"How Forest Area Data Reliability May Influences Tropical Deforestation Drivers Identification?"

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Abstract

The Copenhagen Accord and Cancun Adaptation Framework have been assigned a pivotal role in achieving the GHG emissions stabilization in sustainable forest management. The medium and long-term goal of the international community is the containment of deforestation, particularly in developing countries, by identifying the drivers that affect the sustainability of land use choices. A wide existing literature has focused on this topic relying on forest area time series provided by FAO in the Forest Resource Assessments (FRA), but undervaluing the effects of weak data reliability on estimated outcomes. Comparing cross-country panel regression models, we show how the impact of deforestation drivers may be affected by the *data source* and the *density* level of analysis both on a global and regional *scale*. It follows that any research that aims to set the reasons of deforestation should take into account potential data reliability bias.

Key words: Climate change/ Tropical forest area/ Data reliability/ Panel data

1. Introduction

At the end of 2009, the 15th session of the Conference of Parties (COP 15) of the United Nations Framework Convention on Climate Change took note of the Copenhagen Accord recognizing *"….the crucial role of reducing emission from deforestation and forest degradation and the need to enhance removals of greenhouse gas emission by forests and agree on the need to provide positive incentives to such actions through the immediate establishment of a mechanism including REDD-plus, to enable the mobilization of financial resources from developed countries"*. The Agreement also establishes that *"new and additional, predictable and adequate funding as well as improved access shall be provided to developing countries in accordance with the relevant provisions of the Convention,*

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to enable and support enhanced action on mitigation, including substantial finance to reduce emissions from deforestation and forest degradation (REDD-plus),….” (UNFCC, 2009). The agreement signed at COP 15 stated that REDD+ plays a pivotal role in achieving the objective of stabilization of GHG emissions and ascribe a shared responsibility in the management of forests both to developing and developed countries. Finally, the Parties at COP 16 adopted the Cancun Adaptation Framework (CAF) as part of the Cancun Agreements. CAF provided that developing countries implement a national strategy or action plan to realize the mitigation actions in the forest sector. It “*Also requests developing country Parties, when developing and implementing their national strategies or action plans, to address, inter alia, the drivers of deforestation and forest degradation, land tenure issues, forest governance issues*”(UNFCC, 2010). Thus, the need to overcome the climate change deforestation related issues, calls for the definition of global agreements and has given new impetus to researches that use national data to identify socio-economic variables that determine the conversion of forest area by increasing emission from deforestation. These empirical cross-country studies allow generalizations to be made about the processes responsible to affect the forest cover, and then recommendations for climate change mitigation policies can be properly identified.

Global regression models are used to test the accuracy of deforestation driving forces but, as underlined by recent literature (Scrieciu, 2007), these models have both theoretical and methodological limitations. One of the main limitations, widely undervalued in literature, is the reliability of forest area data. The largest part of deforestation applied works depends on FAO data published in the Forest Resource Assessments (FRAs). Forest area time series have been continuously updated producing dissimilar value attribution over the years. We test how the use of different FRAs data affects the impact of the most commonly analysed variables in tropical deforestation cross-country works by running the same regression models on the set of FRAs. A descriptive indicator for the data source bias is then evaluated. When variables have ambiguous effects in explaining the forest cover reduction, the policies in developing countries might be influenced by biased empirical results.

The present work is organized as follows: In section 2 we review the existing literature on cross-country models linked to tropical deforestation. Section 3 illustrates the forest area data reliability and the implications for empirical analysis are evaluated. In section 4 a framework for the analysis to be conducted is defined. Section 5 introduces data and the methodology undertaken. In section 6 we present the results and the related discussion. Section 7 concludes.

2. The cross-country regression models.

Recent scientific literature provided widespread outcomes on drivers of tropical deforestation (Combes et al., 2009) and the role of tropical forests in REDD (Leplay and Thoyer, 2011).

In order to help the policy maker to set-up international effective policies against climate change, the drivers of tropical deforestation in developing countries need to be clearly identified. The research about socio-economic variables affecting the change in forest cover is a debated issue since the 80s, and across the 90s, that produced a wide, but conflicting output. The "first-wave" studies on tropical deforestation relied massively on cross-country macroeconomics statistics (Barbier and Burgess, 2002). Two works tried to cover the problem of driver identification extensively: the first from Angelsen and Kaimowitz (1998) and the second from Geist and Lambin (2001). Both reviewed the existing research on tropical deforestation to determine the most investigated drivers in related literature. The findings confirmed the existence of three direct drivers with a common impact at global level: agricultural expansion, logging activities and infrastructure expansion. The *land use models* offer an analytical framework oriented to explain the relevance of direct drivers as the consequence of competition for a limited resource: the land (Barbier, 2001). Contemporary, a series of underlying drivers, have been inquired. Those are exogenous variables with respect to land usage conversion decisions, but can potentially affect the direct drivers (Lambin et al., 2003; Galinato and Galinato, 2012). All the regions experienced land constraints and resolutions on alternative land use. Such constraints place strong consensus on the negative impact driven by direct causes at global level as population pressure, increasing food demand (Angelsen and Kaimowitz, 1998; Gibbs et al., 2010), and pasture (Bawa and Dayanandan 1997; Busch and Vance, 2011) rise the needs for land-agricultural-use by causing the shifting of marginal forest area. Economic development, urban market growth, openness to international trade, external debt (Capistrano and Kiker 1995; Culas, 2007; Leplay and Thoyer, 2011) are underlying drivers that affect both the wood extraction and the need of infrastructures (Geist and Lambin, 2001). Nevertheless, it is pointed out, that development of the economic path may also potentially benefit from the so-called *forest transition* by decreasing the rate of deforestation. The channel through which the transition occurs is due to the competition of land use: as the relative value of forest conservation increase, so the deforestation rate decreases (Barbier et al., 2009).

Recently, literature has suggested that the tropical deforestation issue cannot be appropriately generalized on a global level (Scrieciu, 2007). Especially, when the role of forest as a carbon sink is considered, the public good nature of the ecosystem service provided, requires coordinated international shared efforts between developed and developing countries (Chichilnisky and Heal, 1994). Thus, while is still important to define global tropical deforestation drivers, it is equally important to include contextual key elements in order to be able to address a particular country's forest area trend. When specific factors of analysis are ignored the international efforts fail to reach the objective (Pfaff and Walker, 2010). An extensive analysis should rely on regional models (Culas, 2007) that are likely to catch both the *supra*-national and the location-specific level (forest type, crop's variety, land yielding, cultural factors). Lower scale of analysis may improve the selection of specific underlying drivers helping to define the framework for effective intervention measures.

3. Forest area data reliability

FAO provides data on forest area since the 1948 through the first World Forest Inventory. Three following reports came out in the 1955, 1958 and 1963, relying on data response-based from national questionnaires (FAO 1948; 1966). The global assessments were interrupted by a series of *Regional Forest Resource*

Assessments, published between 1975 and 1977. The regional assessments gave an account of forest area valuation relying on a reduction of national questionnaire response data, but also adding further direct research material (FAO, 1981 a; FAO, 1981 b; Sommer, 1976) and expert valuations (Persson, 1974).

The first Forest Resource Assessment was published in 1980; it provided a common technical definition of forest areas that produce consistent reports among the 75 developing countries briefed. The interim report of 1988 gives a valuation for forest area in 1980 (FAO, 1988).

Four further FRAs have been published in 1990, 2000, 2005 and 2010 (FAO 1993; FAO 2000; FAO 2005; FAO 2010). The increasing performance of successive "vintages" produced a quite dissimilar forest area amount among FRAs. Following Grainger (2008), figure 1 shows the global forest area provided by different FRAs for 75 tropical countries. Two points and three different trends are reported as a consequence of previous estimate reviews.

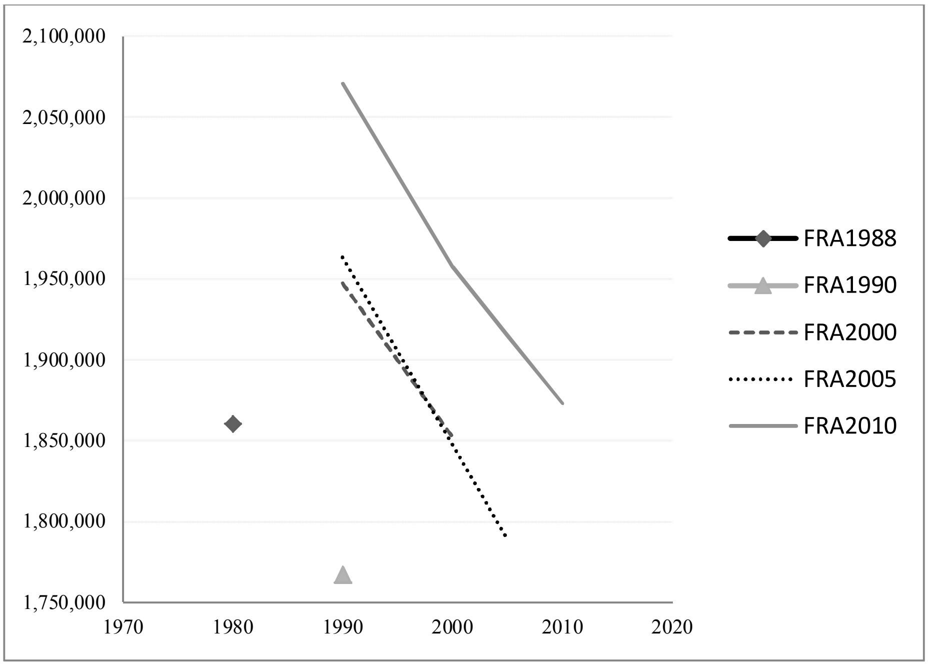

Figure 1: Global forest area trend (Sq.Km): FRAs comparison (n=75)

FRA 1990 the total area is widely lower than subsequent FRAs, as well as than FRA 1988. In order to understand the causes of underestimation we control the total forest area trends at regional level. Figure 2, 3 and 4 illustrate as the main source of global underestimation of FRA 1990 is due to Sub-Saharan Africa region.

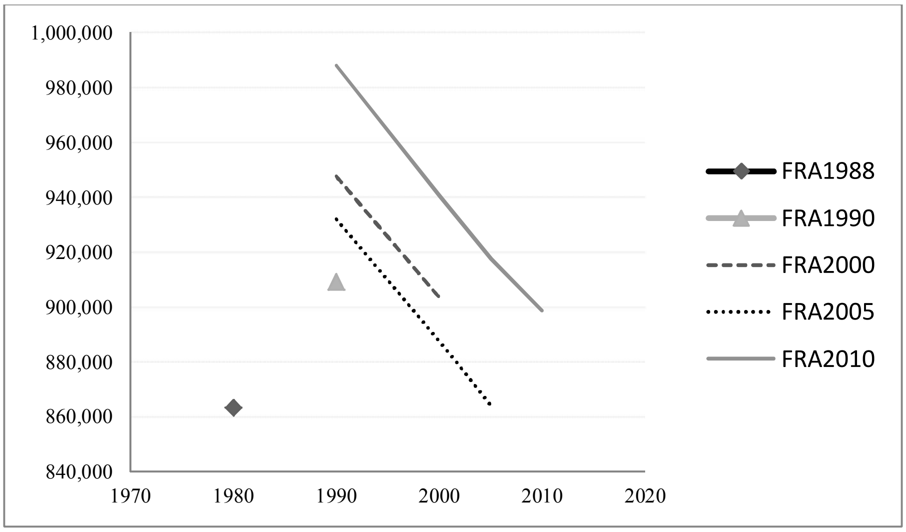

Figure 2: Latin America & Caribbean forest area trend (Sq.Km): FRAs comparison (n = 25)

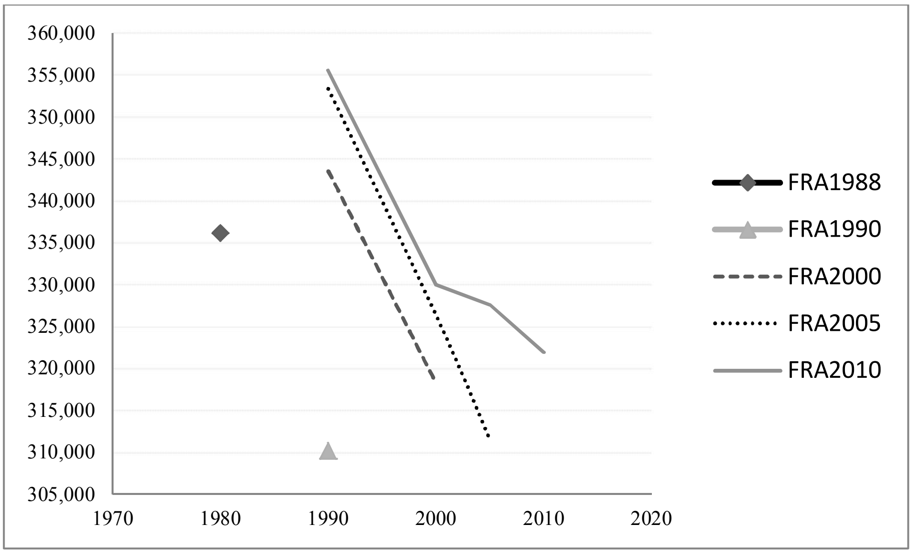

Figure 3: South East Asia & Pacific forest area trend (Sq.Km): FRAs comparison (n = 15)

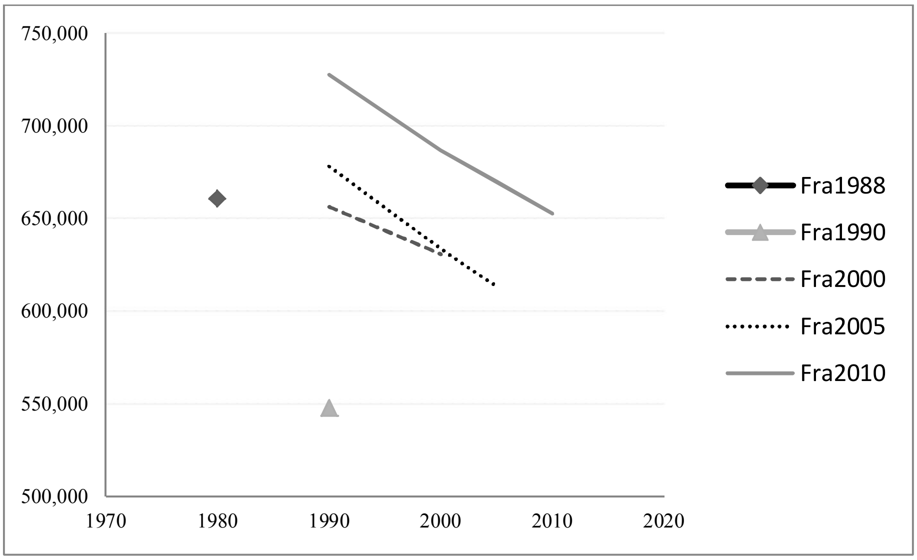

Figure 4: Sub-Saharan Africa forest area trend (Sq.Km): FRAs comparison (n = 35)

Table 1 presents the correlation among FRAs at a regional level. While in Latin America, the Caribbean, South East Asia, and the Pacific the correlation is always close to 1, in sub-Saharan Africa FRA 1990 has a correlation equal to 0.83 with FRA 2000 and slightly higher with FRA 2005 and FRA 2010.

Table 1: Forest area correlation in 1990 by different FRAs

	Latin America & Caribbean (n=25)			South East Asia & Pacific (n=15)			Sub-Saharan Africa (n=35)		
	FRA90	*FRA00*	*FRA05*	*FRA90*	*FRA00*	*FRA05*	*FRA90*	*FRA00*	*FRA05*
FRA00	0.9995			0.9889			0.8256		
FRA05	0.9981	0.9992		0.9926	0.9959		0.9106	0.9537	
FRA10	0.9985	0.9994	0.9997	0.9922	0.996	0.9989	0.9007	0.9547	0.9802

There are two reasons for the difference in forest area valuations among FRAs. The first explanation is related to the adoption of a new common technical definition of forest area starting from FRA 2000. In fact, in 1996 the expert consultation of Kotka III sets a new definition, by adopting the 10% of forest crown as a common reference. This allows accounting for forest area, which was before excluded in developing countries. A second explanation is linked to the difference between areas in 1990 and 1980 according to FRA 1988. The estimations for 1980 are more consistent with FRA 2000 than those in FRA 1990. In fact, in FRA1990 an innovation in estimates was introduced through the "*deforestation model*". This model aimed to project the forest area national data to a common reference year and overcome the potential bias due to expert valuation. Compared to the linear projection method adopted in FRA 1980 and 2000, the model is nonlinear and a function of the population density as the equation (1) indicates:

$$\frac{dY}{dP} = b_1 Y^{b_2} - b_3 Y \quad (1)$$

Y is the percentage of non-forested area, P the population density and b_1, b_2 and b_3 are model parameters (FAO, 1993). By integrating this differential equation, a *Chapman-Richard* function is calculated showing as, in the stated model, the non-forest area value (and so the forest area) is non-linearly dependent on the population density. This could be the reason why in some African countries the forest area is widely underestimated according to FRA 1990. As table 2 displays, the correlation of population density with forest area is indeed higher in sub-Saharan African countries than others regions. In particular, the high correlation of 1990 confirms the relevance of the "*deforestation model*". In FRA 2005 and 2010, FAO allows countries to use the projection methods they thought suitable for their characteristics. Many African countries switched again to non-linear projection (Grainger, 2008) and the correlation in 2005 and 2010 turns out higher than in 2000. Moreover, the "*deforestation model*" may also represent a source of never controlled simultaneous causality between deforestation and the largely investigated demographic variables.

Table 2: Population density and forest area correlation: FRAs comparison

	Latin America & Caribbean (n=25)	South East Asia & Pacific (n=15)	Sub-Saharan Africa (n=35)
	Population density	*Population density*	*Population density*
FRA90	-0.2442	-0.1676	-0.3749
FRA00	-0.2517	-0.1309	-0.3487
FRA05	-0.264	-0.1569	-0.35
FRA10	-0.2563	-0.1553	-0.3575

Despite the consistency in methodology and definitions, FRA 2005 and 2010 display a value gap largely due to wide underestimates in 2005 for Brazil in Latin America and Caribbean[1], Democratic Republic of Congo and Mozambique in sub-Saharan Africa. [2] FRA facilitates the exploitation of panel data to find deforestation drivers (Angelsen and Kaimowitz, 1998; Koop and Tole, 1999; Shandra., 2007). Nevertheless, the "observable" value of forest area over time, are just those related to FRA's year of publication. FAO provides the annual year of deforestation that allows to fill-in the gap in the time series by means of a linear yearly interpolation. This allows reliance on a more "dense" long panel, but the interpolation may produce biased results whether the estimates are obtained by using the long panel are significantly different from those obtained from the "observable" or short panel. When significant difference occurs, the linear trends do not fit well the real trend and better interpolations are needed. Only Combes et al. (2009) use a panel with "observable" data by means of an average of spread deforestation data between 1970 and 2005.

On the other hand, literature focuses on cross-sectional data; this reduces bias in forest area data, but does not catch the heterogeneity hidden in the context-specific. The deforestation issue is highly integrated to the local framework (Angelsen and Kaimowitz, 1998) thus by using panel data, it is possible to set global, or at least regional, drivers while controlling for unobserved countries' effects.

To overcome all the original data problems many works implement proxy variables for deforestation due to agricultural land use (Scrieciu 2007) or roundwood production (Gullison and Losos, 1993), but losing part of the information contained in other competitive land use.

4. A nested framework of analysis for models comparison.

In order to test how the weak reliability and variability of forest area data affects the results of estimation about deforestation drivers' investigation, a systematic framework of comparison is defined. Three levels of analysis are

[1] An average underestimation on 1990, 2000 and 2005 of 53446 Sq.Km (see FRA 2005 and FRA 2010).

[2] An average underestimation of 21318 Sq.Km. in Democratic Rep. of Congo and 21953 Sq.Km. in Mozambique.

identified as illustrated in figure 5. First, we select two groups of drivers to be tested at two different *scale levels*. The direct drivers are associated on a global *scale* level (all the countries of the sample), while three set of underlying drivers are respectively associated at the three regions of interests. After this setting, the same set of drivers for each scale is compared at *data source* level

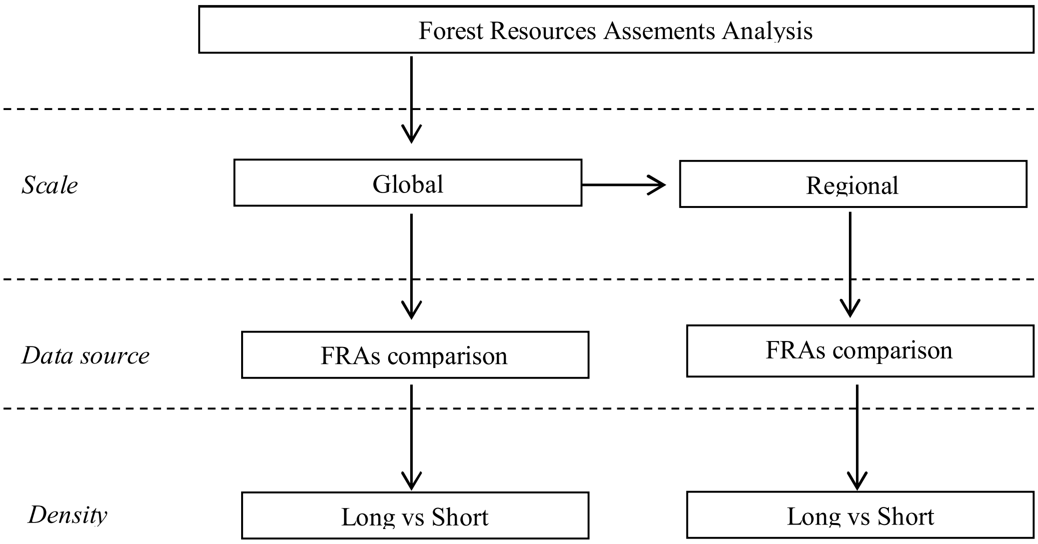

Figure 5: A nested framework for models' comparison

To control the difference in outcome related to different FRA utilization. Last, for the same set of drivers at each scale and for each FRA, a comparison at *panel density* level is developed. The *density* comparison refer to dissimilar estimates obtained through the use of the long (interpolated) and the short (with time gaps) panel.

5. Data and methodology.

The framework developed is tested by controlling the impact of deforestation drivers on forest area. We select 75 tropical countries from which three regional samples are drawn: Latin America & Caribbean, Asia & Pacific and Sub-Saharan Africa[3]. These countries are picked according to the presence of country's data in all FRAs. Following the consolidated literature (Geist and Lambin, 2001), the most

[3] Table 1 in the Appendix displays the list of countries by each region.

explored and reliable direct and underlying drivers with a negative influence on cover are selected for the global and the regional scale (see table 2 in the appendix). The lack of data for regressors defines further sample restrictions.

The general form of the econometric model for our analysis is:

$$y_{it} = \alpha + \mathrm{X}_{it}\boldsymbol{\beta} + v_i + \varepsilon_{it} \quad (2)$$

Where *y* is the logarithm of forest area, *i*=1,..,N countries and *t* is the time index. v_i is the country specific residual, ε_{it} is the error term identically and independently distributed with zero mean, constant variance and $E(\varepsilon_i\varepsilon_j) = 0$, $\mathbf{X}_{it}$ is a vector of logged explanatory direct and indirect variables from table 2 in the appendix, while $\boldsymbol{\beta}$ is the matrix of coefficient to be estimated (Wooldridge, 2003).

Since the data are observations not picked up from a randomly drawn sample and the population of tropical countries concerned with deforestation is almost fully represented, the fixed effects has been preferred to the random effects model (Green, 2011). To this end, the Hausman test applied for each regression confirms the hypothesis (see table 3 and 4 in the appendix). Assuming endogenous fixed effects, the country specific residual is added to the constant term and our model specification is:

$$y_{it} = \mathrm{FE}_i + \mathbf{X}_{it}\boldsymbol{\beta} + \varepsilon_{it}, \quad (3)$$

where FE_i represent the fixed effect that catches unobservable countries' time invariant characteristics such as the type of forest, climatic conditions, land size (Scrieciu, 2007) and institutional variables (Angelsen and Kaimowitz, 1998).

In order to get a descriptive measure of the impact of different data sources a difference-in-estimation indicator, DiE , is created by dividing the number of all the coefficients dissimilar in sign and significance, *i*, by the number of all possible pairwise comparison *N*, both at *data source* and *panel density* level for each *scale*. The (3) shows the formula for DiE:

$$DiE = \frac{\sum_{i=1}^{I}\left(i|\beta_{x_i}^{FRAh} \neq \beta_{x_i}^{FRAj}\right)}{N} \quad for\ h\ and\ j = 2000, 2005\ and\ 2010 \quad (3)$$

where $\beta_{x_i}^{FRAh}$ is the coefficient of x_i regressor according to data of FRA of year h and $\beta_{x_i}^{FRAj}$ is the coefficient for the same regressors for estimations with FRA of year j. *N* is equal to *HI* where *I* represents the total number of explanatory variables included in the model and

H is the number of FRA (2000, 2005 and 2010) compared.

6. Results and discussion.

Table 3 shows the results for the global *scale*. With the long panel, the comparison among FRAs demonstrates that agricultural land and roads always have the expected negative sign but they are significant only in FRA 2005 and FRA 2010. Instead, roundwood has the opposite effect : with regard to FRA 2000 it is significant and has the expected positive sign, while according to FRA 2005 and FRA 2010 it turns out to be neither significant nor an expected result . In the short panel, the FRAs comparison highlights that all the drivers do not have a significant impact on deforestation. Roundwood production confirms that it is irrelevant in the others FRAs.

Comparing long and short panels for each FRA, it is straightforward to control that no relevant slightly differences exist, unless roundwood coefficient in FRA 2000 that shift to be not significant.

Table 3: Direct drivers at global level: FRAs and panel density comparison

	Long			Short		
	(1)	(2)	(3)	(4)	(5)	(6)
	FRA00	FRA05	FRA10	FRA00	FRA05	FRA10
Agricultural land	-0.146	-0.443*	-0.472***	-0.723	-0.543*	-0.543*
	(-0.30)	(-1.93)	(-4.59)	(-1.52)	(-2.12)	(-2.16)
Roundwood	-0.166***	0.0317	0.0366	-0.357	-0.0698	-0.0783
	(-2.84)	(0.39)	(0.57)	(-1.62)	(-0.91)	(-1.03)
oads	-0.0553	-0.221***	-0.196***	0.460	-0.203**	-0.170**
	(-0.57)	(-3.24)	(-3.71)	(0.71)	(-2.84)	(-2.77)
constant	13.69**	15.76***	15.85***	17.79***	18.31***	18.14***
	(2.63)	(6.63)	(12.80)	(3.62)	(7.66)	(7.70)
N	605	721	804	110	131	131
Groups	65	73	73	65	67	67
r2	0.0215	0.131	0.204	0.0837	0.397	0.400
F	3.691	9.144	20.08	2.210	12.80	11.31

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The underlying drivers are tested on a regional *scale*. In Latin America and the Caribbean, as table 4 highlights, the impact of variables shows similar results both, for the long and the short panel. Among FRAs, at both *density* levels the main difference is the insignificance of GDP per capita, GDP per capita square and livestock index according to FRA 2000.

Table 4: Underlying driver in Latin America and Caribbean: data source and panel density comparison

	Long			Short		
	(14)	(15)	(16)	(17)	(18)	(19)
	FRA00	FRA05	FRA10	FRA00	FRA05	FRA10
Pop density	-0.450***	-0.192**	-0.190***	-0.332**	-0.211**	-0.174*
	(-3.54)	(-2.48)	(-2.86)	(-2.71)	(-2.19)	(-2.00)
Agri. Technology	-0.0137	0.0462	0.0339	-0.0772	0.0963	0.0388
	(-0.27)	(1.39)	(1.25)	(-0.78)	(1.55)	(0.77)
GDP pc	-0.268	-0.312**	-0.331**	-0.0628	-0.443*	-0.319*
	(-0.99)	(-2.14)	(-2.27)	(-0.20)	(-1.96)	(-1.94)
GDP pc square	0.0192	0.0283**	0.0290**	0.000284	0.0406*	0.0285*
	(0.82)	(2.31)	(2.38)	(0.01)	(2.05)	(2.00)
livestock_index	-0.0999	-0.128***	-0.145***	-0.0844	-0.186**	-0.166**
	(-1.62)	(-2.90)	(-2.89)	(-1.11)	(-2.68)	(-2.30)
constant	11.11***	9.647***	10.08***	10.67***	9.961***	10.04***
	(8.08)	(15.21)	(17.85)	(6.32)	(14.20)	(19.17)
N	274	404	524	49	74	99
Groups	25	25	25	25	25	25
r2	0.443	0.442	0.526	0.580	0.517	0.511
F	5.309	5.080	6.271	7.465	5.047	6.052

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5 presents the estimated results for South East Asia and the Pacific. A considerable reduction of population density impact is assessed at the *density* level. At *data source* level, in the long panel the GDP per capita is significant accordingly with FRA 2010.

Table 5: Underlying drivers in South East Asia and Pacific: data source and panel density comparison

	Long			Short		
	(17) FRA00	(18) FRA05	(19) FRA10	(20) FRA00	(21) FRA05	(22) FRA10
Pop density	-1.148*	-0.645**	-0.334*	-0.769**	-0.960**	-0.524*
	(-1.92)	(-2.88)	(-2.07)	(-2.35)	(-2.68)	(-1.83)
Agri. Technology	0.160	0.0620	0.113	0.333	0.195	0.228
	(1.04)	(0.71)	(1.12)	(1.10)	(0.84)	(1.43)
GDP pc	3.643	0.173	-0.602*	0.672	1.085	0.172
	(1.64)	(0.28)	(-1.96)	(1.10)	(1.23)	(0.25)
GDP pc square	-0.237	-0.0101	0.0384	-0.0448	-0.0644	-0.00876
	(-1.60)	(-0.21)	(1.73)	(-0.90)	(-1.02)	(-0.19)
Market growth	-0.0635	0.0642	0.000078	0.0928	-0.271	0.0360
	(-0.61)	(0.38)	(0.00)	(0.31)	(-0.82)	(0.21)
constant	0.265	10.80***	12.20***	7.263**	9.174***	9.031***
	(0.04)	(5.20)	(12.95)	(2.79)	(3.47)	(4.93)
N	149	224	298	27	42	56
Groups	15	15	15	15	15	15
r2	0.176	0.109	0.112	0.509	0.433	0.187
F	0.897	2.937	4.463	2.452	1.993	1.137

t statistics in parentheses:* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In sub-Saharan Africa (see table 6) the FRAs comparison, indicates that in the long panel, the population density and market growth are not significant in FRA 2000, while the external debt has a slight an impact according to FR2010. The *density* comparison highlights that the market growth is no more significant for FRA2010.

Table 6: Underlying driver in Sub-Saharan Africa: data source and panel density comparison

	Long			Short		
	(20)	(21)	(22)	(28)	(30)	(31)
	FRA00	FRA05	FRA10	FRA00	FRA05	FRA10
Pop density	-0.282	-0.414***	-0.393***	-0.239	-0.418***	-0.379***
	(-0.96)	(-3.39)	(-3.61)	(-0.84)	(-4.35)	(-3.56)
Agri. Technology	0.0468	-0.0147	-0.0155	0.212	0.00931	0.0145
	(0.64)	(-0.64)	(-0.59)	(0.61)	(0.23)	(0.28)
GDP pc	2.963**	0.917*	0.810**	3.660	1.279*	0.958**
	(2.07)	(1.80)	(2.11)	(1.54)	(2.00)	(2.04)
GDP pc square	-0.257**	-0.0706*	-0.0586**	-0.308	-0.0978**	-0.0718**
	(-2.09)	(-1.84)	(-2.10)	(-1.63)	(-2.06)	(-2.05)
Market growth	0.0195	-0.139**	-0.117**	-0.125	-0.296**	-0.136
	(0.13)	(-2.08)	(-2.07)	(-0.27)	(-2.66)	(-1.38)
External debt	0.00491	0.00817	0.0129**	0.0371	0.0274	0.0347**
	(0.32)	(0.76)	(2.35)	(0.85)	(1.04)	(2.39)
International trade	0.0126	0.0135	-0.0315	-0.104	-0.0193	-0.0555
	(0.27)	(0.49)	(-1.36)	(-1.36)	(-0.31)	(-1.00)
constant	0.737	7.751***	7.939***	-2.325	6.942***	7.052***
	(0.14)	(4.72)	(6.53)	(-0.26)	(3.17)	(4.17)
N	342	514	657	64	97	123
Groups	33	33	33	33	33	33
r2	0.0823	0.307	0.405	0.108	0.493	0.469
F	1.356	3.256	4.148	2.336	4.753	5.888

t statistics in parentheses:* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results from previous regressions determine the *DiE* computation. A rank of low, medium or high presence of difference-in-estimation is then imputed at the global model and on a regional scale for the *data source* and *panel density* level as presented in table 7.[1]

[1] The estimation of *DiE* is from 0 to 1. When 0<*DiE*<0,333 then *DiE*=Low, if 0,333≤*DiE*<0,666 then *DiE*=medium and 0,666≤*DiE*≤1 then *DiE*=High.

Table 7 Difference-in-estimation rate by analysis level.

Scale		*Data source*	*Panel density*
Global		High ($0.\overline{6}$)	Medium (0.44)
Regional	LA&C	Medium (0.53)	0
	SEA&P	Medium (0.4)	Low (0.26)
	SSA	Medium (0.42)	Medium (0.38)

On the global *scale* there is a high DiE when different FRAs are utilized, while the rank is medium, whether long and short panel are compared. On a regional *scale* all areas have a medium DiE from *data source* comparisons. Moreover, sub-Saharan Africa has a medium *panel density* difference-in-estimation. In Latin America and the Caribbean, South East Asia and Pacific there are a zero and low *panel density* DiE values respectively.

The higher bias arises from the analyses assessed at the *global* level confirming the strategic role of regional outlook when a global problem such as tropical deforestation needs to be tackled.

7. Conclusions

Reducing emissions from deforestation is now at the top of the actions that developing countries, particularly in tropical areas, can implement inside a global strategy to fight climate change. Understanding the dynamics of deforestation requires precise and continuously updated data relying on a common international framework.

A great proportion of deforestation applied researches are based on FAO data published in the Forest Resource Assessments (FRAs). Nevertheless, the investigation about drivers of deforestation has resulted in contrasting outputs since forest area time series have been continuously updated producing divergent value attribution over the years. Such a variation may have induced a data reliability bias on empirical works. For this reason, we tested how data on forest area reported in FRAs may have contributed to influence the sign and the significance of direct and underlying drivers largely investigated in literature. The analysis confirms that the data weakness could have an effect both upon the drivers identification and their relevance.

The impact of deforestation drivers results in different outcomes, both at a global and regional level, according to the *data source* as well as to the *density* of the forest area time series adopted.

The weak reliability of forest area data may have produced biased outputs and, thus, different relevant indications for intervention on climate change policies. The consequences of unreliable forest area data can particularly affect the international efforts to reduce emission from deforestation as in the case of inefficient measures to orientate the impact of investigated deforestation drivers or unrealistic carbon credits allocation to developing countries (Combes Motel et al., 2009).

Countries involved in on going climate change agreements not only define objectives and actions, but also collaborate on defining terms, methods of reporting, and improving indicators. In this setting, the availability of reliable data is the basis for a credible analysis in the field of climate change mitigation. The latest data released by FAO constitutes a progress in terms of data comparability and coverage. At the same time further improvements are needed. In particular it is desirable that countries action plan would increase the accountability of national forest inventories by means of common standard definitions

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Appendix

Table 1: List of countries by region

Latin America & Caribbean	*india*	*madagascar*
antigua and barbuda	*indonesia*	*malawi*
belize	*laos*	*mali*
bolivia	*malaysia*	*mauritania*
brazil	*myanmar*	*mozambique*
colombia	*nepal*	*namibia*
costa rica	*pakistan*	*niger*
cuba	*papua new guinea*	*nigeria*
dominica	*philippines*	*rwanda*
dominican republic	*sri lanka*	*senegal*
ecuador	*thailand*	*sierra leone*
el salvador	*vietnam*	*somalia*
grenada		*sudan*
guatemala	***Sub-Saharan Africa***	*united republic of tanzania*
guyana	*angola*	*togo*
haiti	*benin*	*uganda*
honduras	*botswana*	*zambia*
jamaica	*burkina faso*	*zimbabwe*
mexico	*burundi*	*zambia*
nicaragua	*cameroon*	*zimbabwe*
panama	*central african republic*	
paraguay	*democratic republic of congo*	
peru	*congo*	
saint vincent and the grenadines	*côte d'ivoire*	
suriname	*gabon*	
venezuela	*gambia*	
	ghana	
South East Asia & Pacific	*guinea*	
bangladesh	*guinea bissau*	
bhutan	*kenya*	
cambodia	*liberia*	

Table 2: Descriptive statistics

Variable	LA&C	SEA&P Mean (SD)	SSA	Source (1990-2010)
Forest area FRA 2010 [Sq. Km]	42100.798 (109788.04)	21933.387 (26228.72)	15792.498 (18942.424)	FAO
Direct drivers				
Agricultural land [Sq. Km]	233260.4 (531010.97)	229570 (427934.5)	232665.01 (261250.14)	FAO
Roundwood [thousandth cubic meters]	18847248 (48518310)	47884400 (75575284)	10891989 (14134816)	FAO
Roads [Sq. Km.]	133061.89 (370254.48)	398749.99 (871597.17)	34969.975 (38521.508)	World bank
Underlying drivers				
Agricultural Technology [Cereal yield, Kg/Ha]	2233.1556 (1043.9751)	2823.9174 (902.54741)	1224.6614 (653.99991)	FAO
GDP pc [$2000 constant]	2875.3981 (2310.5389)	888.09647 (980.87742)	759.61994 (981.98565)	World bank
Total land [Sq. Km]	757053.3 (1695266.9)	619737.62 (747748.25)	521130.82 (499387.48)	World bank
Livestock index [2004-2006=100]	91.440133 (20.412666)	86.651291 (21.2438)	88.655913 (19.681617)	World bank
External Debt [Debt service on external debt]]	4140000000 (11850000000)	4295000000 (6746000000)	5.118e+08 (1.321e+09)	World bank
Market growth [Gross national expe, $2000 constant]	108.4208 (12.102117)	103.94258 (9.3231932)	108.1763 (14.665831)	World bank
Trade	82.253248 (43.227125)	75.222761 (47.569666)	64.622181 (28.547091)	World bank

Table 3: Direct drivers at global level (long): FRAs comparison

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	FRA90_OLS	FRA00_FE	FRA00_RE	FRA05_FE	FRA05_RE	FRA10_FE	FRA10_RE
Agricultural land	0.374	-0.146	0.604***	-0.443*	0.146	-0.472***	-0.0163
	(1.56)	(-0.30)	(6.91)	(-1.93)	(1.38)	(-4.59)	(-0.18)
Roundwood	-0.149	-0.166***	-0.108***	0.0317	0.0837	0.0366	0.0922**
	(-0.62)	(-2.84)	(-2.70)	(0.39)	(1.64)	(0.57)	(2.45)
Roads	0.560*	-0.0553	0.0288	-0.221***	-0.211***	-0.196***	-0.214***
	(1.85)	(-0.57)	(0.39)	(-3.24)	(-5.20)	(-3.71)	(-6.52)
constant	1.037	13.69**	3.358***	15.76***	8.035***	15.85***	9.788***
	(0.35)	(2.63)	(3.82)	(6.63)	(7.41)	(12.80)	(9.58)
N	55	605	605	721	721	804	804
Groups		65	65	73	73	73	73
r2	0.322	0.0215		0.131		0.204	
F	6.455	3.691		9.144		20.08	
Hausman's χ^2		49.76		123.55		185.61	

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Direct drivers at global level (short): FRAs comparison

	(8)	(9)	(10)	(11)	(12)	(13)
	FRA00_FE	FRA00_RE	FRA05_FE	FRA05_RE	FRA10_FE	FRA10_RE
Agricultural land	-0.723	0.544***	-0.543*	0.512**	-0.543*	0.468**
	(-1.52)	(3.54)	(-2.12)	(3.28)	(-2.16)	(3.08)
Roundwood	-0.357	-0.143	-0.0698	0.0119	-0.0783	-0.00400
	(-1.62)	(-0.98)	(-0.91)	(0.11)	(-1.03)	(-0.04)
Roads	0.460	0.508*	-0.203**	-0.214***	-0.170**	-0.186**
	(0.71)	(2.39)	(-2.84)	(-3.29)	(-2.77)	(-3.06)
constant	17.79***	-0.364	18.31***	5.079**	18.14***	5.575***
	(3.62)	(-0.24)	(7.66)	(3.05)	(7.70)	(3.57)
N	110	110	131	131	131	131
Groups	65	65	67	67	67	67
r2	0.0837		0.397		0.400	
F	2.210		12.80		11.31	
Hausman's χ^2	5.08		60.02		69.88	

t statistics in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$