selection of scenes in the Global Land Survey for Panama (Table 3) as well as observations from the study site for the year 2000, a

common base year for land-cover mapping. In the 22 Landsat images available through USGS for 2000 (many more than for most years), 30% of land has no clear dry-season observation. While eight percent of pixels have no clear observation at all, 22% could be filled with a wet-season observation. Failure to account for seasonality would likely lead to overestimation of forests in these pixels. The remaining pixels have an average of two viewings during the dry or transitional season (Wetness Index <150) and 4.3 viewings during the wet season. An averaged product would likely result in much more class confusion than a dry-season only product. While a metrics or trajectory-based method might be ideal in theory, it is unlikely that there are enough clear viewings for such methods to be feasible with Landsat images as they are with products of satellites that capture imagery daily. Even phenology metrics based on daily observations have been noted to have limited use for moist tropical ecosystems (Brown et al. 2006; Friedl et al. 2000; Ganguly et al. 2010).

4. Conclusions

While most attempts to control for seasonality in forest-cover mapping focus on deciduousness and anticipated errors of omission, this study highlights seasonality in non-forested vegetation and likely errors of commission. Observed indices varied little with seasonality for forested pixels in the wet and humid zones of the study area despite the fact that these forests do include some deciduous trees (Bohlman 2010; Condit et al. 2000) and are less photosynthetically active in the dry season (Ponzoni et al. 2014; Wright 1996). Vegetative indices for non-forested areas varied greatly with season, however, such that they presented values easily confused with forest in wetter images. Studies of wet or growing-season images

elsewhere in the tropics can present spectral index values for low vegetation that overlap with forests (Kalacska et al. 2004) especially for crops such as sugarcane (Bégué et al. 2010; Johnson et al. 2008), thus the need to consider seasonality expands past the study zone to the seasonal tropics in general.

While separate analyses would be needed to assess the degree of separability in different sites, the general problem of seasonal mixing occurs throughout the tropics in global map products. Although the recommendation of using images from the driest period of the year to increase spectral separability and enhance classification accuracy has been made elsewhere (Coppin et al. 2004; Sedano et al. 2005), it is common practice to target images from the wettest or greenest period when mapping forest cover. All of the Landsat-based global products explored here explicitly target the greenest (or "wettest" / "growing season" / "leaf-on") period of the year for tropical images, although persistent cloud cover during the wet season often results in the use of dry season images. This tendency to target wet season images not only yields the negative consequence of low separability of vegetation classes but also results in maps where adjacent areas and temporal products vary widely in seasonality, making it difficult to make meaningful comparisons. If a base map is produced from mostly wet-season images, for example, but subsequent time-series analyses to detect deforestation include dry-season images, deforestation rates are likely to be overestimated due to overestimation of forest extent in the base map. While It is basic text-book knowledge that it is bad practice to use image pairs acquired during different seasons and conditions for change detection (Lillesand and Kiefer 2000; Lunetta 2000), potential users of these products may not realize that such mixing occurs.

Inclusion of only dry-season images, where accumulated soil moisture is negative, in analyses of humid seasonal forests would reduce overestimation of forest area due to highly productive low vegetation. Where present, however, deciduousness would be maximized during this period, resulting in underestimation of some forests. For example, low NDVI values have been observed during the dry-season in patches of forests with high levels of deciduousness in the nearby Panama canal area (Bohlman 2010; Condit et al. 2000). Additionally, discrimination between forest types, such as wetland and upland forest, can be better accomplished in wet season images (Wang et al. 2004). For optimal land-cover mapping, especially for base products, multiple images from different seasons should be incorporated along with explicit seasonal information. When not possible, however, tropical forest maps including wet-season images should be interpreted with great caution.

The results of this study demonstrate the usefulness of even a very simple Wetness Index for selecting images where separability between forests and low vegetation is above a given threshold. The concept of a developing a Wetness Index to facilitate image selection pertains to over 70% of the tropics, where some degree of seasonality occurs (Kottek et al. 2006). The methods used here can easily be adapted for any Landsat scene given knowledge of dry- and wet-season dates and a ballpark figure for precipitation and evapotranspiration during those periods.

As observed in this study, however, a high degree of climatic variation can occur within the area covered by one Landsat scene. In addition to general climatic gradients, local conditions for water storage, such as soil type and slope will influence the wetness of a particular pixel (Daws et al. 2002; Hendrickx et al. 2005; Wagner et al. 2011). Ideally, a wetness

index based on more detailed climate data and terrain-based variables could be applied at the pixel level to guide appropriate image selection. Explicit soil-moisture mapping campaigns such as European Space Agency's Soil Moisture and Ocean Salinity (SMOS) and NASA's higher resolution Soil Moisture Active Passive (SMAP) products offer great promise for future ability to directly estimate local wetness. The current WorldCim products also offer good insight into spatial variation of climatic conditions, although the averaging of estimates across years strips all information regarding inter-annual variation. A shift in even a few weeks in the start of the rainy season in Panama determines whether images from January and even February are dry or still very wet. While synchronizing even the general dates of input images would be an improvement over the status quo, the ideal is to strive for true phenological synchronization of images (Weber 2001).

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841 **List of Figure Captions**

842

843 **Fig. 1: Study site and location of weather stations** for data from Panamanian Empresa de
844 Transmission Electrica (ETESA). Climatic zones digitized from UNESCO 2008. Black square frame
845 shows approximate coverage of Landsat scene (actual coverage varies slightly by date).

846

847 **Fig. 2: Effect of seasonality on three vegetation indices in Humid Seasonal climatic zone**

848

849 **Fig. 3. Separability of forest and all low vegetation by season using NDVI in Humid Seasonal zone**

850 *Error bars indicate one standard deviation*

851

852 **Fig. 4: Separability of forest and all low vegetation by season using NDVI in Wet Equatorial zone**

853 *Error bars indicate one standard deviation*

Figure 1

Figure 2

Figure 3

Figure 4