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Spatiotemporal modeling of fuelwood environmental impacts: Towards improved accounting for non-renewable biomass

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ABSTRACT

The extraction and burning of woody biomass at rates exceeding re-growth (i.e. non-renewable extraction) results in net emissions of CO_2. Quantification of the amount of non-renewable woody biomass through a robust and widely applicable method is urgently needed for a wide variety of applications including cookstove carbon-offset projects, national GHG inventories, and sustainable forest management strategies under REDD+. Within this context, we developed "Mofuss" (Modeling fuelwood savings scenarios), a dynamic model that simulates the spatiotemporal effect of fuelwood harvesting on the landscape vegetation and that accounts for savings in non-renewable woody biomass from reduced consumption. The model was tested in western Honduras where collected and marketed fuelwood is used by the residential sector in both urban and rural settlements. We argue that geospatial modeling, aimed at representing real situations more closely while integrating uncertainty, should be used in calculations of carbon savings from cookstove projects or fuel switching interventions.

Software and data availability

Mofuss integrates a set of scripts that requires some freeware to be installed first. The first step consists in downloading Mofuss user manual: www.mofuss.unam.mx. This document contains detailed but concise instructions for downloading, installing and using Mofuss and any other needed freeware.

Mofuss (version 1.0) was designed and coded by Adrian Ghilardi between September 2011 and April 2015 with contributions from four co-authors of the present work: Jean-François Mas, Robert Bailis, Rudi Drigo and Omar Masera. A fifth co-author, Ernesto Vega, helped with R code issues during debugging. Developer contact details are available in affiliations of authors.

Dinamica EGO (one of the required freeware) is only available for Windows operating system. Mofuss has been tested successfully in various configurations of Windows 7, 8 and 10 versions, and in Intel-based Macs using Boot Camp. There is no recommended hardware as overall processing time will depend on the size of the selected area of interest. For replicating the present study area (4 departments in western Honduras), a desktop with an Intel i7 CPU at 3.40 GHz with 16 GB of RAM should take about 24–36 h for completing each of the three more time demanding processes: IDW submodule and both simulations (BaU and ICS) using 100 MC realizations. A much smaller area with few MC realizations will take a couple of minutes using the same equipment. The user manual also provides a link to already processed IDW indexes for the same study area as shown in this work, in order to gain some time if trying to replicate this particular study example. Both 64-bit and 32-bit systems will work (although under 32-bit some figures will

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Abbreviations and definitions

AGB (aboveground biomass)
CDM (Clean Development Mechanism)
fNRB (fraction of non-renewable biomass): When NRB (defined below) is referred to as a fraction of total fuelwood use, the acronym fNRB is used instead, standing for the "fraction of non-renewable biomass", a number which describes the degree to which of the harvesting of wood is unsustainable
Forest We define forest or "forest cover" broadly, to include sparse and mosaic woodlands and rangelands not necessarily classified as "forest" under more conventional definitions which use thresholds for canopy cover or tree height
Fuelwood, also known as firewood Woody biomass used as an energy source without any thermochemical transformation and with little or no mechanical processing
ICSs (improved cookstoves): Efficient end-use cooking devices using less fuel and emitting fewer pollutants in comparison to traditional (i.e. less-efficient) models. It is used interchangeably with efficient or fuel-saving cookstoves
IDW (Inverse Distance Weighted)
K (carrying capacity): Maximum achievable AGB stock given a certain class of Land Use and Land Cover, plus any other biophysical constraints. K is assumed to remain constant in time within Mofuss
LULCC (Land Use and Land Cover Change): Direct or indirect human modification of the earth's terrestrial surface. Land cover refers to the physical and biological cover over the surface of land, including water, vegetation, bare soil, and/or artificial structures. Land use is defined in terms of human activities such as agriculture, forestry and building construction that alter land surface processes including biogeochemistry, hydrology and biodiversity
MAI (Mean Annual Increment): Equivalent to Maximum Sustainable Yield (MSY)
MC (MonteCarlo simulation)
NRB (non-renewable biomass): Extraction of woody biomass at rates exceeding the rate of natural re-growth within a given time period, most commonly one year
tDM (tons of dry matter)
TOF (trees outside forests): Trees on farmland, household compounds, and roadside commons, where wood is accessed by pruning live trees and/or collecting dead/downed branches. This category also includes shade trees in coffee plantations, which are pruned regularly and constitute a major source of wood in coffee-growing parts of the study region
Simulation Corresponds to the progression of fuelwood harvest - regrowth spatial patterns over a given time period in discrete time steps or iterations. In the particular example of our case study each simulation lasted 30 years, by annual time steps. Iterations cannot be shorter than a week or longer than 10 years, while simulation periods have no upper bounds
Realization Each of many homologous simulations (i.e. set under same parameters and assumptions) that are run to account for uncertainty and sensitivity. Realizations should be understood as the process of how simulations "come out" after each Monte Carlo run

be purposely rendered at lower resolution).

Mofuss and any other needed software are freely available to download and use, and all Mofuss scripts can be opened, edited and saved using any free code editor such as Notepad++ or Sublime Text. Mofuss scripts were coded in Dinamica EGO (.egoml), R (.R), LaTeX (.tex) and Windows batch scripting (.bat). Mofuss scripts and associated files (e.g. ffmpeg.exe, zip.exe, pdf messages) is roughly 45 MB, and the Honduras dataset (spatial raster data in geotiff, spatial vector data, and tables) is roughly 550 MB and is downloadable as a separate file, as explained in the user manual.

1. Introduction

Despite the fact that traditional wood energy (fuelwood and charcoal) is still in widespread use in many developing countries (IEA, 2012a, b), the impact of woodfuel harvesting on forests and woodlands is still a point of contention. Identified as the "other energy crisis" in the 1970s (Eckholm, 1975), fuelwood extraction and charcoal production by poor rural and peri-urban populations were seen then as major drivers of environmental degradation (de Montalembert and Clement, 1983). Some analyses still report a direct connection between woodfuels and "severe deforestation" (e.g. Pang et al., 2013; Singh et al., 2010) or "forest degradation" (e.g. Ahrends et al., 2010; Cantarello et al., 2014; Moroni and Musk, 2014; Orozumbekov et al., 2015; Ryan et al., 2012; Specht et al., 2015). However, others think woodfuel demand has limited impact on forest cover (e.g. Hansfort and Mertz, 2011; Shrestha et al., 2013) because it is overshadowed by other socioeconomic and ecological processes (de Waroux and Lambin, 2012; Dewees and Arnold, 1997; Foley, 1985; Hosier, 1993).

Broad generalizations are inherently misleading, as spatiotemporal patterns of woodfuel supply and demand are site specific and impacts on vegetation vary greatly from place to place (Ghilardi et al., 2007; Wangchuk et al., 2014) and as a result of specific patterns of resource use, e.g. subsistence fuelwood or commercial charcoal (Naughton-Treves et al., 2007). In addition, vegetation responds to disturbance in ways that may impact harvesting practices, changing species preference, extraction sites, and volumes extracted (He et al., 2009; Jagger and Shively, 2014; Ruger et al., 2008).

Within the policy arena, more nuanced and accurate assessments accounting for spatiotemporal effects are needed to better predict the impact of interventions such as improved cookstove (ICS) programs and improved charcoal kilns. In the past, positive impacts have been assumed as a matter of faith in the technology rather than as demonstrated through scientific analysis. Thus, there is a pressing need for models which will robustly assess impacts of interventions, such as carbon fluxes, since program financing is often predicated on the generation of carbon credits.

Geospatial modeling techniques are a promising option to render the spatiotemporal variability explicit (Costanza and Voinov, 2004; Deaton and Winebrake, 2000; Murayama and Thapa, 2011; Paegelow and Camacho-Olmedo, 2008). The core questions that need to be addressed are:

1) How much woodfuel is harvested at a given location within a specific time frame?

2) How does vegetation respond to this pressure, as measured by above ground biomass stock and growth rates?
3) How do changes in woodfuel demand (for example, through the dissemination of fuel-saving stoves) alter patterns of harvest and re-growth over time?

To respond to these questions for the case of residential fuelwood (i.e. firewood), we developed Mofuss (Modeling fuelwood savings scenarios) version 1.0, a spatially-explicit and dynamic model that simulates the effect of fuelwood harvesting on local vegetation. The overall goal in constructing the model was to quantify the expected reductions in unsustainable harvesting of woody biomass resulting from external interventions that reduce fuelwood demand. It is important to note that Mofuss was designed to be applied in study areas where fuelwood is a major energy source for the residential sector, in which collection of wood for self-use and localized markets operates, and not for charcoal dominated landscapes in which harvest patterns and trade markets differ significantly (Masera et al., 2015).

We start by briefly describing the study area and explaining our rationale for choosing to model this location. A synthesis of the modeling approach is developed in Section 3, and is expanded in the online Supplementary Material (Appendix A). In Sections 4 and 5, we provide a summary of the most relevant results, with additional details provided in the online Supplementary Material (Appendix B), including animated maps. Section 6 provides a discussion of innovative features of the model compared to previous approaches. Key improvements to the model are identified in the conclusions in Section 7.

2. Study region

The study area is located in western Honduras, between 14° and 15°30'north latitude and 88° and 89°30′ west longitude (Fig. 1). It consists of four departments (1st level administrative units) covering 15,660 km^2. A Land Use and Land Cover (LULC) map was produced for the year 2000 using Landsat imagery and re-sampled to 100 m resolution. The map depicts a mosaic landscape of urban space, water bodies, and bare land (1%), agriculture (24%), shrublands (14%) and forest consisting of pine (6%), broadleaf (46%), and mixed (9%) stands. According to the national census of 2001 (INE, 2001), there were 5837 towns and villages in the area, hosting164,750households using fuelwood either alone or in combination with other fuels such as liquefied petroleum gas (LPG) and electricity. The two largest towns are Santa Rosa de Copán (pop. 26,000) and Santa Bárbara (pop. 14,000) (INE, 2001). Additional details on the LULC map and fuelwood demand in the study area are provided in Appendices A-1 and A-2 respectively in online Supplementary Material.

Several characteristics make this an ideal area for this study. First, there is widespread and intensive use of residential fuelwood. Wood is obtained both by self-harvest and purchasing from commercial collectors. There is also a successful ongoing ICS project that currently disseminates 2–3000 stoves per month (Proyecto Mirador, 2015). The project plans to expand into neighboring departments, which will allow us to build on the present study. In addition, a moderate amount of basic data required to parameterize the model is available, including fuelwood use and biomass growth parameters from scattered permanent plots. However, this data is not fully representative of the entire landscape, so we developed modules to accommodate uncertainty (described in more detail below). Developing a novel model in a data-rich setting might result in a tool that is difficult to apply in data-poor locations. Since data-poor settings are the rule rather than the exception, the case selected is an appropriate example.

3. Methods

Mofuss projects fuelwood harvesting sites in time based on the accessibility of fuelwood sources. The vegetation responds to harvest in each iteration based on the amount of wood extracted and regrowth functions for trees within and outside forests. A Monte Carlo module accommodates inherent uncertainties associated with input parameters. The model also accounts for observed and

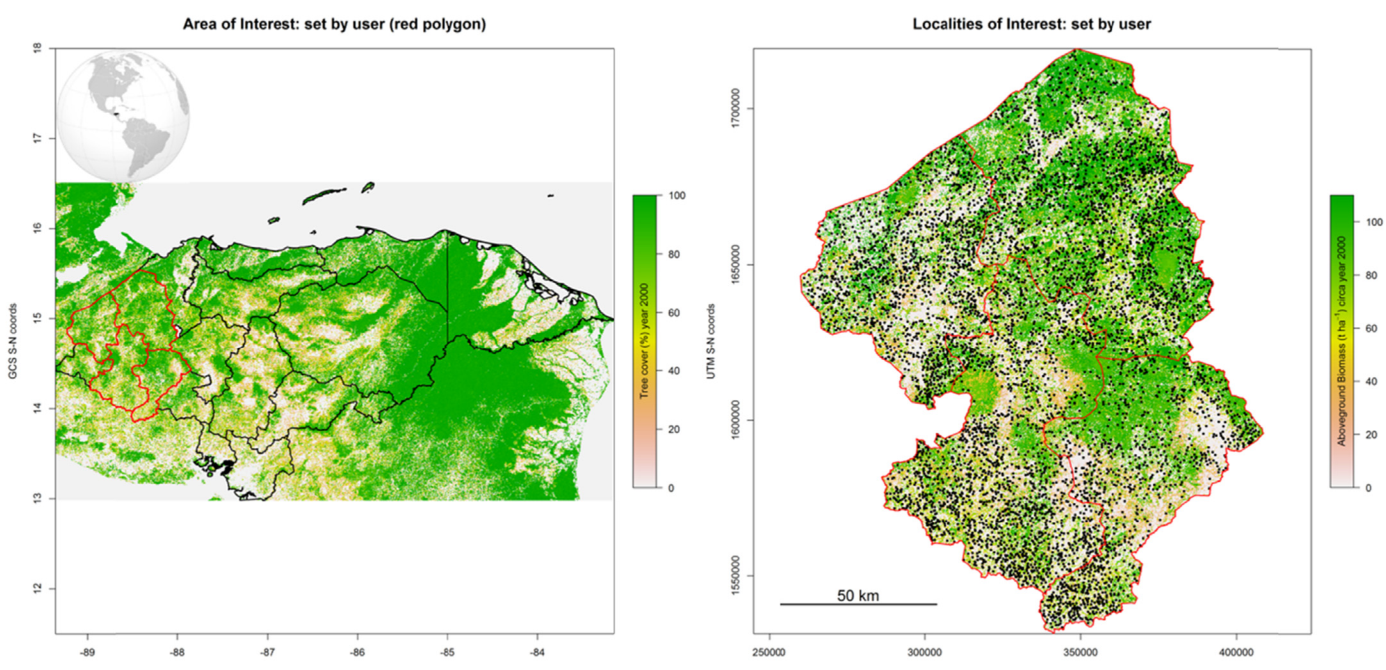

Fig. 1. Study region in western Honduras.
Sources:Tree cover data (2000) downloaded from http://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.1.html (Hansen et al., 2013). Localities of interest (black dots in the map on the right) come from the last available national census (INE, 2001). Aboveground biomass is estimated by the model following the LULC map, biomass growth and stock parameters, and uncertainty assumptions. The spatial resolution is 100 m after cropping and resampling. Please refer to Fig. A.1 in online Supplementary Material for a map depicting LULC classes, annual fuelwood use and road network. Figure automatically generated by Mofuss.

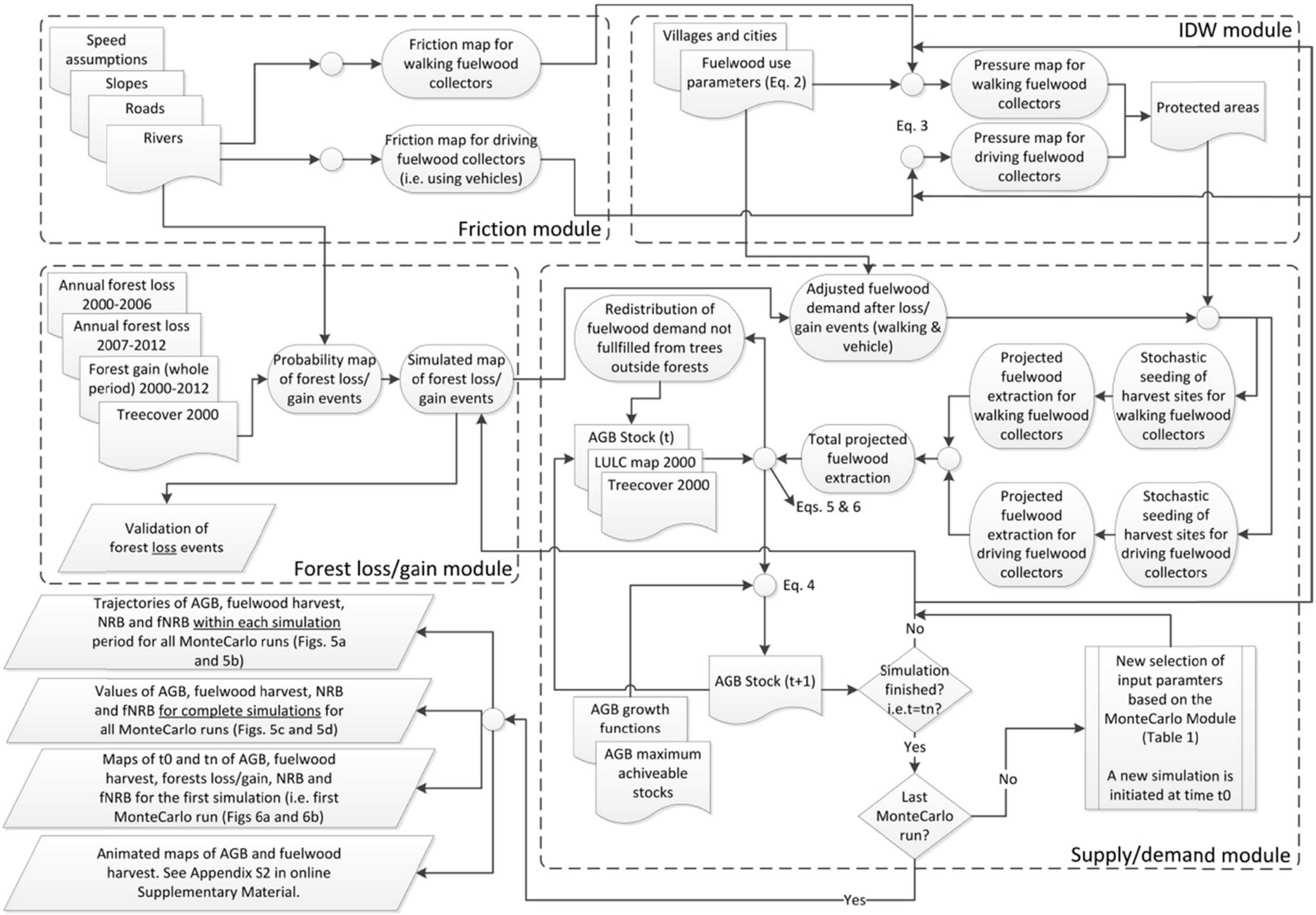

Fig. 2. Simplified flowchart of Mofuss showing main inputs and processes within each of the modules, and final outputs.

expected trends in forest loss and gain that are unrelated to fuelwood harvesting. This allows for some fuelwood demand to be satisfied from by-products of land clearing activities like agricultural expansion, and to adjust the fuelwood supply map at each time step.

Mofuss was built in a freeware modeling environment called "DINAMICA EGO" (EGO standing for *Environment for Geoprocessing Objects*), designed to construct complex models for the analysis and simulation of spatially and temporally dynamic phenomena (Soares-Filho et al., 2010). By using dataflow language (dragging and connecting algorithms via their ports), models are constructed and shown as diagrams, which are relatively easy to comprehend and modify by users unfamiliar with computer languages and scripts. The software has become popular among users analyzing a wide range of dynamic phenomena (e.g. Bowman et al., 2012; Brando et al., 2014; Carlson et al., 2012; Ferraz, 2013; Kolb et al., 2013; Nepstad et al., 2009; Pathiranaa et al., 2013; Perez-Vega et al., 2012; Soares et al., 2010, 2012, 2006; Sonter et al., 2014a; Sonter et al., 2014b). In addition, DINAMICA EGO scripts in Mofuss trigger several external processes running in R (www.r-project.org), FFmpeg (www.ffmpeg.org) and LaTeX (miktex.org) which project, resample, rasterize and crop input data, conduct statistical analyses, generate graphs, animated maps, and a final summary report in pdf.

Mofuss simulates spatiotemporal dynamics in a landscape subject to traditional fuelwood extraction. It describes the changes in a spatial pattern from time t to time $t+1$, such that:

$$X_{(t+1)} = f\left(X_{(t)}, Y_{(t)}\right) \tag{1}$$

where $X_{(t)}$ is the spatial pattern at time "t" and $Y_{(t)}$ is a set of data elements that may represent the transition, such as maps, tables, matrices, mathematical/logical expressions, or constants. Mofuss has three primary functions:

1) Project the pressure exerted by fuelwood harvesting on existing woody biomass sources.
2) Estimate the expected response of the vegetation to disturbance in terms of AGB growth.
3) Estimate the effect of interventions that reduce fuelwood consumption on existing forest stock and growth.

Mofuss consists of four components or modules (Fig. 2): 1) a friction component that creates impedance maps; 2) a modified Inverse Distance Weighted (IDW) algorithm that creates pressure maps depicting the propensity of fuelwood harvest events; 3) a supply/demand component that projects the expected quantity of fuelwood to be harvested in each time frame in each pixel, and the vegetation response to that disturbance; and 4) a forest loss and gain module that projects expected land clearing or forest gain events in each time step, based on past observations. Table 1 lists all input maps and parameters required by the model, and their potential availability for other study areas.

3.1. Location and intensity of harvesting events

3.1.1. Fuelwood demand

The magnitude and spatial distribution of fuelwood demand is

Table 1
Model inputs and parameters.

	#	Input dataset	Type of data[a]	Mandatory/optional	Availability[b]	Description
Spatial data	1	Digital Elevation Model	raster	mandatory	+++++	3 or 1 arc-sec digital elevation terrain model with global coverage available freely at: www.jpl.nasa.gov/srtm.
	2	Tree cover 2000	raster	mandatory	+++++	30 m tree cover map with global coverage available freely at: http://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.1.html.
	3	Forest loss (annual) 2000–2013	raster	mandatory	+++++	30 m forest loss map (annual loss events between 2000 and 2013) with global coverage available freely at: http://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.1.html.
	4	Forest gain (whole period) 2000–2012	raster	mandatory	+++++	30 m forest gain map (gain events for the period 2000–2012) with global coverage available freely at: http://earthenginepartners.appspot.com/science-2013-global-forest/download_v1.1.html.
	5	LULC circa 2000	vector or raster	mandatory	++	Produced for this study from Landsat imagery. See Appendix A-1 in online Supplementary Material.
	6	Villages and cities circa 2000	vector or raster	mandatory	+	Requested specifically for this study. Source: *Instituto de Conservación Forestal de Honduras* www.icf.gob.hn. Optional if a raster map depicting the spatial distribution of fuelwood use is available.
	7	Protected areas circa 2000	vector or raster	mandatory	++++	Requested specifically for this study. Source: *Instituto de Conservación Forestal de Honduras* www.icf.gob.hn.
	8	Road network circa 2000	vector or raster	mandatory	++	*Idem*
	9	Rivers circa 2000	vector or raster	mandatory	++	*Idem*
	10	Mask	vector or raster	mandatory	n.a.	Area for which all input datasets are available.
	11	Analysis area	vector or raster	optional	user defined	Area of interest within mask. Mostly to account for border effects and for debugging purposes as speed is drastically increased when using relatively small areas.
	12	Villages and cities of interest	vector or raster	optional	user defined	Subset of villages and cities of interest for the analysis.
	13	Biophysical parameters eventually affecting biomass growth and stock	vector or raster	optional	+	The model can accommodate other variables (apart from vegetation types from the LULC map) eventually affecting woody biomass stock and growth rates such as site quality, solar radiation, soil type, rainfall, temperature, among others.
	14	Land tenure eventually affecting accessibility	vector or raster	optional	+	If spatial information about land tenure and rules about access to resources are know, then it can be accommodated to affect accessibility; in a similar way as protected areas do.
Non-spatial data	15	Fuelwood use	csv table or spatial attribute table	mandatory	++	Table showing collected and marketed fuelwood use in each village and city in a business as usual scenario i.e. assuming ALL households cook with traditional devices most commonly found in the study area. See Appendix A-2 in online Supplementary Material.
	16	Pixel size (spatial resolution)	Real value	mandatory	user defined	Should be set in accordance with resolution and scale of input spatial data. Resolution greatly affects the speed of geoprocessing operations.
	17	Iteration length (temporal resolution)	Integer value	mandatory	user defined	Time length in weeks for each time step, assuming 48 weeks in a year, i.e. a value of 48 is equal to one year.
	18	Simulation length	Integer value	mandatory	user defined	Time length for each simulation in years. In our case study it was set to 30 years.
	19	Monte Carlo runs	Integer value	mandatory	user defined	Number of Monte Carlo runs.
	20	Startup year	Integer value	mandatory	user defined	Should be set to year 2000 unless all spatial datasets are available for a different year.
	21	AGB growth parameters table	csv table	mandatory	user defined	Table in csv format with values by LULC class for maximum sustainable yield (r_{max}) mean and SD, maximum achievable stock (K) mean and SD and initial stock (optional) mean and SD.
	22	Trees outside forest (TOF) fuelwood supply potential	csv table	mandatory	user defined	Amount of fuelwood potentially available from TOF assuming dead collection and pruning. Mean and SD values are required.
	23	r_{max} values passing through Monte Carlo	yes/no	mandatory	user defined	If NO, r_{max} mean is used for all Monte Carlo runs.
	24	K values passing through Monte Carlo	yes/no	mandatory	user defined	If NO, K mean is used for all Monte Carlo runs.
	25	Initial stock values passing through Monte Carlo	yes/no	mandatory	user defined	If NO, Initial stock mean is used for all Monte Carlo runs.

(*continued on next page*)

Table 1 (*continued*)

#	Input dataset	Type of data[a]	Mandatory/ optional	Availability[b]	Description
26	Use tree cover as initial stock i.e. % of K	yes/no	mandatory	user defined	If NO, then initial stock values by LULC class must be defined in AGB growth parameters table.
27	TOF assumptions passing through Monte Carlo	yes/no	mandatory	user defined	If NO, mean value of fuelwood from TOF is used for all Monte Carlo runs.
28	Fuelwood savings	Integer value	optional	user defined	Fuelwood savings as a percentage of use in previous iteration and across ALL villages and cities. Assumes an even spatial dissemination pattern (due for example to the progressive deployment of ICS). The model can also accommodate an uneven spatial dissemination of savings, but pressure maps are then re-calculated for each new time step, extending considerably the processing time - moreover for very large analysis areas.
29	Instant fuelwood use modulator	Integer value	optional	user defined	Modulates unitary fuelwood use (read from Fuelwood use table - parameter#15) in any of both BaU and Intervention scenarios. Mostly for sensitivity purposes.
30	Fuelwood users growth rate	Integer value	optional	user defined	Annual growth rate (as per thousand rate) of fuelwood users, or alternatively, of total population as proxy if saturation is assumed to remain stable in time.
31	Forest loss/gain	yes/no	mandatory	user defined	If No, prospective simulation of forest loss/gain events is bypassed. If Yes, a prospective landscape simulation model will run in ensemble with fuelwood harvest and regrowth patterns. If no parameters are modified, the Forest loss/gain submodel will run as a fully deductive (i.e. statistical) model. Otherwise, an arrange of parameters can be tuned to increase its predictability. See Appendix A-6 in online Supplementary Material.
32	Percentage ratio of fuelwood from forest loss events to be sold	Integer value	mandatory	user defined	Percentage of fuelwood eventually available from deforestation that will be sold, instead of gathered by walking collectors. Bypassed if Forest loss/gain is set to NO.
33	Ease to enter protected areas	Integer value	mandatory	user defined	A value of 100% means that protected areas pose no access restriction to fuelwood collectors. It alters the pressure map. Different values can be assigned to different protection classifications.
34	Harvest threshold walking	Integer value	mandatory	user defined	Minimum amount of AGB per pixel “attractive” enough for walking fuelwood collectors.
35	Harvest threshold vehicle	Integer value	mandatory	user defined	Minimum amount of AGB per pixel “attractive” enough for driving fuelwood collectors.
36	Harvestable pixels walking	Integer value	mandatory	user defined	Percentage of the landscape assumed to be visited by walking fuelwood collectors at each time step.
37	Harvestable pixels vehicle	Integer value	mandatory	user defined	*Idem* but for driving fuelwood collectors.
38	Harvestable pixels passing through Monte Carlo	yes/no	mandatory	user defined	If Yes, the percentage of the landscape assumed to be visited in each time step will vary randomly assuming a 100% SD.
39	Prune factor for walking fuelwood collectors	Integer value	mandatory	user defined	A value that multiplies the number of all harvestable pixels with the highest pressure, to allow for a stochastic subsequent “re-selection”. For example, a prune factor of 10 means that 10 times the amount of harvestable pixels with the highest pressure will be selected. Within this new sample, 10% of pixels will be randomly re-selected. Prune factor high values drive the seeding mechanism to fully stochastic while a prune factor equal to 1 would drive the seeding mechanism to fully deterministic.
40	Prune factor for driving fuelwood collectors	Integer value	mandatory	user defined	*Idem*, but for driving fuelwood collectors.
41	Modified IDW exponent	Real value	mandatory	user defined	Modulates the interpolation function (“n” in Eq. (3)) to be more or less concentrated around demand centers. Can be calibrated with ground-data showing fuelwood collection points.
42	Modified IDW exponent passing through Monte Carlo	yes/no	mandatory	user defined	If NO, the modified IDW exponent set value is used for all Monte Carlo runs.
43	Cost-distance passes	Integer value	mandatory	user defined	Number of passes from DINAMICA's cost-distance map tool. The higher the value, the most accurate results, in detriment of geoprocessing time.
44	Maximum distance for gathering fuelwood	Integer value	mandatory	user defined	Maximum cost-distance in hours that could possibly be travelled by vehicle or walking to gather fuelwood. Should be set to a precautious maximum, e.g. two days.
45	Number of Monte Carlo histograms per figure for forests and woodlands	Integer value	mandatory	user defined	Value of histograms in multiple of five to be accommodated in each Tiff figure. Will depend on number of LULC classes.
46	Number of Monte Carlo histograms per figure for TOF	Integer value	mandatory	user defined	*Idem*

Table 1 (*continued*)

#	Input dataset	Type of data[a]	Mandatory/ optional	Availability[b]	Description
47	Re-run Monte Carlo	yes/no	mandatory	user defined	If NO, the same Monte Carlo datasets are used every time. Useful when comparing scenarios or conducting sensitivity analysis.
48	Maps and animations switch	yes/no	mandatory	user defined	If NO, maps and animations (eventually time consuming) are not produced.
49	Path to R.exe	string	mandatory	user defined	Path to R executable file, for 32 or 64 bit OS.
50	Path to FFmpeg.exe	string	mandatory	user defined	Path to FFmpeg executable file, for 32 or 64 bit OS.
51	Number of CPU cores	Integer value	optional	user defined	Number of CPU cores (physical or virtual) to be used by different modules.

[a] Almost any raster or vector format is accepted as Mofuss uses the Geospatial Data Abstraction translator Library: www.gdal.org.
[b] Guesstimate based on global datasets accessible from the Internet.

calculated following Eq. (2).[2] (parameter#15 in Table 1):

$$C_{(t)} = \left(\sum_{i=1}^{n}\sum_{j=1}^{n} hh_{ij}\cdot u_j\cdot fc_i\right)_{(t)} + \left(\sum_{i=1}^{n}\sum_{j=1}^{n} hh_{ij}\cdot u_j\cdot fb_i\right)_{(t)} \tag{2}$$

where $C_{(t)}$ is total residential fuelwood consumption in tDM for any time step "t"; hh_{ij} is the number of households using fuelwood, by community "i" using a cooking device "j" (a traditional or even improved stove but considered as the business as usual (BaU) scenario); u_j is household consumption in tDM; fc_i is the average fraction of fuelwood that is collected; and fb_i is the average fraction of fuelwood that is bought. Additional details are provided in Appendix A-2 in online Supplementary Material.

3.1.2. Friction maps

The spatial distribution of fuelwood harvesting and collecting sites is determined in part by their proximity to demand centers. Friction or impedance maps are a geo-processing means to account for "proximity" in a realistic way (Salonen et al., 2012). In these maps, each pixel or cell can be characterized by the time a fuelwood collector needs to travel through it on foot or by vehicle (depending on the pathways used in a given locality). The data required to construct friction maps are displacement velocities of both walking and driving fuelwood collectors, as affected by topographic features such as slope, road conditions, rivers and water bodies, or land cover types (e.g. dense or thorny vegetation reduces displacement velocities). Additional details are provided in Appendix A-3 in online Supplementary Material.

3.1.3. Seeding harvesting sites based on pressure maps, a stochastic component and overall fuelwood demand

An IDW component creates a pressure map (i.e. depicting the probability or propensity of each pixel to be harvested for fuelwood) for two types of fuelwood collectors: 1) people who travel on foot and gather fuelwood for home use, and 2) commercial wood sellers who use vehicles, which allow them to access distant areas and carry large volumes of wood. Eq. (3) defines how pressure maps are calculated:

$$P_{(t)k} = \left(\sum_{i=1}^{n} \frac{C_{ik}}{d_{ik}^{n}}\right)_{(t)} \tag{3}$$

where $P_{(t)k}$ is an index that indicates the pressure by both types of fuelwood collectors "*k*" for any time step "*t*"; C is residential fuelwood consumption in tDM by locality, village or city "*i*"; *d* is the cumulative time (cost-distance) needed to reach any pixel from each locality or village; and *n* is a real positive number that modulates the decay function of the interpolation.

The resulting index is a modified Inverse Distance Weighted interpolation, in which distance (in linear units) is replaced by cumulative cost (in time units). The power of this simple equation resides in the fact that every pixel within the analysis area is influenced by all consumption centers. This avoids the necessity of determining fuelwood-reachable areas or so called "fuelwood-sheds" (Ghilardi et al., 2009) or "reachable" areas (The Gold Standard, 2011), which do not account for overlapping demand centers and are difficult to define. The fact that people are more likely to collect fuel nearer their place of residence is built into the model in the form of travel costs. If some harvesting frequencies and locations are known (from ground GPS measurements for example), then the decay function *n* can be calibrated to reflect observed collection patterns. This calculation has been previously reported by various authors (Bailis et al., 2015; Chen et al., 2014; Ghilardi and Mas, 2011).

Pressure maps are then loaded into a seeding module ruled by a stochastic mechanism. Finally, overall consumption of self-collected and purchased wood from the study area is distributed over the maps resulting from the stochastic seeding mechanism. An expanded description of the seeding harvesting mechanism coupled with the stochastic component to render a distribution of harvested fuelwood per pixel is available in Appendix A-4.

3.2. Modeling fuelwood supply

There are three primary sources of residential fuelwood:

1) Forests and Woodlands: fuelwood is supplied by pruning or cutting live trees or collecting fallen branches and dead wood.
2) Trees outside forests (TOF): includes trees on farmland, household compounds, and roadside commons, which are accessed by pruning live trees and/or collecting dead/downed branches. This category also includes shade trees in coffee plantations, which are pruned regularly and constitute a major source of wood in coffee-growing parts of the region.
3) Land clearing activities: includes clearing forest or scrubland for new cultivation or grazing and forms an important source of wood supply.

Woody biomass growth is assumed to be a function three factors: the stock in the previous iteration, the maximum growth rate (r_{max}: the first derivate of the "S-type" curve), and the maximum biomass density or "carrying capacity" (K) (Bailis et al., 2015). Both r_{max} and K depend on biophysical parameters such as land cover, soil, hydrology, insolation, and altitude, among others. However, data for multiple biophysical growth parameters is rarely available. In our case study,

[2] Equations are expressed in their discretized form, as the model works in discrete time steps at least one week long; and also, because fuelwood collection is best described by discrete events. Given that all equations are applied to raster data, we avoided the use of a pixel index for clarity.

for example, we define K and r_{max} based solely on LULC class (Table 1). Eq. (4) describes this relationship (parameter#21 in Table 1):

$$AGB_{(t+1)i} = AGB_{(t)i} + AGB_{(t)i} \cdot r_{max} \cdot \left(1 - \frac{AGB_{(t)i}}{K_i}\right) \tag{4}$$

$AGB_{(t)I}$ and $AGB_{(t+1)i}$ are above ground woody biomass suitable for fuelwood in LULC class "i", at times "t" and "t+1" respectively. The initial biomass stock, $AGB_{(t=0)}$, will determine the future behavior of AGB during the simulation period. Mofuss accepts LULC maps with as many classes as available, but stock and growth parameters for each class are also required. Maps showing a continuous spatial distribution of $AGB_{(t=0)}$ (e.g. Cartus et al., 2014) are equally valid (even desirable) because Eq. (4) is calculated on a pixel by pixel basis.

In addition, if AGB falls below a tunable threshold, pixels become "unharvestable" until natural re-growth raises them over the threshold. In this set of simulations, the threshold was set to 5.0 $tDMha^{-1}$for people using vehicles and 0.1 $tDMha^{-1}$for people harvesting on foot. It is worth noting that these values are "guesstimates" with no literature or field data backup. But given that they only apply to woodlands and forests, it is expected that people will turn to neighbor areas where AGB is above these values or at least keep pruning trees outside forests and collecting scattered dead wood from closer non-forest areas. Additional details are provided in Appendix A-5.3 in online Supplementary Material.

3.3. Integrating uncertainty of input parameters

Mofuss includes a Monte Carlo (MC) simulation to accommodate the inherent uncertainty of woody biomass growth patterns and AGB stock accumulation. With each MC run, all woody biomass growth parameters vary randomly following truncated normal probability density functions (Fig. A.6 in online Supplementary Material). The default number of runs was set to 100.

Other parameters passing through the MC module but not related to biomass growth are the portion of the landscape "visited at least once" for fuelwood collection in each iteration and a prune factor that regulates the degree of stochasticity of the seeding mechanism (Fig. A.7 in online Supplementary Material). Both parameters are listed in Table 1.

3.4. Sensitivity analysis

Sensitivity of results to some input parameters shown in Table 1 was tested by running 6 simulations of 100 Monte Carlo realizations each, while allowing one parameter per simulation to vary randomly and holding the others constant. Parameters analyzed were: percentage of landscape harvested at each iteration, prune factor, biomass maximum achievable stock K, growth rate r_{max}, and available fuelwood from trees outside forests (Section 5).

3.5. Model outputs: supply-demand balances, NRB and *fNRB*

As defined in the list of acronyms, non-renewable biomass (NRB) is the amount of harvested wood that exceeds natural regrowth over a given time period, most commonly one year. When NRB is given as a fraction of total fuelwood use, fNRB ("fraction of non-renewable biomass") is used instead. This describes the proportion of the fuel wood harvest that is unsustainable.

In the model, each time step is one iteration (one year in our case study) and n-steps constitutes a simulation. Mofuss runs for any specified simulation period times the number of Monte Carlo runs that are set, producing three main output parameters: a) the remaining AGB stock (growth minus harvest at t = n), b) NRB calculated in pixels where decreases in AGB have occurred (Eq. (5)), and c) *fNRB*, calculated as the fraction of total fuelwood consumption that is non-renewable (Eq. (6)). These two basic outputs are modeled: 1) within each iteration (mimicking a static supply-demand analysis); 2) within each simulation period; and 3) for the entire set of Monte Carlo realizations for NRB and *fNRB*. For each pixel:

$$NRB_{(t=n)} = \begin{cases} AGB_{(t=0)} - AGB_{(t=n)} & if\ \ AGB_{(t=0)} > AGB_{(t=n)} \\ 0 \quad if\ \ AGB_{(t=0)} \le AGB_{(t=n)} \end{cases} \tag{5}$$

Where $NRB_{(t=n)}$ is the amount of fuelwood in tDM which, when harvested, results in a net decrease in AGB between time t = 0 and t = n. In this assessment, n can consist of one or many single-step iterations: one iteration corresponds to the static supply-demand analysis described above as output1; n = 30 corresponds to the entire simulation described above as output 2. Each MC run generates a different value of $NRB_{(t=n)}$ by repeating Eq. (5) in each run (output 3). $NRB_{(t=n)}$ is calculated at the pixel-level, meaning that it does not account for any increment of AGB occurring in areas where $AGB_{(t=n)} \ge AGB_{(t=0)}$. In other words, $NRB_{(t=n)}$ is not the net decrease of AGB over the entire "fuelwood-shed". Instead, it accounts for losses of AGB only in the set of pixels where a loss occurred.

Finally, the fraction of NRB relative to wood harvested is calculated as:

$$fNRB_{(t=n)} = \frac{NRB_{(t=n)}}{C_{(t=n)}} \tag{6}$$

3.6. Simulation scenarios: baseline and mitigation

As mentioned above, Mofuss runs for many time step iterations within a simulation. $C_{(t)}$ can be expressed as $C_{(n)}$, corresponding to the summed fuelwood consumption between time 0 and time n (Eq. (6)). As $C_{(t)}$ is loaded at each single-step iteration, temporal (and spatial) changes in fuelwood use, which may be induced by a gradual and spatially uneven diffusion of ICS, can be simulated in Mofuss. However, if spatiotemporal information about past and expected deployment of ICS is lacking, Mofuss can simulate hypothetical ICS diffusion that is evenly distributed in space, i.e. proportional to fuelwood use trends in the BaU scenario.

We ran Mofuss from 2000 to 2030 under two scenarios: BaU, assuming average values of fuelwood use associated with traditional stoves, and a project scenario, assuming a gradual and spatially even diffusion of ICS between 2000 and 2030. Under this scenario it was assumed that an annual decrease of 5% in fuelwood use was achieved by a "successful" intervention project.

4. Results

Fig. 3a,b shows trajectories for AGB, NRB (Eq. (5)) fNRB (Eq. (6)) and total fuelwood use. Red lines were generated using mean user-defined parameters shown in Table 2 while light grey lines show each MC realization using varying parameters from Fig. A.6 and A.7 in online Supplementary Material. AGB trajectories in the BaU and ICS scenarios were quite similar, even when considering large variations in MC realizations. A very slight decline can be seen in the BaU scenario for the mean (red) trajectory, as compared to the ICS one. In any case, this shows that fuelwood use appears to have very little impact on AGB for the whole area.

However, fuelwood harvesting occurring in some places is non-renewable as shown by NRB trajectories. In the BaU scenario, NRB increases over time in most MC realizations, driven by steadily increasing fuelwood consumption. Also, in certain places, the annual increment of woody biomass is less than the harvested volume of fuelwood. The ICS scenario shows a different outcome, where NRB trajectories approach zero within the 30 year simulation, driven by a steady decrease in fuelwood use.

Positive NRB trajectories do not necessarily mean that woodlands within the studied landscape are being degraded into depletion. Across the landscape, woodlands show some resilience because the pixels experiencing positive NRB change with each time step. This allows many pixels with positive NRB to recover, effectively losing their "NRB" status. This results in lower losses than if harvesting sites were permanently fixed, which closely mirrors real harvesting practices and shows the importance of 1) defining a time frame for an NRB study, and 2) avoiding static analyses or snapshots (e.g. Ghilardi, 2010; Ghilardi et al., 2009).

This pattern of pixels shifting in and out of NRB status during the simulation is sensitive to the number of harvest events, which is directly related to the temporal and spatial resolution of the simulation. We explore the sensitivity of outcomes to the percentage of landscape being harvested at each iteration or time step below.

In addition, because fNRB is defined as the ratio of NRB and C_t (Eq. (6)), its behavior over time is driven by both factors. This explains the near constant trajectory of fNRB in the BaU scenario: both NRB and fuelwood consumption increase at a similar rate. With ICS dissemination, fNRB steadily declines for most of the simulation.

To summarize entire simulations, Mofuss produces box-plots showing distributions of NRB, fNRB, fuelwood use and fuelwood use occurring only in NRB pixels, i.e. fuelwood use that directly contributes to deforestation or degradation (Fig. 3c,d). Annual average NRB consumption in the BaU scenario is about 3.5 times larger than in the ICS scenario; the intervention saves between 50,000 and 215,000 tDM. Similarly, fNRB decreases by 10–50%.

In the BaU scenario, roughly 300,000 tDM $yr^{-1}$was harvested within NRB pixels, 100,000 tDM of which was NRB. Total fuelwood savings between the BaU and ICS scenario are nearly 200,000 tDM per year, which is two times the amount needed to "neutralize" NRB. However, NRB consumption still averages about 30,000 tDM yr^{-1}. This is because the model deploys ICS evenly in space and time, which is common practice in ICS projects. Thus, much of the fuelwood savings occur in places with little or no NRB.

Table 2
Woody biomass growth parameters used in the case study.

LCLU category	r_{max}		K	
	Rate	SD	tDM ha^{-1}	SD
Forests and Woodlands				
Coniferous forest	0.030	0.015	92	23
Broadleaf forest	0.020	0.010	110	28
Shrubland	0.015	0.008	10	3
Mixed Forest	0.025	0.013	50	13
Trees Outside Forests				
Water bodies	n.a.	n.a.	0.1	0.1
Crop & Livestock	n.a.	n.a.	0.5	0.5
Bare land	n.a.	n.a.	0.2	0.2
Urban	n.a.	n.a.	0.2	0.2
Other	n.a.	n.a.	0.1	0.1

Note: Values for coniferous and broadleaf forests come from unpublished data recorded in permanent plots in Honduras. Values for mixed forests were estimated based on broadleaf and pine forests. Standard deviation values (SD) are conservative guesses used in the Monte Carlo simulations. SD values recorded in the field are narrower, but were not used as they do not account for the expected natural variation given the array of biophysical conditions across the study area. Trees Outside Forests represent annual availability of wood, assuming mild pruning of live trees and dead wood collection, but no cutting of live trees. Woody biomass supply of water bodies represent dead wood usually found beside rivers and lakes. A small amount is also assigned to urban environments and bare land as reflected by various case studies. Parameter#21 in Table 1 for forests and woodlands and parameter#22 in Table 1 for trees outside forests. Additional details are provided in Appendix A-5 in online Supplementary Material.

An alternate approach would be to prioritize ICS dissemination in zones with higher NRB. But how can we know the location of communities that contribute the most to NRB? Fig. 4 shows the spatial distributions of AGB, NRB, fNRB, fuelwood from deforestation and total fuelwood use in both the BaU (Fig. 4a) and ICS (Fig. 4b) scenarios for the first MC realization (red line in Fig. 3a,b). The spatial distribution of NRB and fNRB are shown for the full simulation period. These maps could help identify communities with the highest fuelwood use, lying within or nearby high NRB "areas". The process of selecting key villages contributing the most to NRB could

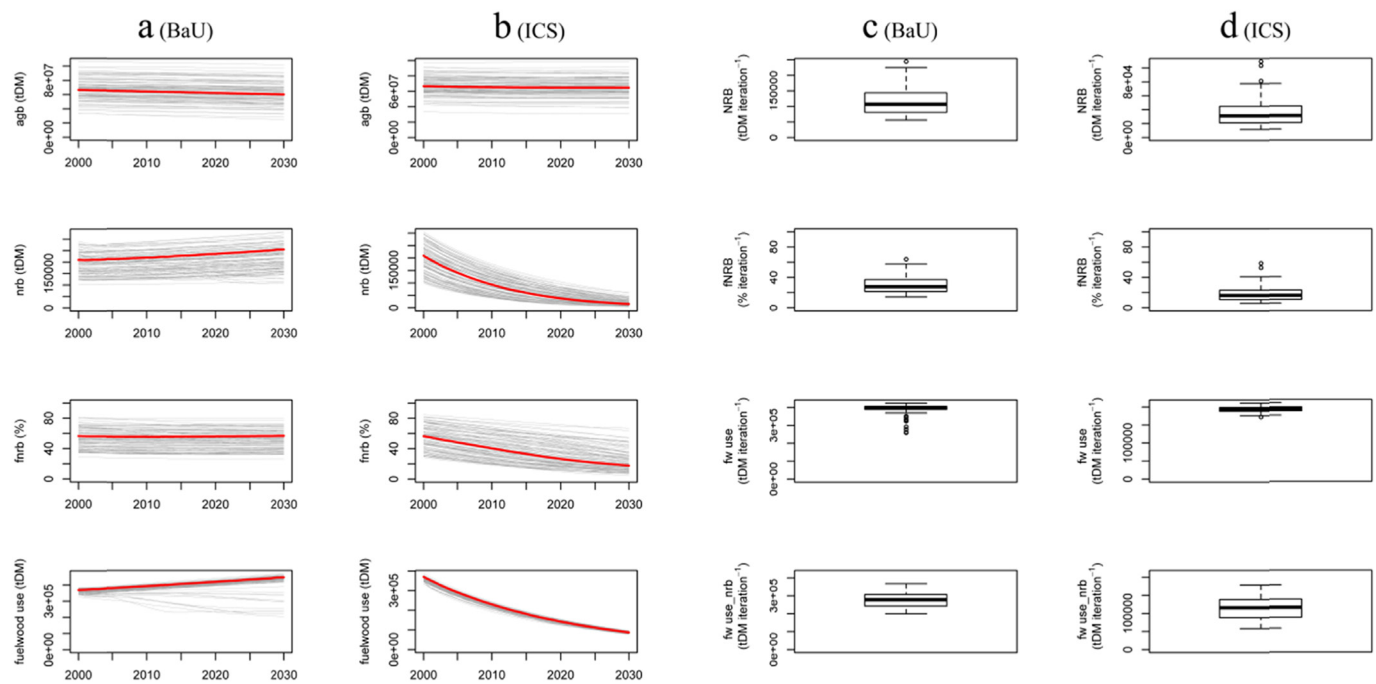

Fig. 3. Behavior of AGB, NRB, fNRB and total fuelwood use between BaU and ICS scenarios. Note: Red lines were generated using mean user-defined parameters shown in Table 2, while light grey lines were generated in each of 100 MC realizations using varying parameters shown in Fig. A.6 and A.7 in online Supplementary Material. fNRB is calculated as the fraction between NRB and total fuelwood consumption. Fuelwood use in the BaU scenario increases at a rate of 0.7%, driven by the population growth rate of Honduras and assuming growth to be evenly distributed across regions and socioeconomic strata. Box-and-whisker plots show the median of the MC distribution as a dark line, inter-quartile range (IQR) by the top and bottom of the box, and min/max of the range by the whiskers. Some plots have outliers, defined as data points between 1.5 and 3 IQR's from either end of the box, shown by small circles. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

be done manually, or by an optimization procedure (e.g. genetic algorithm) that maximizes a reduction in NRB based on selective deployment of ICS in space and time and could explicitly incorporate logistical or market-based constraints. Appendix B-1 in online Supplementary Material show an extra output from Mofuss: the spatial distribution of the standard deviation for NRB (Fig. B.1), total fuelwood use (Fig. B.2) and fuelwood use driving forest degradation (Fig. B.3). Appendix B-4 shows summary results by administrative unit (Departments) and Appendix B-5 compares the effect on AGB of fuelwood harvest versus forest losses and gains.

5. Sensitivities

Sensitivity of results to five input parameters are shown in Fig. 5a,b. AGB shows greatest sensitivity to variations in K, the maximum achievable woody biomass stock per unit area. AGB is also affected by growth rate (r_{max}) towards the end of the simulation, but is insensitive to changes in other parameters. In contrast, NRB and fNRB are sensitive to all parameters except for the prune factor (the fuelwood harvest stochasticity modulator – see Appendix A). In the case of the percentage of harvested landscape, NRB and fNRB rises when a lower proportion of pixels are visited at each iteration. The fuelwood harvested in each pixel is proportional to $P_{(t)k}$, an index of harvesting pressure by both types of fuelwood collectors, given proximity to demand centers (Eq. (3)). When only a fraction of the entire “harvestable” landscape is selected, the more inaccessible places are not visited, and fuelwood is collected from more accessible pixels (subject to the stochastic seeding mechanism - see Appendix A). When only a third or less of all “harvestable” pixels are visited (Fig. A.7a), NRB and fNRB increase, as more fuelwood is harvested from fewer sites. In addition, the proportion of pixels harvested within a landscape is related to the size and spatial distribution of villages using fuelwood, as well as the spatial and temporal resolution of the analysis: i.e. both pixel size and time step are important.

NRB and fNRB are also sensitive to K and r_{max}, as both parameters modulate the vegetation response after fuelwood extraction. If accurate estimates of K and r_{max} are unavailable, uncertainty can be built explicitly into the model's MC simulation. On the other hand, if data showing how K and r_{max} vary according to different biophysical parameters, such as soil quality, solar radiation or altitude, Mofuss can accommodate extra layers in the supply module to explicitly include these relationships. This could make the model's fuelwood supply component more accurate. It also allows for potentially interesting simulations estimating the impacts of factors like drought or other climatic shocks.

NRB and fNRB are also affected by the availability of fuelwood from TOF. These resources are known to be important sources of fuelwood, but stock and growth data are rare. Thus, this parameter should be allowed to vary within a wide but plausible range of values in order to capture TOF contributions (Fig. 3).

The proportion of the landscape that is harvested also affects fuelwood consumption. This effect arises because in some cases, the fuelwood demand can exceed the standing biomass stock in a given time step. When this occurs, the model is designed to allow the stock to be fully cleared even though demand is not completely satisfied. Effectively, wood harvesters return home with less fuelwood than they desire. When the proportion of the landscape visited for harvesting is allowed to vary, this result is useful because it shows that low proportions of visited land lead to unrealistic reductions in fuelwood use. Modelers should expect people to visit roughly the number of pixels necessary to fulfil their demand, with some variation both above and below the exact number. However, they probably will not visit all parts of the landscape due to factors like restricted access to certain properties. There is also a lower limit because of the desire/need to meet their energy needs. Therefore, the proportion of harvested landscape should be allowed to vary widely, particularly if data on specific harvesting sites is unavailable. However, varying this parameter should not lead to unrealistic reductions in fuelwood consumption.

6. Discussion

The results are congruent with what we know about deforestation and forest degradation associated with wood energy demand (Masera et al., 2015). Based on three decades of study, we know that fuelwood collection and harvesting for residential purposes can contribute to localized deforestation and forest degradation under certain conditions, some of which were explored in our study by means of landscape-level spatiotemporal modeling.

Mofuss is composed of four salient technical features, some of which were explored in previous models (e.g. Ghilardi et al., 2009; Linderman et al., 2005; Pokharel et al., 2004; Rüger et al., 2008; Sankhayan and Hofstad, 2001; Top et al., 2006; Whitman et al., 2011). This is the first time the features are integrated as an ensemble designed for landscape-level assessments:

1) It is a dynamic model, meaning that the results for a given time step depend on the state of the system in the previous step, making supply-demand dynamics much closer representations of real-life situations, compared to the static balances used in other models (Ghilardi et al., 2009). Static models use the maximum sustainable yield (r_{max} in this assessment) as the only forest growth parameter. This is misleading because it assumes a constant harvest rate in space, without leaving any room for regrowth periods if harvesting occurs elsewhere. The need for modeling forest dynamics when accounting for NRB and fNRB has already been stressed in the literature (Whitman et al., 2011). In our case, we model growth by two parameters: r_{max} and the maximum achievable stock (K). This simplified representation of biomass growth is a dynamic one, exhibiting a density-dependent response. Temporal dynamics are implicitly included through periodic harvest events, which alter biomass density.
2) It is spatially-explicit: growth dynamics described above occur at the pixel level, where the function parameters in Eq. (1) depend on the location, given type of forest, soil, slope, aspect, accessibility, among many other variables. So supply-demand dynamics occur in each pixel, nearly independently of other pixels. However, pixel-level dynamics are not completely independent for two reasons. First, there is auto-correlation of underlying variables (mostly biophysical parameters) and second, the fuelwood harvest pressure in one pixel depends, in part, on previous harvest events in other pixels. In brief, the spatio-temporal nature of the approach allows not only for integrating relations that are known to occur closely in space, but also to tune the model's functions to the spatial variations of the parameters that compose them, in order to produce maps.
3) Most static fuelwood spatial models define a fixed area that is accessible to collectors. These “fuelwood-sheds” (Ghilardi et al., 2009) or “reachable” areas (The Gold Standard, 2011), are bounded in space by “maximum distance that would be traveled to collect fuelwood” from a given demand center (Avoided Deforestation Partners, 2010). These are inherently artificial constructs because they do not overlap and require fixed thresholds in distance or time that are difficult, if not impossible, to pinpoint or define. In Mofuss, all pixels are influenced by all communities to a degree, varying with a) the cost-distance from demand centers, b) fuelwood consumption in villages and cities, and c) means of transportation. Rather than thresholds, we use continuous decay functions based on the modified IDW component described above that are relatively easy to calibrate with field data.

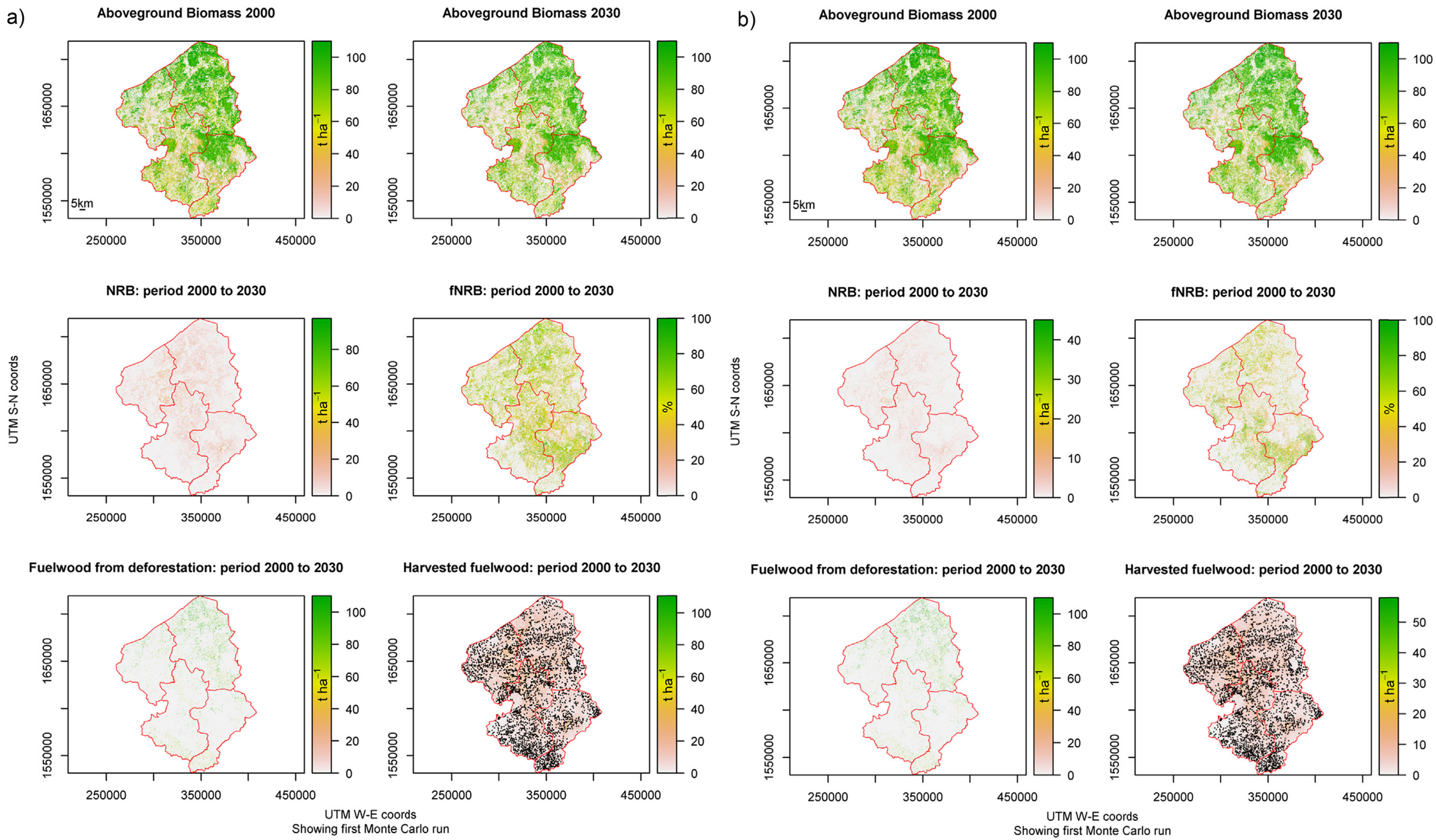

Fig. 4. a. Spatial behavior of AGB, NRB, fNRB, fuelwood from deforestation and total fuelwood use in the BaU scenario. b. Spatial behavior of AGB, NRB, fNRB, fuelwood from deforestation and total fuelwood use in the ICS scenario. Note: Figure automatically generated by Mofuss.

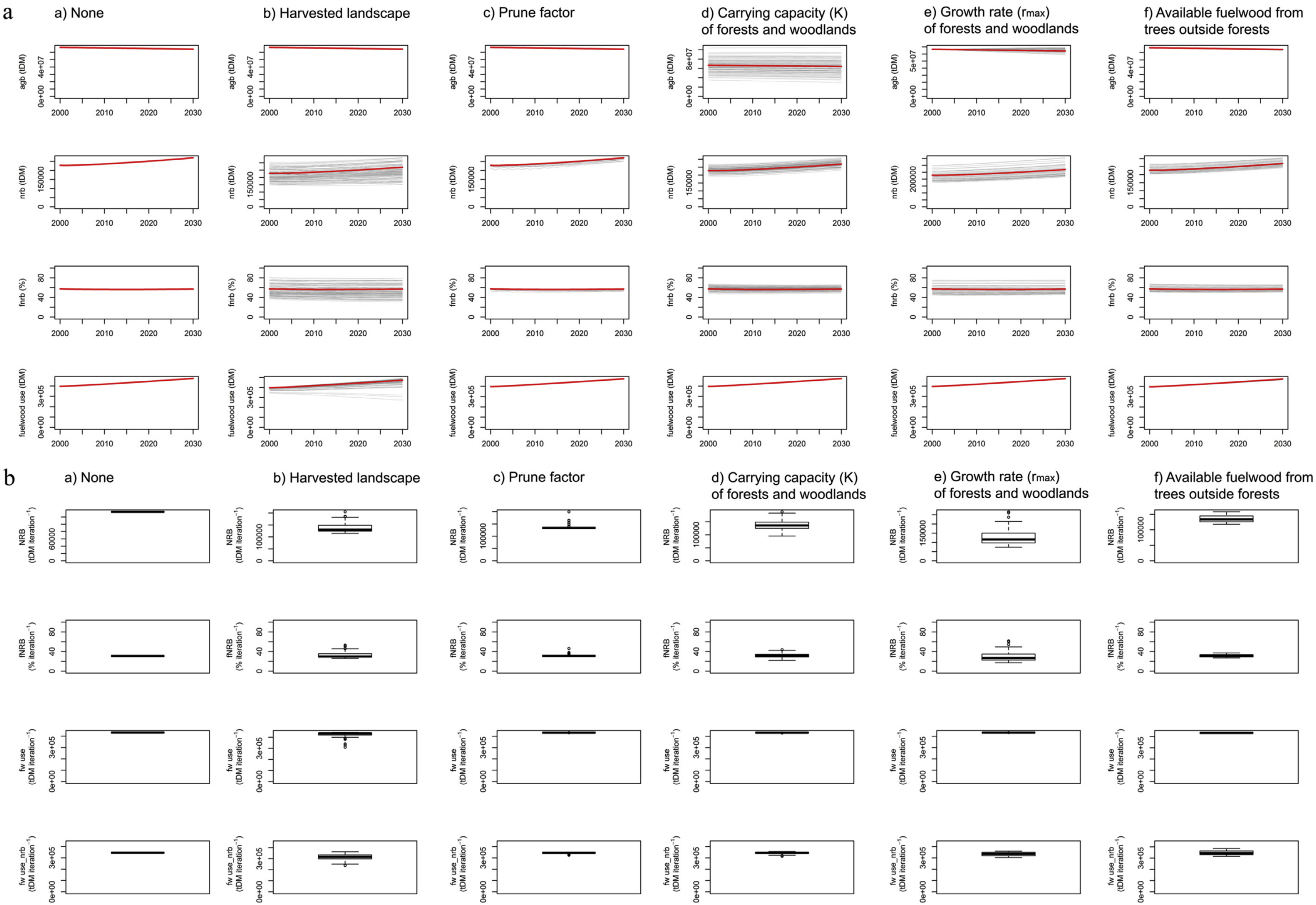

Fig. 5. Sensitivity of trajectories and annual average estimates over an entire simulation to variation of single parameters.

4) Mofuss integrates the uncertainty of input parameters through the MC module. To our knowledge, ours is the first fuelwood modeling effort to use this approach within a spatially-explicit context. Uncertainty is understood in this context as the relative lack of accuracy and precision in the parameters that define critical inputs into Mofuss. These may represent statistical variation in the original data, such as per capita fuelwood use, which was measured by directly surveying households, or lack of information on variables such as forest growth rates. In this latter case, unknown parameters are defined by estimates derived from a plausible range of values, such as measured growth functions in similar forest landscapes.

7. Future research directions and conclusions

The proposed model, Mofuss, which we tested for the case of Honduras, incorporates new features as compared with previous models (Bailis et al., 2015; Ghilardi, 2009; Top et al., 2006), and represents real-life situations more closely at the landscape level regarding traditional fuelwood harvesting for residential purposes. However, further improvements are needed in order to integrate other common patterns and process associated with fuelwood supply and demand. The most relevant improvements to be developed in the future would be:

1) Verifying results with empirical field-based data is a highly challenging but necessary task. One way to move forward is to use remote sensing techniques for quantifying forest degradation (e.g. Ryan et al., 2012) over areas and time spans forecasted by the model (e.g. 2000 to 2015), in places where degradation driven by fuelwood extraction should be significant. The task has to cope with multiple complexities, such as separating overlapping drivers to prove causality in any observed changes. Additional insights into validation of results are provided in Appendix B-3 in online Supplementary Material.
2) Add an elastic function for demand based on scarcity: as fuelwood sources and supplies diminish, driven by over-harvesting or more commonly by LULC processes, unitary consumption should tend to diminish as well, and the propensity to change to alternative energy carriers such as LPG should rise. These assumptions are strongly influenced by various spatial (e.g. proximity to the LPG distribution network) and non-spatial (e.g. socio-economic data) parameters (Khuman et al., 2011). We are modifying equations of the type 'predator-prey' to achieve this.
3) In addition to fuelwood use for residential purposes, include other uses such as charcoal or fuelwood for small industries.
4) Include a module that looks for hypothetical cookstove diffusion patterns that maximize carbon savings compared to alternative dissemination patterns. The "best solution" module could be based on a genetic algorithm that maximizes a so-called optimization function given a set of penalization variables which represent the logistic constraints of any particular cookstove project.
5) Alternatives to "one-factor-at-a-time" sensitivity procedures, which assume parameters to be independent from each other, have been proposed in the literature (Saltelli and Annoni, 2010) and should be explored for the present modeling approach.

Other important improvements for higher-end versions of the model include:

6) A "climate" component that integrates emission factors of traditional stoves and ICS and consequently translates NRB into greenhouse gases or CO2eq values for BaU and project scenarios.
7) New versions of the woody biomass growth component will include succession leading to different landscape mosaics, biodiversity, competition between species, or responses to selective logging (e.g. Medvigy and Moorcroft, 2012; Medvigy et al., 2009, 2010; Ruger et al., 2008).
8) A longer term development is to cluster improved versions of Mofuss with other DINAMICA-based models for grazing (e.g. Bowman et al., 2012) and fires (e.g. Soares et al., 2012), so as to integrate other forest degradation drivers. A notable example of this, and with the broader scope to understand the biogeochemical cycle, is the work by Liu et al. (2004). In this study, woodfuel harvest and fallow activities are integrated with both LULCC and Climate Change scenarios to explore long term impacts on carbon dynamics. Although fuelwood harvest patterns are modeled in a different way than the present study, it can be taken as a solid reference in terms of techniques and approach for integrating various drivers of ecosystem change in one modeling ensemble.

In conclusion, we have developed a model that explores the impacts of complex processes such as fuelwood harvesting on the environment. The model may be used in a range of applications including quantifying the carbon dynamics in traditional fuelwood systems, increasing our understanding of the processes that affect energy security of poor, forest dependent people, and examining various strategies to ensure long-term sustainability of woody biomass resources.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.envsoft.2016.04.023.

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