Environmental Science and Policy 109 (2020) 103–115

Contents lists available at ScienceDirect

Environmental Science and Policy

journal homepage: www.elsevier.com/locate/envsci

From global drivers to local land-use change: understanding the northern Laos rubber boom

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ARTICLE INFO

Keywords:
Crop boom
Agricultural expansion
Price signal
Imitation
Bayesian network

ABSTRACT

Crop booms in forest frontiers are a major contributor to land conversion and deforestation. In this study, we investigate the smallholder-driven northern Laos rubber boom in two case study areas (CSAs) with different speed and intensity of rubber expansion. We assess the relative importance of market, contextual, and behavioral factors in fostering or hindering the conversion of forest to rubber plantations. We develop a Bayesian network (BN) model of land-use change based on household surveys, expert interviews, market price data, and land use maps covering the period 2000–2017. We use regression analysis to inform the structure of the BN, compare model results, and analyze time-varying effects. The BN and regression models incorporate perceived price signals as a combination of market price and local price knowledge, and local self-reinforcing imitation dynamics as a combination of aggregate rubber conversion and imitation behavior elicited in the survey. Results show that deforestation was lower in strictly protected areas but not in forests with lesser protection status. Imitation had a large effect on rubber uptake in both areas. In the CSA that experienced the most intensive spread of rubber, price signals transmitted through social networks had a significant impact, especially throughout the stage of rapid expansion. Rubber expansion continued in both areas during periods of descending prices mainly because of increased cash availability and access to inputs. Our research sheds light on the underlying dynamics of crop booms and contributes to the understanding of agricultural expansion processes.

1. Introduction

Crop booms in forest frontiers are an important driver of global deforestation (e.g., Gasparri et al., 2016; Koh & Wilcove, 2008). These booms are generally characterized by a slow start followed by rapid expansion and a subsequent slowdown (Ornetsmüller et al., 2019). The resulting changes in land use, tenure, and ownership induce socio-ecological regime shifts (Müller et al., 2014) and have wide-ranging socioecological impacts that are compounded by the speed of change (Heemskerk, 2001). As yet, few studies provide quantitative analyses of crop boom landscapes that can inform policies during all stages of the boom. In particular, it is important to understand the effects of forest protection policies in deterring agricultural expansion into forests (Bruggeman et al., 2018).

Agricultural expansion can be explained in terms of distant or exogenous drivers such as economic, demographic, or technological changes (Alexander et al., 2015; DeFries et al., 2010; Keys & McConnell, 2005; Weinzettel et al., 2013), the local biophysical and socioeconomic context moderating the spatiotemporal dynamics of land conversion (Meyfroidt, 2015), and the decisions of the actors involved (Hettig et al., 2016; le Polain de Waroux et al., 2018; Meyfroidt, 2013; Rindfuss et al., 2007; Rudel, 2007). The latter are typically classified as agri-business companies and smallholder or family farmers, who frequently coexist and interact (Barbier, 2012; Cramb et al., 2017; Meyfroidt et al., 2014; Pacheco, 2012). Land-use models are widely used in land systems science (LSS) to assess the relative importance of drivers and contextual factors, to gain insight into complex dynamics, and to communicate this knowledge (Verburg et al., 2019).

One central question in agricultural economics and LSS is the complex role of commodity prices in driving agricultural expansion.

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https://doi.org/10.1016/j.envsci.2020.04.013
Received 3 January 2020; Received in revised form 20 April 2020; Accepted 21 April 2020

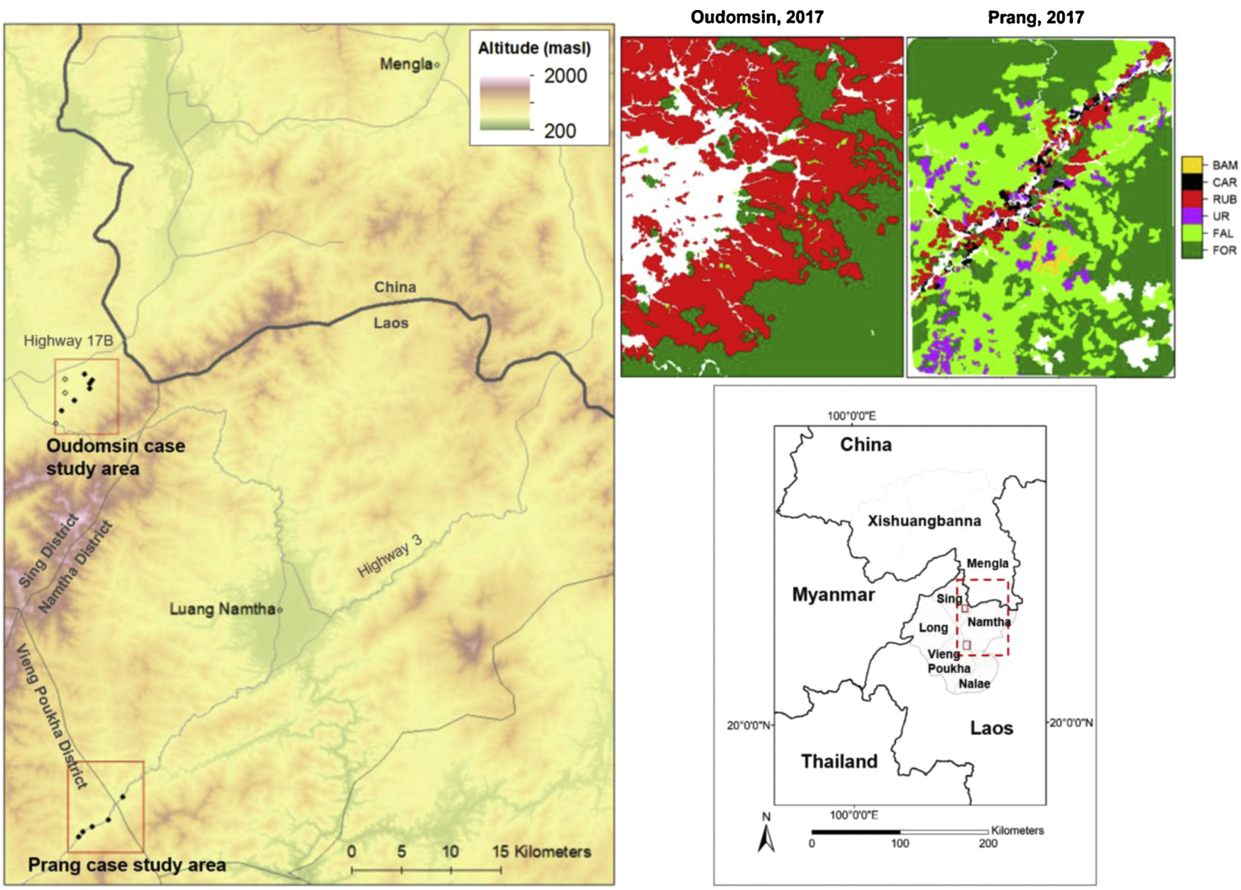

Fig. 1. Map of the two CSAs with CSA villages studied indicated by solid dots on the map. Luang Namtha Province is shaded in gray in the map on the bottom right. Top right: Land-use maps for 2017. FOR = Forest, FAL = Fallow, UR = Shifting Cultivation, RUB = Rubber, CAR = Cardamom, and BAM = Bamboo.

Capital surplus from past high prices may allow for a current expansion, especially for capital-constrained farmers (Richards and Arima, 2018). Current prices may have a limited impact on long-term investment decisions (Hartley et al., 1987). Low prices may also spur investment to maintain past income levels. While high or rising prices may be the most important factor influencing investment decisions for large agribusiness companies, farmers also consider other aspects (Heemskerk, 2001) such as the availability of economic alternatives, perceived ability (e.g., labor, assets, education, or power position), risk preference, labor drudge, heritability (Caldas et al., 2007; Celio et al., 2019; Feintrenie et al., 2010; Heemskerk, 2001; Overmars and Verburg, 2006; Sun & Müller, 2013; Vanwambeke et al., 2007), or making land claims (Kronenburg García & van Dijk, 2019).

Decisions around land-use are also influenced by the decisions of others, especially those who are socially close (Akerloff, 1997). Imitation thus becomes an important driver of crop adoption and diffusion (Pomp & Burger, 1995). This occurs through processes ranging from herd behavior, based on the assumption that others have better information (Besley & Case, 1994; le Polain de Waroux, 2019; Pomp & Burger, 1995), and social learning (Bandura, 1971), to conformist transmission (Henrich, 2001). However, quantitative assessments of the normative and informational role of imitation in commodity expansion are rare.

Another key question is the mechanism through which distant drivers such as market prices affect decisions around local land use. The mediation of price signals occurs, in part, through classical price transmission between actors along the marketing chain (Meyer & von Cramon-Taubadel, 2004), but it also occurs outside of the marketing chain as information is transmitted in social or information networks (Aker et al., 2016; Mazur & Onzere, 2009). Land-use models have addressed various effects of prices on decisions, e.g., price lags, capital surplus, or spatial heterogeneity (Aguiar et al., 2007; Richards et al., 2012), but seldom consider the social transmission or local perception of prices.

The expansion of rubber in the north of the Lao People's Democratic Republic (hereafter, Laos) after 2002 (Thongmanivong et al., 2009; Vongvisouk et al., 2014) and across montane Southeast Asia in the last decades (Li & Fox, 2012; Ziegler et al., 2009) was mostly smallholder-driven (Byerlee, 2014; Epprecht et al., 2018; Fox & Castella, 2013). It is a typical example of a forest frontier crop boom for its speed and intensity (Junquera & Grêt-Regamey, 2019; Shi, 2008). Explanations for this expansion include the rise of rubber prices after 2002, increased demand for latex in the People's Republic of China (hereafter, China), the development of regional transport infrastructure, new land-use policies incentivizing cash crop production in Laos, and the influence of cross-border kinship and trade networks (Shi, 2008; Sturgeon, 2013). Earlier work in the two case study areas (CSAs) under analysis also showed the importance of widespread imitation behavior in fueling the boom and the role of cross-border networks in the transmission of information about the market price and benefits of rubber; furthermore, the designation of protected areas and a lack of accessibility seemed to deter deforestation (Junquera & Grêt-Regamey, 2019). However, the interdependence between these factors and their relative impact on rubber expansion remain to be assessed.

Here, we employ a modeling approach to address this issue. We develop two complementary land-use models. We build a Bayesian network (BN) model that links the probability of local land-use change with forest protection status, biophysical and socioeconomic indicators, price signals, and imitation dynamics. The network structure of BNs and their reliance on causal diagrams allow for the explicit representation of dependence relations. We conduct sensitivity and scenario analyses to show the relative importance of predictor variables on land-use change outcomes. We further develop a regression-based model to inform the BN model structure, complement BN model results, and assess changing variable impacts over time.

We introduce two innovations compared to most land use change models. First, we implement a rubber price "signal" as a combination between market price and the local knowledge of price. Second, we operationalize self-reinforcing imitation dynamics as a function of aggregate rubber planted and the degree of self-reported imitation in rubber adoption decisions.

We focus on two case study areas located at the forest frontier in northern Laos' Luang Namtha Province, near the border to China. These areas have had different intensities of rubber expansion in the last two decades. We hypothesize that: (i) a mixture of exogenous drivers and local factors determined rubber expansion in each CSA; (ii) price signals were most influential at the beginning of the boom, and less important in later stages, after the adoption decision had been made; (iii) imitation was significant throughout the boom, especially in the middle and later stages; and (iv) the designation of protected areas reduced deforestation.

2. Case study areas

Land use in the two CSAs, referred to as Oudomsin and Prang (Fig. 1), includes agricultural and forested areas, including a portion of the Nam Ha National Protected Area (NPA). Before the cultivation of cash crops for export, farmers relied on rice production in lowland paddies and traditional upland rice production (shifting cultivation). Today, both areas remain largely rice self-sufficient, although rubber has almost entirely displaced shifting cultivation in Oudomsin, which experienced a boom-like, i.e., rapid and intensive, expansion of rubber production. Rubber expansion was significantly lower and slower in Prang.

Oudomsin is located in Sing District, roughly three kilometers from the Chinese border and along the highway that leads to Mengla County in China. It includes nine villages and covers 9,100 hectares (8.7 × 10.5 km). Its upland areas are more accessible than in Prang, and the population density is higher. Revenue from cash crops, mainly rubber and sugarcane, accounted for 58 percent of household income in 2017, when the median income was USD3,900. Many households leased out their paddies for banana production during a short-lived but lucrative banana boom starting around 2011 (Friis & Nielsen, 2017, Friis and Nielsen, 2016), but banana plantations were mostly replaced by sugarcane by 2017. Villagers in Oudomsin have long-standing close cross-border social ties to Chinese villages (Lagerqvist, 2013; Sturgeon, 2013).

Prang is located in the districts of Vieng Poukha and Namtha, approximately 60 kilometers from the Chinese border along the highway that links Bangkok, Thailand, to Kunming, China. It includes five villages and covers 11,580 hectares (9.5 × 12.1 km). Revenue from rubber and cardamom accounted for 72 percent of household income in 2017,[i] when the median income was USD1,100. Unlike Oudomsin, Prang does not have close cross-border social ties to Chinese villages.

Several policy and economic changes triggered the expansion of rubber production in Luang Namtha Province, which started around 2001[ii] and increased rapidly from 2004–2008. The 2004 opium replacement program (ORP) provided incentives for Chinese rubber investments in Laos and spurred the development of a local rubber market, including processing facilities and a proliferation of traders (Lu, 2017). A land-use policy around 2004 declared cattle owners liable for the damage caused by their animals, making the cultivation of high-value crops more attractive.

Land-use planning and land allocation (LUPLA) activities were implemented in Oudomsin area villages with the establishment of village boundaries and protected forest categories in 1997–2002, and land allocations in 2002–2006. Land titles were not assigned to shifting cultivation fallows older than three years, encouraging conversion of fallows to plantations. In the Prang area, LUPLA activities similarly took place in 2006–2010 and 2010–2014. The Nam Ha NPA was established in 1994, but boundaries and restrictions were not clearly communicated until the first phase of LUPLA.

Rubber trees take seven years to mature after which they produce very little latex in years 8 to 10; production peaks around year 20 and ends between years 30–35 (Manivong & Cramb, 2008). The market price of rubber started an upward trend in 2002 and increased six-fold until 2011 (Fig. 2), resulting in windfall incomes for Chinese smallholder farmers with mature rubber plantations dating from the 1980s. These farmers became a powerful example of social and financial success to their relatives in Laos (Sturgeon, 2013). In fact, obtaining direct evidence about the economic benefits of rubber—whether from relatives in China or through local villagers and investors—became the main reason for rubber adoption in both CSAs. Furthermore, imitation (or "following others" in the area) motivated 40 percent of adoption decisions in both areas (Junquera & Grêt-Regamey, 2019).

3. Methods

3.1. Data collection

3.1.1. Household surveys, focus groups, and interviews

A total of 110 household surveys were conducted in October–December 2016 and November 2017–January 2018. Ten households were randomly selected within the six villages selected in Oudomsin ($N = 60$) and in all five villages in Prang ($N = 50$). The survey elicited information on household agricultural plots including size, location, biophysical characteristics, land use, and land use history (type of land use since the plot was first claimed or acquired and years of land use changes). Yield and cash crop prices in 2017 and in the year the cash crop was first planted were also collected. For fallow land, the age of the fallow and the approximate diameter of the trees was elicited. For cash crops, the reasons for adoption were asked.

Focus groups were conducted in each village to understand village and land-use history. In addition, interviews were carried out with one cardamom and three rubber companies as well as with Luang Namtha district and provincial authorities.

3.1.2. Spatial data

We use annual time-series land-use maps (shapefiles) of each CSA covering 2000–2017. These maps were developed following the methodology outlined in Llopis et al. (2019) and Zaehringer et al. (2018).[iii] The approach combines object-based spatial delineation of agricultural plots based on very high-resolution (0.5 m/pixel) remote sensing imagery with participatory methods.

Land-use planning (LUP) maps for Sing District covering Oudomsin were obtained as shapefiles from the Sing District Office of National Resources. These maps show the boundaries of agricultural areas and protected areas, including NPAs, conservation forests, water sources protection (WSP) forests, joint WSPs, HL protected areas, use forests, regeneration forests, and land belonging to the District Area Forestry Office (DAFO). For the Prang area, we only obtained LUP maps for two villages (Prang and Talong) from the Vieng Poukha DAFO, showing the NPA boundary within each village but no other forest categories. We use a digital elevation model (DEM) at 50-meter resolution (MRCS, 2000) to calculate elevation and slope values for both CSAs.

[i] Other sources of income in Oudomsin and Prang CSAs included agricultural wages (26 and 7%, respectively), cattle sales (2 and 16%), and non-agricultural income (15 and 5%); remittances were negligible in 2017 (Junquera and Grêt-Regamey, upcoming).

[ii] With the exception of early adopter villages Ban Had Nyao and a few borderland villages, which planted rubber in the mid-1990s (Dianna, 2005).

[iii] As of yet unpublished.

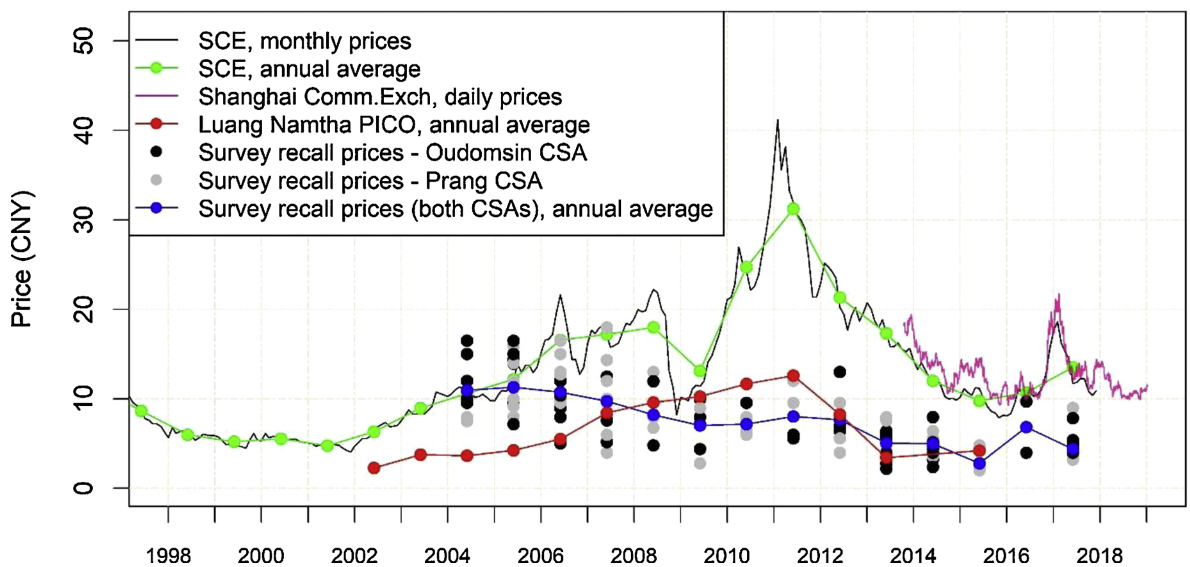

Fig. 2. Rubber prices from the Singapore Commodity Exchange (SCE), Shanghai Commodity Exchange, Luang Namtha PICO, and prices elicited in the household survey. CNY = Chinese Yuan.

3.1.3. Rubber prices

We obtain monthly rubber market prices at the Singapore Commodities Exchange (SCE) for 1998–2017 (Indexmundi, 2018) and find that they are similar to rubber market prices in the Shanghai Commodities Exchange from 2013–2019 (Quandl, 2019) (Fig. 2). Others have suggested a mismatch between international and Chinese rubber market prices, including a possible time lag and distortions due to price supports in China (Alton et al., 2005; Vongvisouk & Dwyer, 2017). In fact, Fig. 2 suggests that Chinese rubber market prices may have a price floor of CNY10/kg. However, in the absence of definitive evidence about this difference, we use prices from the SCE as a proxy for Chinese rubber market prices. Furthermore, ordinary least squares regression analysis yields a high correlation between annual averages from the SCE and rubber prices calculated by the Luang Namtha Provincial Investment and Commerce Office (PICO) (coefficient = 0.42, SD = 0.03, $p < 0.001$, $R_{adj}^2 = 0.92$) (see S1a). Since PICO prices are pegged to Chinese rubber market prices with a factor of 0.42 (Vongvisouk & Dwyer, 2017, p.13), this underscores that SCE rubber market prices are a reasonable proxy for Chinese market prices.

Rubber prices reported by villagers were close to SCE prices during the early years of the expansion (Fig. 2), reflecting the Chinese origin of price information, whether obtained from Chinese relatives or from local investors. Local knowledge of rubber prices increasingly reflects farm-gate prices after around 2008, as rubber plantations started maturing and local sales increased. Farm-gate prices in turn diverge from PICO prices, which are recommended prices, due to variably in quality, contract arrangement,[iv] market intermediary, and the market power of rubber processors and traders (Vongvisouk & Dwyer, 2017). This also explains differences in farm-gate prices between Oudomsin and Prang after around 2009, although these are not statistically significant.

3.2. Definition of variables used in the analysis

3.2.1. Spatial variables

We convert the land-use and LUP shapefiles and the DEM rasters into 10-meter resolution rasters, i.e., smaller than agricultural plots. Raster cells covering two or more land uses are assigned the dominant land-use category. We digitize village locations in each CSA. Slope is calculated based on the DEM. We calculate cost distance as an inverse measure of accessibility based on distance from the nearest village and using slope as a measure of friction. While it seems more accurate to account for roads and paths in the calculation of cost distance, many upland roads were built or expanded at the beginning of the rubber boom and are thus endogenous with rubber expansion. We classify as upland those areas with rubber, cardamom, forest, fallow, upland rice, or bamboo in 2017 (see S1b). For each CSA, we calculate aggregate annual hectares of rubber planted (represented by *R_Converted*). Table A 1 contains a summary of all variables used in the analysis.

3.2.2. Household variables

We refer to planting the first rubber plot as adoption and subsequent plots as expansion. Household-level binary variables are created (1 if mentioned, else 0) to code the self-reported motivations for rubber adoption (response $N = 99$). Answers indicating being told about, hearing about, or seeing the benefits of rubber are ascribed to the category *told*. Answers indicating imitation (e.g., "I followed others") are categorized as *follow*. Answers corresponding to more than one category ($N = 11$) are classified as *told*. We define a plot-level variable indicating whether the household knew the price of rubber prior to planting. Next, we calculate yearly CSA averages for these three variables, representing the fraction of households, among the households who planted a rubber plot in a given year, who: adopted rubber based on receiving direct information (*Told*), adopted rubber based on imitation behavior (*Follow*), and knew the market price when planting rubber (adoption or expansion) (*KnowPrice*). Due to a lack of panel data on household income, we use as a proxy cash flow from cash crop sales and paddy leases. To avoid correlation with the price variable, income from rubber is estimated using average rubber prices over the study period.

3.2.3. Price signal and rubber conversion signal

We define the price signal for each CSA as the interaction between rubber market price and the fraction of households who knew the price of rubber in a given year. Similarly, we define the rubber conversion signal, i.e., imitation, as the interaction between cumulative rubber planted in the CSA in a given year and the fraction of households who cited following others as the main reason for adoption (Fig. 3). In the regression analysis, we specify these signals as interactions between those two variables. In the BN, they are implemented by multiplying the two variables and by dividing by their respective maximum values to adjust the range from 0–1.

[iv] A few households in the Prang area had contracts, whereas all Oudomsin households sold directly to traders (Junquera & Grêt-Regamey, 2019).

Fig. 3. Conceptualization of Price Signal as the interaction of commodity price and local price knowledge, and Rubber Conversion Signal (Imitation) as the interaction of local rubber conversion and local imitation behavior.

For rubber market prices, we use the SCE price as a proxy for rubber prices in China (*Price_R_CHN)*. We could have used rubber prices elicited in the household survey as an alternative measure of rubber market price; however, we believe that price information elicited in the survey does not accurately reflect local market prices. The changing origin of local rubber pricing information throughout the boom from price knowledge originating in China to the progressive formation of a local market introduced a downward trend in locally known rubber prices (Fig. 2), which we believe is not reflective of the local perception of rubber prices, i.e., the local price signal.

We use *KnowPrice* instead of *Told* as the variable indicating knowledge of market conditions as it more accurately reflects the transmission of price information and it is not correlated with the variable *Follow*.

3.3. Land-use change models

We use two complementary modeling approaches with identical explanatory variables (except for the operationalization of the signals) to assess the relative effect of spatially explicit and time-varying variables on land use change (BN model) and on rubber expansion (logistic regression) in each CSA (hypotheses i and iv). The use of a BN makes these dynamics and relationships explicit, allows for user-friendly scenario analyses, and allows for comparability with regression analysis. Independent variables are based on literature and field experience. Specifically, we include household income to reflect perceived ability, rubber price signal, imitation, accessibility (distance, cost distance, and elevation), and protected area status. Regression results are used to identify relevant variables and optimal discretization of variables in the BN. We further use regression analysis to assess the changing influence of price and imitation over time on rubber expansion (hypotheses ii and iii). We restrict the analysis to upland areas, since rubber is only planted in upland plots.

3.3.1. Regression analysis

As the dependent variable, we define a binary metric indicating whether there was conversion to rubber in a given time slice (Δt). To assess changing dynamics throughout the boom we define four periods (2002–2005, 2006–2009, 2010–2013, and 2014–2017).

The regression dataset is a systematic sample ($n = 500$) extracted from a stack of spatially explicit variables, including elevation, cost distance, distance, slope, and protection status. In the Oudomsin area, we exclude cells located in China. To minimize spatial autocorrelation, we use a distance of 430 m in Oudomsin and 500 m in Prang, which is larger than the size of a village-level rubber cluster planted in one year, estimated as 16 hectares. We specify the following models:

$$\textbf{Model 1 (time}-\textbf{independent)}\text{:}\ Prob(rconv_i) = \log\left(\frac{rconv_i}{1 - rconv_i}\right) = \beta X_i^{'} \tag{1}$$

where the dependent binary variable $rconv_i$ measures whether a sampled pixel i has been converted to rubber between Δt = 2000-2017 (0 = no, 1 = yes), X_i is the matrix of spatially-explicit variables (accessibility and protected area status), and β is the vector of regression coefficients.

$$\textbf{Model 2 (time}-\textbf{dependent)}\text{:}\ Prob(rconv_i) = \log\left(\frac{rconv_i}{1 - rconv_i}\right) = \bigwedge(\mu_i + \beta X_{it}^{'}) \tag{2}$$

where the dependent binary variable $rconv_{it}$ measures whether a pixel i has been converted to rubber between $\Delta t = (t-1) - t$, where t = 2001, 2002, …, 2017 (0 = no, 1 = yes); X_{it} is a matrix where spatially-explicit variables are repeated for each time slice t, and time-dependent variables are repeated for each sampled pixel i and include household cash flow, *R_Converted*, *Price_R_CHN*, *KnowPrice*, and *Follow*; μ_i are normally distributed individual effects; and $\bigwedge$ is the logistic cumulative distribution.

Model 3 (time-dependent, period interaction): Similar to Model 2, but where *R_Converted* and *Price_R_CHN* are interacted with the period.

We used a generalized linear model (GLM) with a binomial distribution and a logit link. In Model 1, we test for spatial autocorrelation in the residuals by calculating Moran's I using a vector of spatial weights for neighboring data points, i.e., all sample points within 1,000 meters (Dormann et al., 2007). To measure goodness of fit we calculate the McFadden pseudo-R2 (Cameron & Windmeijer, 1997).

For Models 2 and 3, we used a panel GLM with random effects, which assumes that there is an individual-specific normally distributed error component for sample points within each time slice, uncorrelated with the regressors (Croissant & Millo, 2008). All statistical and regression analyses are conducted using the R statistical language and environment (R Core Team, 2019).

3.3.2. Bayesian network (BN) model

BNs apply Bayesian inference for probability computations based on Bayes' theorem, which links the probability of event A conditional on event B as $P(A|B) = P(B|A) \times P(A)/P(B)$. The joint probability distribution over the set of variables $X_1, X_2, \dots X_n$ in the BN can be factorized as $P(X) = \prod_{i=1}^{n} (X_i|X_{pa(i)})$, where $X_{pa(i)}$ indicates the set of parent variables of X_i. Thus, the joint probability distribution of a BN is determined by specifying (or parameterizing) the probability distribution of each variable conditional on its parents, i.e., adjacent upstream variables (Kjaerulff & Madsen, 2013). The probability of a variable conditional on its parents is expressed in the form of conditional probability tables (CPTs). In a BN, information is propagated forward and backward when the probability distribution of a variable is updated (or instantiated). BNs have a limited ability to handle continuous variables, which requires their discretization into intervals or states (Kjaerulff & Madsen, 2013).

We implement the BN using the Netica™ software (version 5.24), which includes a graphical interface and built-in algorithms for Bayesian inference. Netica™ calculates discretized probability distributions as density histograms.

We develop the model structure based on local knowledge elicited in interviews and focus groups and our understanding of dynamics in the CSAs. The BN model represents conversion of forest, fallow and upland rice between each other and to rubber for each one-year step $\Delta t = (t-1) - 1$, where t = 2001, 2002, …, 2017. The model output *LUt1* is a raster expressing the probability distribution of future land use at the pixel level at the end of year t. *LUt0* refers to the land use at the end of year $t-1$. It does not include rubber, because rubber was not converted to other land uses. We assume that household income, imitation, price signal, accessibility, and protected status have a direct impact on land-use change and reflect this by connecting these variables as well as *LUt0* with *LUt1*. We use cost distance as the sole measure of accessibility as elevation does not significantly improve the model (Table A 2). We discretize each node intending to reflect the original distribution as best as possible while minimizing combinations of parent states with a low frequency count.

The BN model is parameterized by learning using expectation maximization, which maximizes the probability of the data for the given BN structure (Norsys Software, 2019). Nodes are parameterized using the same data as for the panel regression (Models 2 and 3) except for *Price_Signal* and *Rubber_Conversion_Signal.* These two nodes are parameterized using an equation that multiplies the values of their parents and by dividing by their respective maximum values. We use the online platform gBay (Stritih et al., 2020) to link the BN to input data, run the BN at the pixel level, and generate spatially-explicit output.

We measure model sensitivity using the mutual information metric, which is the expected reduction in entropy of one variable when another is known (Marcot, 2012; Norsys Software, 2012). We also conduct scenario analyses to show the influence of predictor variables on the outcome variable (Marcot, 2012). We evaluate BN model performance by comparing conversion to rubber predicted by the model with conversion to rubber in the land use maps. Quantity and exchange difference metrics are calculated following Pontius and Santacruz (2014).

4. Results

4.1. Rubber expansion

Both CSAs experienced an initial phase of rubber expansion when international rubber prices were rising, although rubber uptake started later in Prang (Fig. 4B and C). A second wave of expansion took place around 2011–2016, when rubber prices were rapidly decreasing. In Oudomsin, this second wave coincided with maturing rubber plantations and with the banana boom, which freed up household labor. The two rubber uptake peaks in the Prang area coincided with the visits of rubber investors around 2005 and 2013. These investors informed villagers about the market price and benefits of rubber, offered contracts, and facilitated access to inputs such as costly rubber seedlings.[v] While obtaining direct evidence about the benefits of rubber was the main reason for adoption in both areas, it did not imply knowledge of rubber prices, which was higher in Prang than in Oudomsin (Fig. 4F). The fraction of imitators among adopter households was roughly constant over the boom in Oudomsin. In Prang, it was higher after the first and before the second uptake peaks (Fig. 4E).

4.2. Regression results

Imitation and accessibility (*CostDistance*) were the most important variables affecting rubber expansion in both areas. Moreover, imitation had a larger and more significant effect than its components, namely rubber planted annually (*R_Converted)* and *Follow* (Table A 3, Table A 4). Imitation was significant in periods 2–4 in Oudomsin, and during period 4 in Prang (Table A 5). In absolute terms, the effect of imitation was similar to that of the NPA and accessibility in Oudomsin, and second to accessibility in Prang (Table A 4, Model 2 g). In both study areas, cost distance was a large and significant deterrent to conversion to rubber (Tables A 2-4). Spatially explicit variables explain between 36–41 percent of the variability in the dependent variable of Model 1, as measured by the pseudo-R2 metric (Table A2).

In Oudomsin, where rubber expanded primarily into forests (Fig. A1), the deterrent effect of protected forest areas was roughly proportional to their stringency. Deforestation to rubber was lowest in the NPA, corresponding to the highest level of protection, followed by conservation and WSP forests (Table A 2). Less stringent protected areas had no identifiable effect. In the Prang area, the NPA had no significant effect mainly because most conversion took place in shifting cultivation fallows and not in forests (Fig. A1).

Rubber price and the rubber price signal had a significant effect on conversion in the Oudomsin area, although Model 3 reveals that this effect was only significant during periods 2 and 3 (Table A 5), corresponding to the first wave of expansion. Price had a smaller impact than the NPA and accessibility had (Table A3, Table A 4). The effect of the price signal is larger and more significant than the effect of price alone (Models 2d and 2f), suggesting that this metric adequately captures the influence of market prices.

In Prang, neither rubber price nor the price signal had a significant effect on conversion. In fact, the largest expansion peak, around 2014, coincided with low rubber prices (Fig. 4B and C). In contrast, the first and largest expansion peak in Oudomsin, around 2006, coincided with relatively high rubber prices.

Household income from cash crops (*CashFlow*) is not correlated with rubber expansion in Prang but shows a large and significant effect in Oudomsin. Increasing household income in Oudomsin coincided temporarily with the second rubber expansion peak around 2014, whereas in Prang, these did not coincide (Fig. 4C and D).

4.3. Bayesian network model

The parameterized BN model (Fig. 5) shows that Oudomsin had a higher probability of conversion to rubber than Prang, in line with the more intense expansion of rubber in that area. In both areas, rubber expansion occurred mostly at intermediate accessibility. BN model configurations that included both the *Rubber_Conversion_Signal* and the *Price_Signal* resulted in a proportional and positive relationship between those two signals and the probability of rubber in the land-use outcome (*LUt1*), as expected. Model configurations that did not include price or rubber planted annually as signals did not result in such proportional relationships (Figure A 2). Thus, incorporating the influence of these two variables as signals (Fig. 3) improves the model response.

Sensitivity and scenario analyses (Figs. A3 and A4) show that land-use change and conversion to rubber in Oudomsin were most sensitive to imitation, followed by cost distance, protection status, and price signal. In Prang, imitation and cash flow were the most influential variables.

These results are generally consistent with regression coefficients, except for cash flow in Prang, which is not significant in regression results but has a large influence in the BN. This may be caused by the binarization of the variable in the BN into high and low, and the fact that the period of high cash flow coincides with the arrival of an investor, which might confound the effect of cash flow. BN sensitivity results further indicate that cost distance had a negligible impact on land-use change in Prang, whereas regression results show it to be significant. In Prang, rubber expansion occurred mostly along the highway and the villages nearby, and thus within a narrow range of cost distance values (Fig. 1), which the coarse discretization of this variable in the BN may not properly capture. Sensitivity analysis further shows that the cumulative entropy reduction of all variables included in the model with a direct impact on land-use outcome (*LUt1*) was around 40 percent in each CSA.

4.4. Land-use change simulations and BN model validation

In the model prediction for 2018 (Fig. 6A), the highest probability of rubber is 35 percent for Oudomsin and 23 percent for Prang. There is no

[v] Rubber trees in northern Laos are clones from Chinese varieties that require grafting; they cannot be grown from seeds. Oudomsin villagers had access to lower cost seedlings directly across the border in Mengla County, China.

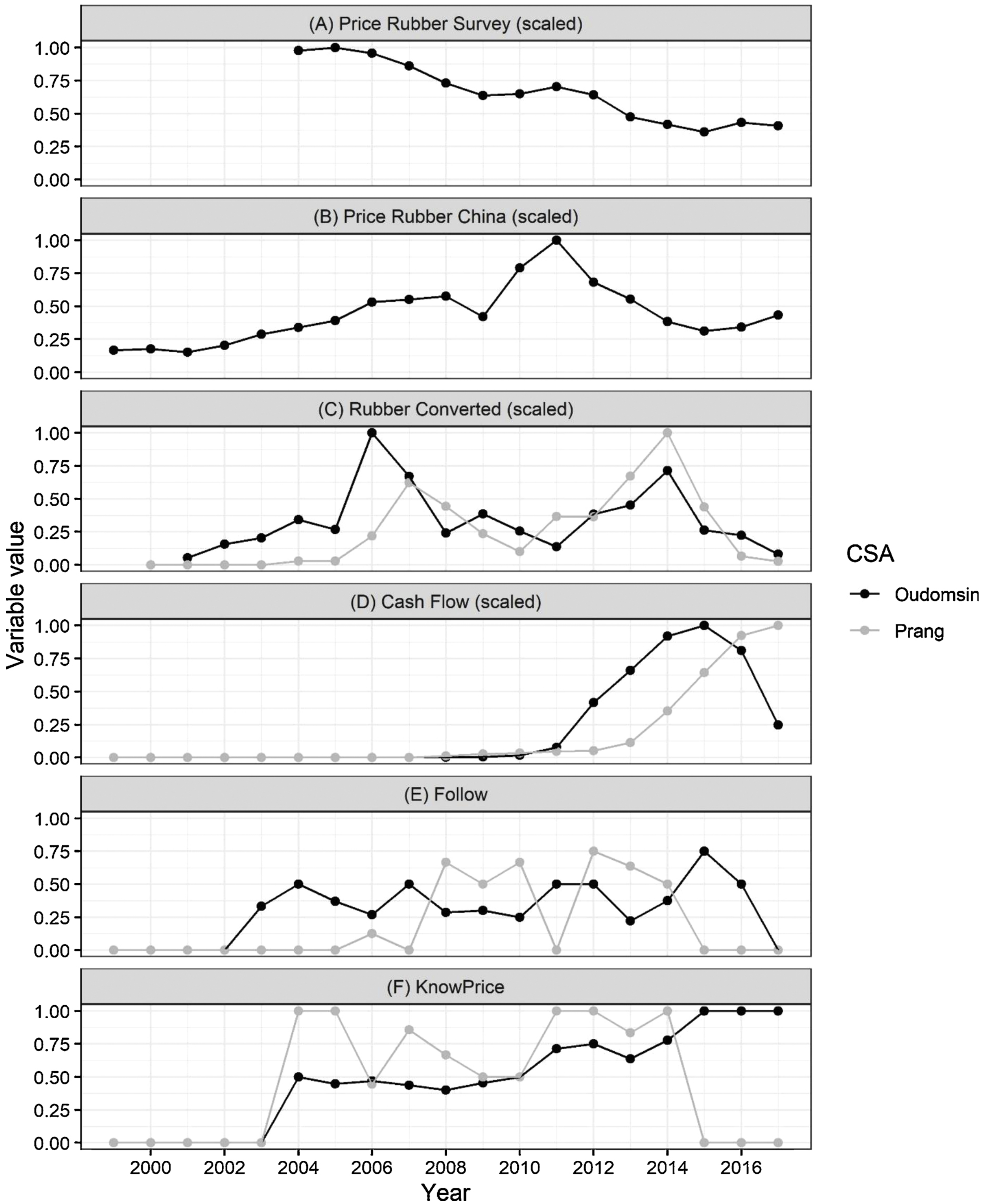

Fig. 4. Selected variables used in the regression analysis and in the BN. Rubber prices (shown in the first two graphs) were the same for both CSAs. For comparability between the CSAs in this figure, rubber prices, Rubber Converted, and Cash Flow were scaled to 1 by dividing by the maximum value in each CSA.

pixel where rubber is the most probable land use. Given that conversion to rubber had significantly slowed down in 2017, we expect little to no conversion to rubber in 2018. However, predictions for the years 2007-2008, when there was strong rubber expansion in both areas, do not exceed 49 percent rubber for Oudomsin and 19 percent for Prang in any pixel (Fig. 6B). If the most probable land use in each pixel is used as the predicted land use, the model would under-predict conversion to rubber.

The under-prediction of conversion to rubber stems in part from the dilution of land-use conversion over 17 time periods. To address the difference in the predicted conversion, the threshold used to determine conversion to rubber can be lowered (Marcot, 2012). A probability threshold of 31 percent for Oudomsin minimizes the quantity difference between rubber conversion in the land-use maps and rubber conversion predicted by the model (Figure A5). For Prang, the model output for 2008 yields only two probability cutoffs (11 and 19 percent), below which the model significantly over-predicts the quantity of rubber converted (Figure A5). With regards to the location of land use change, the model predicts it relatively well in both CSAs (Fig. 6B).

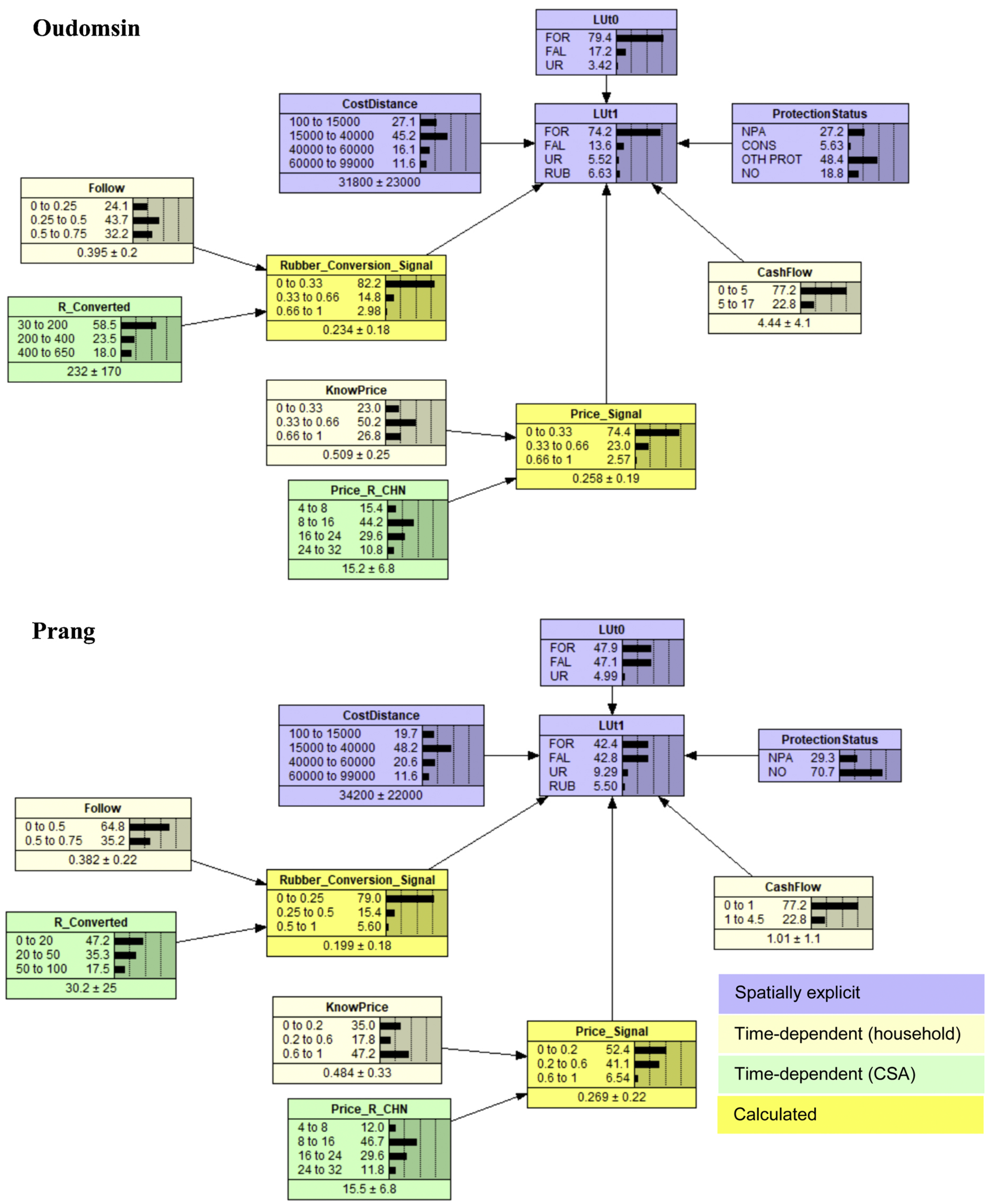

Fig. 5. BN Model of land-use change in upland plots in the Oudomsin and Prang CSAs. Color indicates the variable type.

5. Discussion and conclusions

5.1. Drivers of rubber expansion

Smallholder rubber expansion in northern Laos was precipitated by a conjuncture of policy and market triggers, and intensified or mitigated, i.e., moderated, by context-specific factors. Regression models show the confluence of drivers at different phases of the boom, with periods where price signal strongly mattered, and periods where imitation played a stronger role. Our results highlight the importance of imitation in fueling the boom and of lack of accessibility (cost distance) in limiting rubber expansion. Cost distance had a particularly strong effect in Prang, confirmed by villagers' narratives that they did not plant rubber in certain shifting cultivation areas "because there is no road". Except for one village, other Prang villages did not build or improve forest roads, as happened in Oudomsin. This underscores the well-established bi-directional relationship between agricultural frontier expansion and transport infrastructure development (Angelsen, 2010).

5.2. Impact of protected forest areas

Protected forest areas were an effective stopping mechanism for deforestation in Oudomsin, where practically all other upland areas

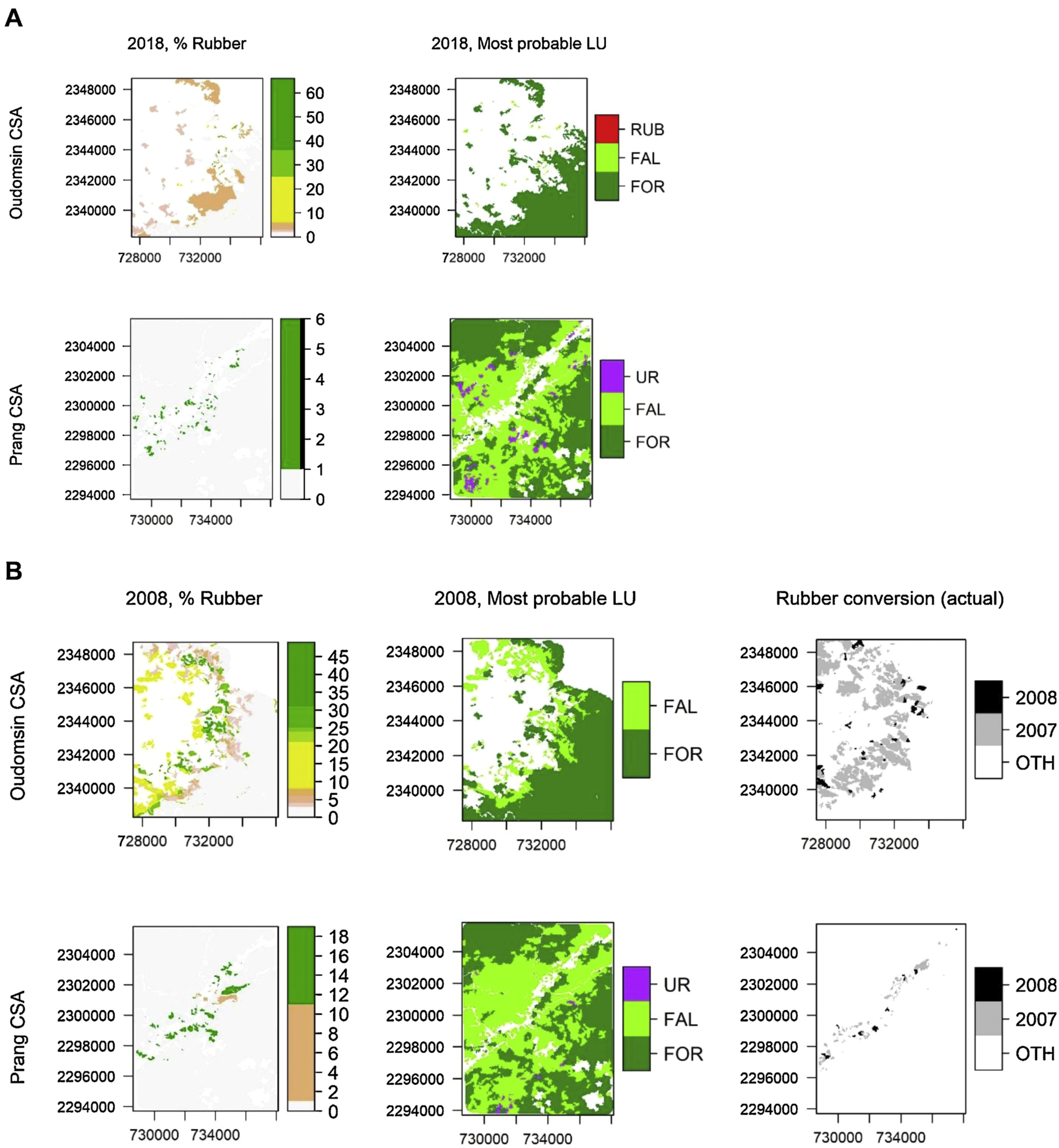

Fig. 6. Output from the BN interface gBay showing projections of % Rubber or Most probable land use (LU) for (A) t0 = 2017, t1 = 2018 and (B) t0 = 2007, t1 = 2008. FOR = Forest, FAL = Fallow, UR = Shifting Cultivation, RUB = Rubber. Rubber conversion (actual) shows actual rubber area planted in 2008 (black), or in 2007 and earlier (gray).

were converted to rubber. This effect was only significant in the strictest protected areas due to differentiated enforcement and timing of deforestation. In early boom years (2004–2006), Oudomsin villagers converted centrally-located use and regeneration forests with relative impunity and were even granted land titles for rubber plantations in these forests. After around 2007, enforcement was stricter, especially in the NPA. This was reflected in villagers' concern about fines and prison sentences. The majority indicated that they would continue to plant rubber if land were available but considered protected forest, and the NPA in particular, to be off limits. Thus, forest categorization and perceived enforcement mattered greatly. This is confirmed by the lower deforestation in conservation and WSP forests, similarly accessible as use and regeneration forests.

Our findings are in line with other case studies that show the effectiveness of protected areas in reducing deforestation (Bruggeman et al., 2018; Carranza et al., 2014), including in Southeast Asian crop boom areas (Kong et al., 2019). Given the strong relationship between accessibility and conversion to rubber, this suggests that the designation of protected areas is especially impactful in accessible locations, which is in line with the findings of Bruggeman et al. (2018).

However, our analysis does not evaluate spillover and indirect effects of forest protection regulations (Ewers and Rodrigues, 2008; Garrett et al., 2019; Lambin et al., 2014), which have been shown to be significant in similar agricultural frontiers (Llopis et al., 2019). Further, our remote sensing analysis provides no information about forest health and biodiversity. Forests near the villages in both study areas are degraded, as evidenced by a near-total absence of animal sounds and old trees, and villagers' reports that hunting game has become very scarce.

5.3. The role of rubber price

Our hypothesis that the influence of rubber price was highest at the beginning of the boom is not fully confirmed by the results, which show no correlation in the first stage of the boom but significant correlation through the expansion phase in Oudomsin. In Prang, price was uncorrelated with rubber uptake. Similarly, Celio et al. (2019) found that price had little effect on smallholders' decisions to expand cash crop plantations in Madagascar, and Ornetsmüller et al. (2019) found that spatial price heterogeneity did not significantly explain the spatial pattern of a maize boom in Laos. This highlights the difficulty of adequately integrating the effect of price in land-use models, i.e., of reflecting true price signals.

An innovation introduced by this work is to represent the local price signal as a combination of market price and local price knowledge. This signal captures the face value of the market price as well as the local "reception" of this information, which implicitly reflects the mediation of the signal.

However, our operationalization of a price signal misses several mechanisms through which commodity prices affect decisions. First, many villagers were aware of the economic benefits of rubber without knowing the price. This knowledge is better captured with the variable *Told* than by *KnowPrice. KnowPrice* also does not capture knowledge of price trend, actual price values, or the perceived quality of the price signal. Whereas villagers in Oudomsin obtained direct and powerful evidence of the benefits of rubber by seeing their relatives get rich, villagers in Prang were informed by investors and other socially-distant persons. With similar price information in both areas, the strength of the signal may nevertheless have been higher in Oudomsin. This could be addressed by integrating social distance in the price signal. Furthermore, while we use a proxy for rubber prices in China as market price, it would be preferable to use actual market prices at the origin of the information—in this case, Mengla County, China.

A common feature of crop booms is the large income difference between a cash crop versus alternative land uses (Ornetsmüller et al., 2019). The difference between growing rubber and upland rice is very high (Feintrenie et al., 2010) at almost any price of rubber (Vongvisouk & Dwyer, 2017). Furthermore, given its productive period of almost 30 years, rubber is a long-term investment (Manivong & Cramb, 2008). Many villagers planted rubber despite price fluctuations as they expected that the price would rise again. This may explain some of the apparent disconnect between price and expansion.

Finally, because the initial phase of a crop boom is often characterized by slow growth, analyses that establish relationships of proportionality between price and expansion cannot capture the triggering effect of price. Triggers and drivers of agricultural expansion correspond to different temporal effects. Triggers provide the initial push for a major transformation; they can bring about persistent change through subsequent lock-in, path-dependency (Sutherland et al., 2012) or other self-reinforcing mechanisms (Ramankutty & Coomes, 2016), and they can help explain the timing of events (Meyfroidt, 2015). Drivers imply causality, though in various, less specific roles than triggers (Meyfroidt, 2015). We propose that the price of rubber acted as a trigger at the beginning of the boom and as a driver through the expansion stages. Our regression analysis captures the latter but does not adequately capture the trigger effect of price.

5.4. The role of imitation

We conceptualize imitation as a self-reinforcing mechanism that influences rubber uptake based on local aggregate expansion. Some adoption and diffusion models also include measures of aggregate uptake to reflect learning (e.g., Busch & Vance, 2011) or imitation specifically (Pomp & Burger, 1995). An innovation in this work is the addition of self-reported imitation to this signal. This implementation captures herd effects (e.g., "I wanted to make money; I did not know how rubber would make me money, but I just followed others") and cultural transmission (e.g., "I just followed the community"), both of which are categorized as *follow*. It also captures the self-reinforcing effect of a so-called land rush, whereby local expansion fuels more expansion.

Results show that imitation was strongest during and after periods of intense growth but not in the early stages, indicating that early adopters are more prone to make knowledge-based decisions while late adopters are more likely to follow the example of others. Previous work showing that households who followed others planted less rubber than those who received direct evidence (Junquera & Grêt-Regamey, 2019) highlights the importance of the analytical scale. At a household level, imitation behavior lowered rubber uptake. At the CSA level, imitation had a strong and self-reinforcing effect on rubber expansion.

5.5. Model limitations

The BN and regression models are not fully comparable as they model land-use change trajectories and conversion to rubber, respectively. However, given the minimal transition from forest to upland rice or fallow during the analysis period, both models mostly capture the same dynamics. Furthermore, the BN is not a model of land-use decisions, but rather a model of land-use change. The former would have required household-level disaggregated variables, whereas the household variables in this model are aggregated at the level of the CSA. Nevertheless, a strength of this model is that it incorporates behavioral elements of decision-making such as price knowledge and imitation. The BN model structure is based on our understanding of local dynamics, and different or additional variables may influence the results. BN model results are sensitive to variable discretization; however, regression results are robust to variable additions. Parameterizing the BN model with data for 17 time periods dilutes the land use conversion signal in the data, but using fewer time periods would require averaging or eliminating time-dependent variables.

Some important triggers of rubber expansion are not reflected in the BN model. LUPLA, rising rubber prices, and the ORP were key triggers of the boom. Because they occurred at the beginning of the study period, we do not have data to represent temporal or spatial variability over the time period of the analysis. For the same reason, other important factors such as proximity to markets (Ornetsmüller et al., 2019) are not included in the model. Triggers that occurred during the modeling period, such as investor visits, could be incorporated and might improve the model response in Prang. Some variables could be improved, e.g., by basing the percentage of followers (*Follow*) on all uptake decisions (i.e., adoption and expansion); using total household income or capital surplus (Richards & Arima, 2018); and incorporating additional protected forest categories in Prang.

BNs are based on past observations and have a limited ability to reflect temporal dynamics, feedbacks (Kelly et al., 2013; Uusitalo, 2007), and hence the non-linear dynamics of crop booms and regime shifts. Other modeling approaches may overcome some of these limitations (Filatova et al., 2016), although developing any model that can emulate—let alone predict—such dynamics is generally difficult (Müller et al., 2014). The choice of a BN in this work was motivated by the transparency of the model structure and comparability with regression analysis.

5.6. Policy relevance

We show that key self-reinforcing mechanisms, including imitation and a closely-related land rush, propelled rubber expansion, particularly in the Oudomsin area. The land rush was compounded by village relocation and land-use policies that increased population density and perceived tenure insecurity, highlighting the role of such policies in triggering and intensifying a boom. Rubber was planted in part as a strategy to claim and secure land during titling processes, a reaction also mentioned in connection with other crop booms in shifting cultivation landscapes (e.g., Mahanty & Milne, 2016). LUPLA thus contributed to the boom-like expansion of rubber plantations and extensive deforestation, which should be an important consideration for similar processes elsewhere. Typical land-use policies are not designed to preclude social dynamics such as imitation, but their potential impact on social and behavioral dynamics and the associated consequences on land use should be examined.

Yet LUPLA also provided stopping mechanisms through the enforcement of protected forest areas, although deforestation was only reduced in areas with the strictest protection status. Furthermore, enforcement was not effective in the early stages of the boom. Our results highlight the relationship between accessibility, transport infrastructure, and deforestation. To efficiently prevent deforestation, forest areas need to be either inaccessible (a condition rarely met), or forest protection must be timely and effective. Beyond deforestation bans, preserving forests should also address their biodiversity, for instance through the enforcement of hunting restrictions.

As with all case study analyses, generalizability is limited. However, numerous studies of crop booms identify similar dynamics, namely the initial confluence of policy and market triggers, and subsequent reinforcing or lock-in mechanisms (Li, 2014; Mahanty & Milne, 2016; Shi, 2008). In particular, LUP and titling processes, generally aimed at curbing shifting cultivation, were important triggers of several documented booms (Lu, 2017; Mahanty & Milne, 2016). Environmental degradation and changing market conditions have also frequently turned booms into a bust. Observed at a larger scale and over longer periods, crop booms seem to shift in time and space (Ornetsmüller et al., 2019). Indeed, rubber has been booming in Southeast Asia since the 1980s (Byerlee, 2014; Fox & Castella, 2013).

This points to three broad conclusions. First, while the location and timing of individual booms are largely unpredictable (Müller et al., 2014), analyzing boom patterns can provide important insights about their underlying dynamics. Second, crop booms will lead to widespread deforestation unless forest protection is effective from the start. Third, crop booms in areas with communal or customary tenure regimes are likely to increase inequalities because of their speed and first-come-first-served nature. In turn, this highlights the need for further and broader-scaled research about crop boom dynamics and the importance of well-adapted local LUPLA processes.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

Acknowledgments

The authors would like to thank Robert Huber, Andreas Kohler and Chiara Vanetta for their help on the statistical analysis, and Oliver T. Coomes and two anonymous reviewers for their suggestions on an earlier version of the manuscript. This work was supported by the Swiss Programme for Research on Global Issues for Development (R4D Programme), funded by the Swiss National Science Foundation (SNSF) and the Swiss Agency for Development and Cooperation, grant number 400440 152167. This work contributes to the Global Land Programme.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.envsci.2020.04.013.

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