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Understanding farmers' influence on land-use change using a participatory Bayesian network approach in a pre-Alpine region in Switzerland

Enrico Celio* and Adrienne Grêt-Regamey

Department of Civil, Environmental and Geomatic Engineering, Institute for Spatial and Landscape Development, Planning of Landscape and Urban Systems (PLUS), ETH Zurich, Zürich, Switzerland

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Land-use models can be used to assess the importance of different drivers of land-use change. Local actors make land-use decisions on the basis of both biophysical and policy aspects, but they can also be considered as autonomous drivers as their attitudes and beliefs influence land-use substantially. We use a Bayesian network-based Land-use Modeling Approach (BLUMAP) to analyze influences of local actor characteristics on land-use change in a spatially explicit manner. Our analysis shows that local actor characteristics have a greater influence on land-use change than changes in agricultural policy schemes. Furthermore, focusing on the probabilities of land-use occurrence under different scenarios facilitates the quantification of influences of local actor characteristics on land-use changes and aids in the detection of where land-use changes are more likely to occur. We demonstrate that local actor characteristics could override land-use policy trends; thus, greater consideration should be paid to actors in land-use development processes.

Keywords: land-use modeling; local actors; analysis of land-use drivers; probability; Bayesian networks

1. Introduction

Governments spend money on programs in forestry, settlement development, and agriculture in order to drive land-use decisions. These programs may involve financial incentives for land managers or introduce regulations restricting land managers' actions. Such regulations may be intra-sectoral, e.g., agricultural law, but they may also originate from environmental law or spatial planning regulations (cf. compliance and cross-compliance, OECD 2010). The influence of public policy on farmers is, however, not a straightforward causal relationship. Biophysical conditions may prevent farmers from acting promptly according to policy aims, but farmers' intentions and self-concepts are also important land-use decision drivers (cf. Hersperger *et al*. 2010 for a classification of actors). Valbuena *et al*. (2010), for example, describe how endogenous and exogenous regional processes are the origin of changes in the density of landscape elements and the proportion of natural areas in a Dutch rural area.

To find out more about these causal relationships, scholars have developed models focusing on various aspects of land-use change (LUC). Early land-use modeling (LUM)

*Corresponding author. Email: ecelio@ethz.ch

efforts only took biophysical drivers into account (Veldkamp and Lambin 2001). However, Bacon, Cain, and Howard (2002) argued that models should work at a scale suitable for reflecting land-use management, and Verburg *et al.* (2006) criticized the way actors' decision-making in LUC processes is often not explicitly addressed in modeling efforts. Recently, however, there has been an increase in participatory modeling approaches that take into account local actors (land users) as a crucial factor in LUC processes.

Voinov and Bousquet (2010) provide an overview of such approaches, focusing on how to involve stakeholders in model-building processes and on using participatory models to find solutions to a given problem. Agent-based modeling (ABM) approaches explicitly take local actors and their decision-making into account, requiring the set-up of if–then rules specific to the agents (cf. Matthews *et al*. 2007 for review; and Le *et al*. 2008; Le, Park, and Vlek 2010; Valbuena *et al*. 2010 for applications).

Such approaches facilitate the modeling of interactions between agents, but multiple agent interactions – i.e., the output of an agent-based model – may be hard to understand and relate to the factors driving LUC. Furthermore, matching the spatial scale of the available geodata with the scale needed for the agent analysis remains a challenge (Filatova *et al*. 2013). If appropriate data is available, statistical approaches to analyzing local actor characteristics are effective. Overmars and Verburg (2005), for example, used logistic regression focusing on land use and identified influencing factors on corn, banana, and wet rice cultivation in three different models. In their 'mainstream geographic approach', different distance measures (e.g., distance to the nearest village) were significant; in their household model, they found ethnicity and slope to be significant; and in the enhanced model (geographic and household data), distance, tax declaration, and slope were significant. A recent paper by Brown *et al*. (2014) uses a theoretical ABM application to show that rational and irrational agents react differently to global and regional demands. Thus, if local actors are to be better integrated into modeling, more should be known about how much local actor characteristics influence LUC. None of the reviewed approaches have been able to quantitatively assess the importance of local actor characteristics on LUC in a spatially explicit manner. This is due to the lack of causal relationships between drivers and LUC in the implemented approaches. In contrast, causal relationships can be introduced in a Bayesian network (BN) approach by developing or validating these relationships with the help of experts. Using BN approaches allows the inclusion of actor characteristics as variables causally connected to land use. The actors' influence on LUC, for example, can be expressed in terms of a change in the probability distribution of the land-use node. These probabilities were also used by Kocabas and Dragicevic (2007) to estimate LUC in calculating 'the probabilities of each future land-use state given the defined land-use drivers'. A recent study by Meyer *et al*. (2014) used expert knowledge and statistical data to set up their BN and interpreted the posterior probabilities in a similar way 'as suitability for a certain land use'.

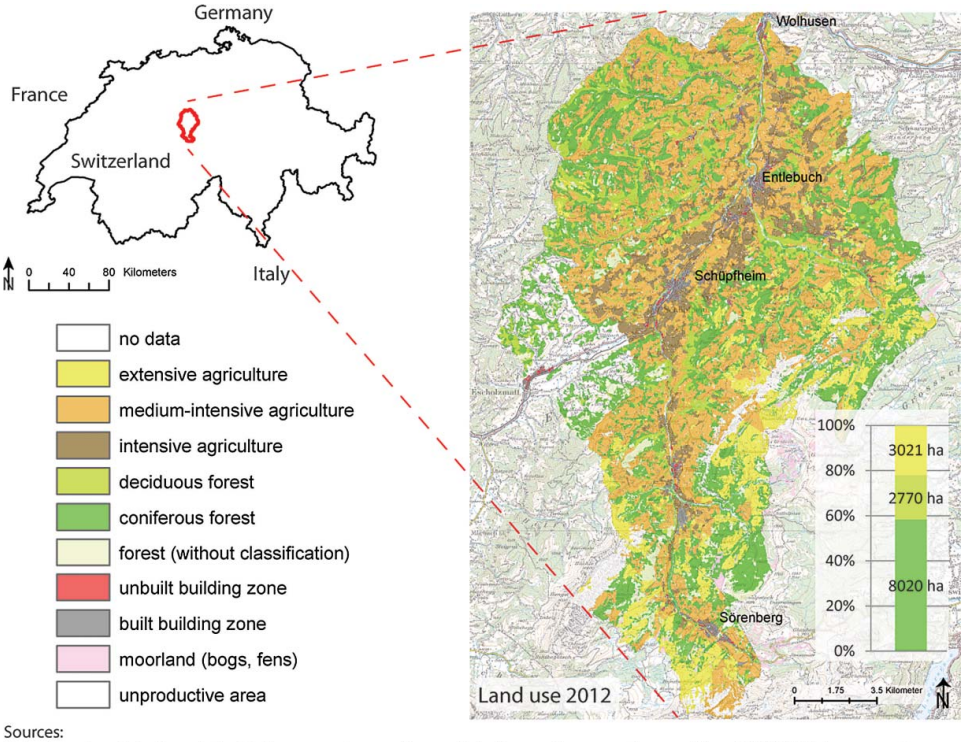
The study presented here builds and expands on the BN-based Land-use Modeling Approach (BLUMAP) presented in Celio, Koellner, and Grêt-Regamey (2014). The aim of this study is to better understand to what degree local actor characteristics influence LUC when compared to agricultural policies. We focus primarily on archetypical local actor characteristics in agriculture such as ecology- and production-oriented farmers. The spatially explicit LUCs are simulated for a pre-Alpine area in Switzerland. After describing our methods and results, we discuss the advantages and disadvantages of using a BN approach to investigate the influences of various land-use drivers on small-scale LUC.

2. Method

2.1. Study area

The study area encompasses an upstream section of the Kleine Emme catchment (Figure 1) in the UNESCO Biosphere Entlebuch (UBE), Switzerland. We did not cover the entire upstream catchment because administrative borders divide the area, which made it difficult to obtain comparable data. The area modeled comprises 315.8 km^2 with a population of about 14,500 (BFS STATPOP 2013). This mostly rural area lies between 20 and 50 km (driving distance) from the city of Lucerne. Mean yearly precipitation is around 1500 mm (MeteoSwiss 2012), and according to the Köppen climate classification, the region has a Cfb climate, which is warm temperate and fully humid with warm summers.

The agricultural sector is important, with 30% of the working population employed in agriculture, forestry, or fishing compared to 7.7% in the entire Canton of Lucerne and 4.2% in Switzerland (BFS STATPOP 2008; LUSTAT 2013). In the UBE, the number of farms decreased by 15% from 1994 to 2004; farms up to 20 hectares experienced an exceedingly pronounced decline (Schmid 2004). In our sample, the mean farm size is 17 hectares (median 13 hectares), and most of the farmers are between 40 and 50 years old. Farmers focus their production on cow-calf and dairy products. Crops are of minor significance.



Sources:
Swiss boarders: SwissBoundaries3D data set, swisstopo. Names: SwissNames data set, swisstopo. Rivers: VECTOR25 data set, swisstopo. Reproduziert mit Bewilligung von swisstopo (JA100120), Bundesamt für Landestopografie swisstopo (Art. 30 GeoIV): 5704 000 000. (c) GIS Kanton Luzern, Swisstopo (PK100) reproduziert mit Bewilligung von swisstopo (JA100120), Bundesamt für Landestopografie swisstopo (Art. 30 GeoIV): 5704 000 000., BFS (AS2004). Data availability: Data for Canton of Lucerne. No agricultural data for the municipality of Escholzmatt. Moorland inventory for total Switzerland available.

Figure 1. The case study area in the upstream area of the Kleine Emme catchment. The diagram (on the right) shows the area for selected land-use categories including extensive agriculture (yellow), deciduous forest (light green), and coniferous forest (dark green). See online color version for full interpretation.

2.2. Bayesian network model

We used a land-use decision modeling approach to analyze where and how much influence local actor characteristics have on LUC. BLUMAP was developed for the participatory modeling of land-use decisions in rural areas in Switzerland (Celio, Koellner, and Grêt-Regamey 2014).

BNs are directed acyclic graphs with nodes representing variables and arcs representing causal relationships. Each node and its relationships are specified through a conditional probability table. Focusing on two nodes in a BN, the Bayesian rule of conditional probability is applied to infer posterior probabilities, $P(x \mid e) = P(x, e)/P(e)$, where x is the probability of a parent node state and e is the evidence of a child node state.

For entire network structures, algorithms based on the Bayesian rule are used in software that provides graphical user or application programming interfaces (Jensen and Nielsen 2007; Kjaerulff and Madsen 2008; Norsys 2009, 2011). The main characteristic of BLUMAP is that it was set up as an expert-based process (Celio, Koellner, and Grêt-Regamey 2014). It allows updating in a *spatially explicit* manner using questionnaire information and supports the analysis of LUC in terms of changes in the probability of a certain land use at a given location (Celio, Koellner, and Grêt-Regamey 2014). We use the term 'update' or 'updating' for characterizing certain BN nodes – and also the BN baseline/trend/expert configuration – with more precise information and the expression 'probability of (land-use) occurrence' to describe the marginal probabilities of the target node in the BN. While a land-use map provides spatially explicit information on land-use types, the probabilities estimated with BLUMAP provide information on how probable it is that a certain LUC will occur, thus providing more detail on the effects of different drivers on LUC than using only a land-use category map.

Because we applied our BN in a spatially explicit manner, the probability measure is given for each modeled parcel; this allows for the investigation of differences between policy influences and influences of local actor characteristics on LUC.

2.3. Set-up process

Developing a model using a participatory approach is usually an iterative process (Voinov and Bousquet 2010). In this section, we describe the five partially iterative steps of setting up this model in more detail (cf. Celio, Koellner, and Grêt-Regamey 2014): (1) local experts' process to parameterize the basic structure of the BN; (2) preparing the geodata; (3) spatially explicit updating of the BN with data from a survey of local actors; (4) calibrating and validating the model; and (5) analyzing the outputs. A comprehensive illustration of the participatory set-up of a BN may be found in Marcot *et al*. (2006).

2.3.1. *Experts' process to parametrize the basic structure*

A structured experts' process, from which we defined nodes and states as well as causal relationships and estimated conditional probabilities, was applied for the set-up of the BN. We chose a participatory modeling approach similar to a 'group model building' process (Voinov and Bousquet 2010) and worked with a group of stakeholders with expertise in agriculture, forestry, or settlement development. Using data obtained from workshops and interview sessions with this group of six experts, we built a conceptual model and parameterized the BN. The sessions were conducted alternately with individual experts and with the group to reveal uncertainties in the model set-up.

The rationale for the model was based on need to assemble the most relevant factors influencing LUC in three different BN representing land-use decisions, namely in the agricultural, forest, and settlement sector. Different land uses and their probabilities of occurrence were passed on to the next time step for processing the information about the drivers of this time step (see Figure 2 for the conceptual model). Time steps were separately defined through the experts' process described above: settlement cells were recalculated after 2.5 years, agricultural cells after 5 years, and forest cells after 25 years. By using three different BNs, we were able to incorporate the different decision rationales of local actors in these sectors and take into account the different time dynamics of the sectors. Hence, the three BNs are independent; however, whenever a parcel changes to another sector (i.e., main land-use category), e.g., from agriculture to settlement, the BN called for processing the information changes too and represents the new sector. Each node reflects a focused question about LUC, e.g., changes in the intensity of agricultural cultivation in the agricultural BN. Hence, the node 'financial situation' uses relative terms regarding the modeled land-use decision (states such as 'pro-extensification'), and states are inherently related to the knowledge of the parameterizing experts. Figure 3 shows the BN for the agricultural sector (see Appendix 1 for the BN for the settlement and forestry sectors), online supplemental data.

Since the first version of BLUMAP did not sufficiently address questions posed by stakeholders and others who reviewed our modeling approach, we adapted BLUMAP to better address these questions. We made the following changes: (1) we added a third category of agricultural intensity (see Section 2.3.2); (2) we further developed the updating procedure with questionnaire information (see Section 2.3.3); (3) we introduced

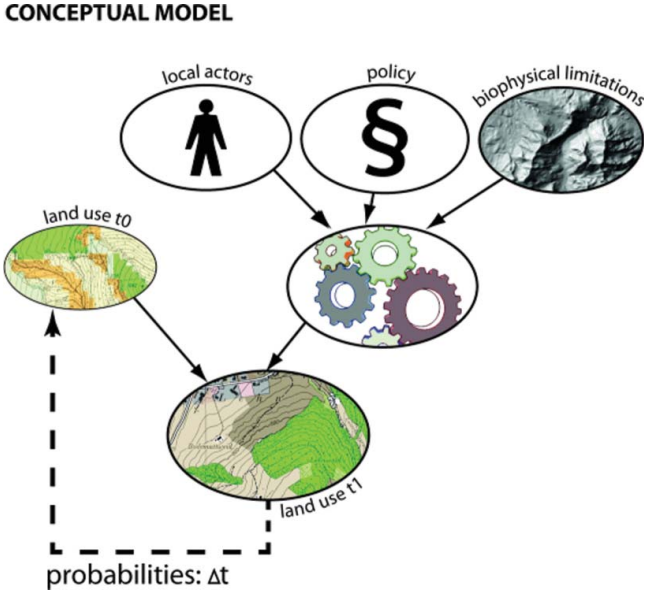


Figure 2. Conceptual model of BLUMAP. Drivers of land-use change are categorized into local actor characteristics, policy, and biophysical limitations. These drivers are processed in the BN and indicate land-use categories after a decision period. Based on raster cells, the probability of land-use occurrence for each land-use category is calculated, saved, and used as input for the next decision period.

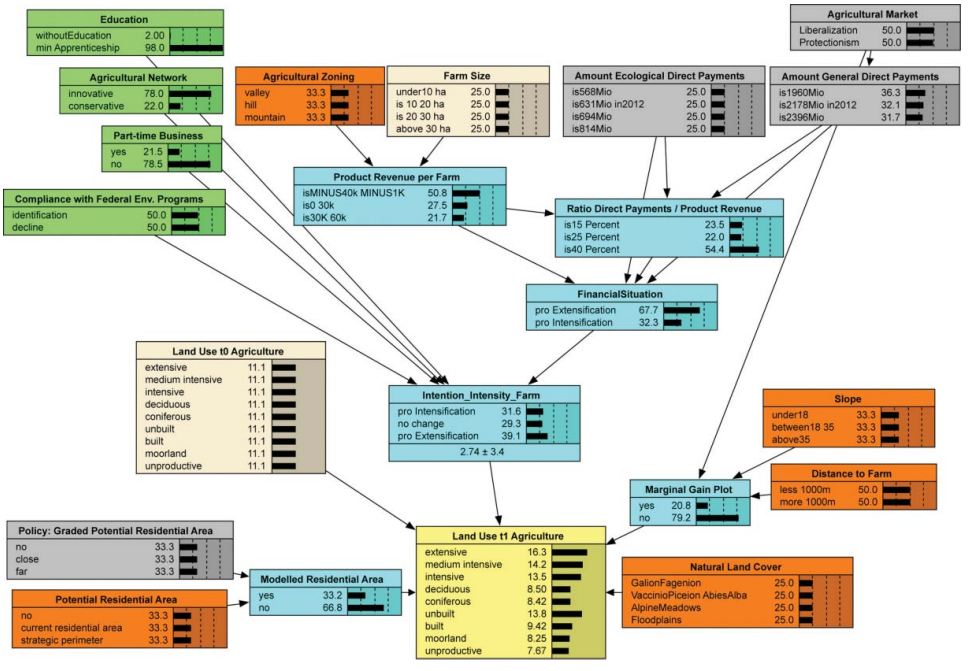


Figure 3. Bayesian network for the agricultural sector with nodes showing preliminary information and nodes without any knowledge (uniform probability distributions). The probabilities of land-use occurrence are shown at the bottom (node 'Land-use t1 Agriculture'). Yellow: target node, grey: policy nodes, green: local actor characteristics, orange: geodata nodes (mostly biophysical influences). See online color version for full interpretation.

the conversion of unbuilt settlement zones back into agricultural zones as a possible process; (4) we included geodata as ESRI grid files instead of ASCII files; (5) we removed trend-nodes; and (6) we changed the implementation of financial incentive payments (direct payments). The previous implementation of direct payments in the model was insufficient because we could not distinguish between ecological and general payments and specify the importance of direct payments relative to the returns from product revenues. The nodes were therefore further developed with the help of the expert group; we introduced a distinction between ecological and general payments as well as a trade-off between direct payments and product revenues for this adapted version of BLUMAP. Furthermore, stakeholders such as employees of the Canton's administration or land users who were confronted with the Celio, Koellner, and Grêt-Regamey (2014) version of the model did not see the need for the overarching trend nodes, such as 'business cycle', 'demand', 'management of natural resources', 'migration inside Switzerland', 'Switzerland's population growth', and 'energy policy' implemented in the earlier version. We therefore removed them from our model.

Table 1 shows all of the nodes of the agriculture BN. A similar table for forestry and settlement is provided in Appendix 2 , online supplemental data. The BNs are different for these three sectors because decision-making processes are influenced by different drivers. If, for example, an agricultural parcel is driven toward settlement, the probability of the settlement land-use category 'unbuilt' rises, and once the probability for a settlement land-use category is higher than the probability of an agricultural land-use category, the settlement BN is used to model land use on that parcel.

Table 1. Variables of BNs, their states, and data sources used to estimate associated probability distributions. Nodes are organized according to the different land-use sectors and to the categories: target node (TA), policy nodes (PO), geodata nodes (GD), including nodes from spatial data sources, nodes representing local actors' characteristics (LA), nodes representing overarching trends (TR), and intermediate nodes (IN). Probability distributions are given either as a conditional probability table (CPT) estimated by experts or as a prior distribution (PRIOR) as a uniform distribution if no prior knowledge was available or populated by a-priori knowledge.

Node	States	Type and source of probability distribution
Agriculture		
Land-use t0 Agriculture (GD)	Extensive agriculture; medium-intensive agriculture; intensive agriculture; deciduous forest; coniferous forest; unbuilt plot; built over plot; moorland; unproductive land	PRIOR: uniform distribution UPDATING: land-use geodata
Land-use t1 Agriculture (TA)	Extensive agriculture; medium-intensive agriculture; intensive agriculture; deciduous forest; coniferous forest; unbuilt plot; built over plot; moorland; unproductive land	CPT: experts' appraisal
Potential natural land cover (GD) Summarized plant formation map produced for Switzerland (raster cell size: 1 km^2)	Galion-Fagenion; Vaccinio-Piceion & Abies alba forest; vegetation of Alpine meadows; floodplains	PRIOR: uniform distribution UPDATING: digitalized map from Hegg, Béguin, and Zoller. (1993)
Distance to farm (GD) Linear distance of a raster cell to the farm building	<1000 m; >1000 m	PRIOR: uniform distribution UPDATING: geodata (farm sites[1], own calculation: distance of plot to farm)
Slope (GD) Slope derived from DEM25	<18%; 18%−35%; >35%	PRIOR: uniform distribution UPDATING: geodata (DEM25[2] from swisstopo[3])
Marginal gain plot (IN) Modeled if a plot is potentially abandoned (criteria: slope and distance to farm)	Yes; no	CPT: experts' appraisal
Graded potential residential area (PO) Policy decision whether to enlarge settlement area	No; close; far	PRIOR: uniform distribution UPDATING: according to scenario
Potential residential area (GD) Strategic plans in spatial planning reveal future priorities for settlement construction ('(regionaler) Richtplan')	No; current residential area; strategic perimeter	PRIOR: uniform distribution UPDATING: geodata

(*continued*)

Table 1. (*Continued*)

Node	States	Type and source of probability distribution
Intention farm intensity (IN) Intention towards behavior of farmer concerning farm intensity (e.g., input of nutrients)	Pro-intensification; no change; pro-extensification	CPT: experts' appraisal
Financial situation (IN) Reflects the incentives from an economic point of view (according to product revenue and direct payments received)	Pro-extensification; pro-intensification	CPT: experts' appraisal
Agricultural network (LA) Perceived attitude of professional network (colleagues) of the farmer	Innovative; conservative	PRIOR: pretest survey data[4] UPDATING: survey sent to farmers to obtain spatially explicit hard evidence
Part-time business (LA) If farmers earn less than 50% of their total income from farming, they are classified as part-time business (according to federal rules)	Yes; no	PRIOR: pretest survey data[5] UPDATING: survey sent to farmers to obtain spatially explicit hard evidence
Education (LA) Distinguishes between farmers who have at least an apprenticeship and those without any agricultural training	Without agricultural training; with agricultural training	PRIOR: pretest survey data[6] UPDATING: survey sent to farmers to obtain spatially explicit hard evidence
Federal ecological aims and programs (LA) Some federal goals clearly focus on animal welfare and protection of cultural landscapes	Identification; decline	PRIOR: uniform distribution (no prior knowledge available) UPDATING: survey sent to farmers to obtain spatially explicit hard evidence
Amount general direct payments (PO) Total of direct payments distributed by the federal government. Relatively seen in relation to today's level	About 1960 Mio. (90% of 2012 level); about 2178 Mio. (2012 level); about 2396 Mio. (110% of 2012 level)	PRIOR: uniform distribution UPDATING: according to scenario
		PRIOR: uniform distribution UPDATING: according to scenario

(*continued*)

Table 1. (*Continued*)

Node	States	Type and source of probability distribution
Amount ecological direct payments (PO) Amount of spent ecological direct payments in Switzerland	About 568 Mio. (90% of 2012 level); about 631 Mio. (2012 level); 694 Mio. (110% of 2012 level); about 814 Mio. (130% of 2012 level)	
Agricultural zoning (GD) Classification of agricultural land according, e.g., climate conditions (vegetation time) and traffic connectivity	Valley, hill, mountain (according to geodata and merging alpine pastures to mountain areas)	PRIOR: uniform distribution UPDATING: geodata[7]
Product revenue per farm (IN) Categories of possible product revenues per farm according to Agricultural Report 2012. Approximation for states definition: turn over − direct payments − material costs	Between −40,000 and 0; between 0 and 30,000; between 30,000 and 60,000	CPT: experts' appraisal (IN)
Ratio direct payments/product revenue Proportion of direct payments to product revenue	Is about 15%; is about 25%; is about 40%	CPT: experts' appraisal (IN)

[1] GIS Canton of Lucerne (dataset: LWBKTLU0_PT).
[2] Digital height model based on Swiss National Map 1:25,000.
[3] Federal Office of Topography.
[4] Survey data of 400 farmers in the study area (valid sample size: 101) asking whether they would join an ecological network project (77.2%) and whether they are certified with a label (78.2%). Priors were set to 78% innovative.
[5] Same survey as in [4]. Question whether the farm is a sideline farm (yes: 21.5%).
[6] Same survey as in [4]. Question on the farmers' education (2% no education, 98% apprenticeship or a higher education).
[7] Geodata copyright: Bundesamt für Landwirtschaft (BLW).

2.3.2. Preparation of the geodata

We included nine land-use categories: 'extensive agriculture', 'medium-intensive agriculture', 'intensive agriculture', 'deciduous forest', 'coniferous forest', 'unbuilt settlement', 'built settlement', 'moorland' (i.e., bogs, fens), and 'unproductive area'. The land-use data for agricultural land use were created by joining the geodata of farm plots ('Betriebsparzellen', GIS Canton of Lucerne) to codes describing the type of crop or pasture. If more than one type of cultivation was found per farm plot, the intensity of a plot was calculated as a weighted average. This resulted in three categories depicting extensive plots (yield $<$ 30 dt dry matter/ha), medium-intensive plots (30−100 dt dry matter/ha), and intensive plots ($>$100 dt dry matter/ha). In the forestry sector, we distinguished between coniferous and deciduous forest defined by the tree species ratio ('Waldbestand', GIS Canton of Lucerne). Settlement plots were split into built and unbuilt plots ('unüberbaute Bauzonen', GIS Canton of Lucerne).

A recent revision of Switzerland's spatial planning law triggered the improvement of the settlement BN from the former version of BLUMAP. The probability of a zone being converted from unbuilt settlement (back) to agricultural land was based on three drivers of settlement expansion: suitability for settlement, slope, and the need for new settlement plots within the next 15 years. These were defined with the help of the experts as well as settlement inventories and population growth projections. Moorland (bogs, fens) and unproductive areas were not modeled because these categories showed only marginal changes from the past and are − in the case of moorland − strongly protected areas. Geodata were fed into the model via ESRI grid data, which requires the handling of ArcObject license files.

2.3.3. Driving factors of land-use change

The most important factors driving LUC were identified in a literature review followed by explorative expert interviews. The final set of factors was weighted and selected by an expert group. In order to understand the importance of local actor characteristics in relation to other driving factors on LUC, we selected two policy schemes and two local actor archetypes for comparison.

2.3.3.1. Policy schemes. A new agricultural policy was introduced in Switzerland on 1 January 2014. The new system includes the abolishment of state payments per cattle unit and a re-orientation of payments for 'cultural landscapes' and for the provision of food. We refer to this new system as 'AP14-17' and to the former system as 'AP2012' because the payment references we used for that system are based on 2012 information. Table 2 presents an overview of the two agricultural policies and payment schemes. In order to define scenarios combining ecology- and production-oriented farmers with AP2012 and AP14-17, we specified the BN nodes by identifying local actors' support for 'federal ecological aims and programs', the property of their 'agricultural network', and the amounts of direct payments. These BN nodes are linked to the actors' intentions; hence, actor characteristics and direct payments, amongst other factors, drive LUC intentions.

2.3.3.2. Local actor characteristics. We intentionally refer to 'local actor characteristics' because local actors (e.g., land users) are essentially responsible for LUC. Because agricultural policy reforms are currently being discussed in Switzerland, we concentrate here on agricultural actors and their land use. We represent these agricultural actors through two local actor archetypes: production- and ecology-oriented farmers. To

Table 2. Former agricultural direct payment scheme and the newly introduced payment scheme.

Payment categories according to AP2012	New payment instruments (AP14-17)
(A) General direct payments	
Area Payments 'Flächenbeiträge' Direct payments for keeping roughage-consuming farm animals (Beiträge für die Haltung raufutterverzehrender Nutztiere) Direct payments for livestock farming under difficult production conditions (Beiträge für die Tierhaltung unter erschwer-enden Produktionsbedingungen) General payments for cultivation on steep slopes (Hangbeiträge)	Payments to secure supplies (Versorgungssicherheitsbeiträge) Payments for the cultural landscape (Kulturlandschaftsbeiträge) Transition payments (Übergangsbeiträge)
Percentage of total direct payments in AP2012: 77%−78%	Percentage of total direct payments in AP14-17: 68%−74% In order to simulate AP14-17, the general payments are assumed to be 1960 million CHF (as a yearly mean for all program years)
(B) Ecological direct payments	
Eco payments (different single programs) Ethological programs	Biodiversity payments (Biodiversitätsbeiträge) Landscape quality payments (Landschaftsqualitätsbeiträge) Production system payments (Produktionssystembeiträge) Resource efficiency payments (Ressourceneffizienzbeiträge)
Percentage of total direct payments in AP2012: 22%−23%	Percentage of total direct payments in AP14-17: 26%−32% To simulate AP14-17, the ecological payments are assumed to be 814 million CHF (as a yearly mean for all program years)

characterize these archetypes, we relied on data derived from three types of questionnaires – one for each land-use sector, namely agriculture, forest, and settlement. The response rate was good (for a Swiss context); about one-third of the questionnaires were returned ('settlement': 34.8% (77 respondents), 'forestry': 36.9% (147 respondents), 'agriculture': 37.1% (122 respondents), and combined 'forestry & agriculture': 29.6% (21 respondents)).

For each local actor characteristic, an item box was created (Appendix 3 , online supplemental data, shows the single items for each local actor characteristic). We used seven-point Likert items to deduce the Likert scales from the item boxes. These seven-point Likert scales were summarized and classified according to the node states defined in the BN set-up process. These updated nodes allowed for the specification of local actor characteristics reflected in the BN nodes and were used to create the actor archetypes. We operationalized the following local actor characteristics:

- For the agriculture BN: attitude toward 'federal ecological aims and programs', configuration of the 'agricultural social network', level of 'education', and whether an actor was engaged in 'part-time' or 'full-time farming'.

- For the settlement BN: 'personal attitude toward the development of unbuilt settlement plots', 'attitude of the social network toward the development of unbuilt settlement plots', and the 'existence of a contract limiting the non-development to a certain period of time'.
- For the forestry BN: 'environmental awareness of the owner', and configuration of the 'professional forestry network'.

The participants were informed that the questionnaires were coded and that we intended to use the data in an anonymous and aggregated way to conduct spatial analyses. If a farmer identified himself with the federal ecological aims and programs and if he perceived himself as having an innovative professional network helping him, i.e., in order to adapt to new trends, he was defined as 'ecology-oriented'. A 'production-oriented' farmer, in contrast, would have a conservative professional network and would not be in support of the federal ecological aims and programs. Appendix 5, online supplemental data, provides more details about the states of the variables used in the BNs to define the local actor archetypes.

The settlement and forestry sectors were treated in a similar way: in nodes reflecting local actor characteristics, spatially explicit questionnaire information was included (the property type of the settlement and forestry plots, the opinion regarding tree species of the social network of forest plot owners). We used 'soft evidence' for the whole study area (the attitude and opinion regarding settlement development in general of the social network of settlement plot owners) and 'hard evidence' (the environmental awareness of forest plot owners) to frame the scenarios.

2.3.4. *Calibration and validation*

For calibration, we used the expert inputs (see Section 2.3.1). In Celio, Brunner, and Grêt-Regamey (2012) and Celio, Koellner, and Grêt-Regamey (2014), a quantitative validation (based on cross-tabulation matrices) and a subjective (qualitative) validation (based on an expert workshop) of BLUMAP are presented. Our version, however, was not validated in detail because the steps described by Celio, Brunner, and Grêt-Regamey (2012) could not be repeated in a new time-intensive transdisciplinary process.

We analyzed the effects of different thresholds in the classification of sampled actor characteristics on land-use categories (e.g., by counting the middle state of the seven-point scale to one or the other node state in a dichotomous node), which led to changes in land-use shares per category of 1.5%−3.1% in the agricultural sector.

2.3.5. *Analysis of driving factors on LUC*

The junction tree algorithm and belief propagation of the BN software (Netica 4.16) was used to calculate the probabilities of occurrence for each modeled land-use category based on the land use and all other spatially explicit input variables provided in a 25 × 25 m^2 raster dataset. The framework was implemented in a Java project using Eclipse Juno (Version: 4.2.1), Netica-J, and ESRI ArcObjects 10.1 and 10.2.

The influence of farmer characteristics on LUC was investigated in two different ways:

(1) The baseline BN structure was updated with the spatially explicit information obtained from the questionnaire. In other words, these data were used as evidence in the BN. By comparing the model outputs with and without updating with

questionnaire information (using ArcGIS 10.2), we mapped 'the influence' (as described by Marcot 2012) of local actors on LUC and modeled it under the AP2012 and AP14-17 policy schemes. In our approach, posterior probabilities of the target node are interpreted as probabilities of occurrence of a certain land-use category; these are the units of analysis. The baseline scenario is relevant because it shows the LUC trends as estimated by experts without the information from our spatially explicit questionnaires about local actor characteristics and specific policy schemes. In comparison to Marcot (2012), this is an approach for creating a 'normative' model scenario in contrast to updating the nodes with the normal or expected state value.

(2) A second analysis consisted of analyzing the differences in the probabilities of occurrence when using different driving factors (using R 3.0.2 and RStudio 0.98.309). The results under the different driving factors (scenarios) were compared using a two-sample Kolmogorov–Smirnov test.

3. Results

3.1. Land-use categories mapping

We mapped LUC using different driving factor configurations to better understand the influence of local actor characteristics on LUC. Simulations for the year 2030 (see Figure 4) were based on the two agricultural policies (AP2012 and AP14-17) and the two different archetypes of local actor characteristics (ecology- and production-oriented farmers).

The following general statements were deduced from mapping the land-use categories and are condensed in the bar plots in Figure 4: (1) there is less forest in the AP14-17 scenarios than in the AP2012 scenarios comparing Figure 4(a) and 4(b) (AP2012) with Figure 4(c) and 4(d) (AP14-17); (2) agricultural plots are more extensively used in the AP14-17 than in the AP2012 scenarios; and (3) by looking at the difference between Figure 4(a) and 4(c) versus Figure 4(b) and 4(d), we see that if ecology-oriented local actor characteristics are fed into the BN, the agricultural land use turns out to be completely extensive. To specify how the scenarios differ, a stacked column diagram was added to the maps in Figure 4, featuring three land-use categories, including extensive agriculture, and deciduous and coniferous forest under the different scenarios.

In comparison, the parametrization of the expert group (all input nodes provided in a uniform distribution) shown in the baseline map (Figure 5) demonstrates an inherent trend in LUC toward more extensive agriculture, more forest, and more built settlement areas.

3.2. Land-use probability mapping

Breaking down the results of the land-use category level analysis into probabilities of land-use occurrence allows for the quantification of local actor influences. We analyzed these patterns by looking at the differences in the probabilities of land-use occurrence when run under different driving factors.

The maps showing the differences between the policies (Figure 6(a) and 6(c)) have probability differences of less than 10%, whereas the maps run under different local actor characteristics (Figure 6(b) and 6(d)) display relatively more variance. As the number of extensively used agricultural plots under AP14-17 driving factors is higher than when run

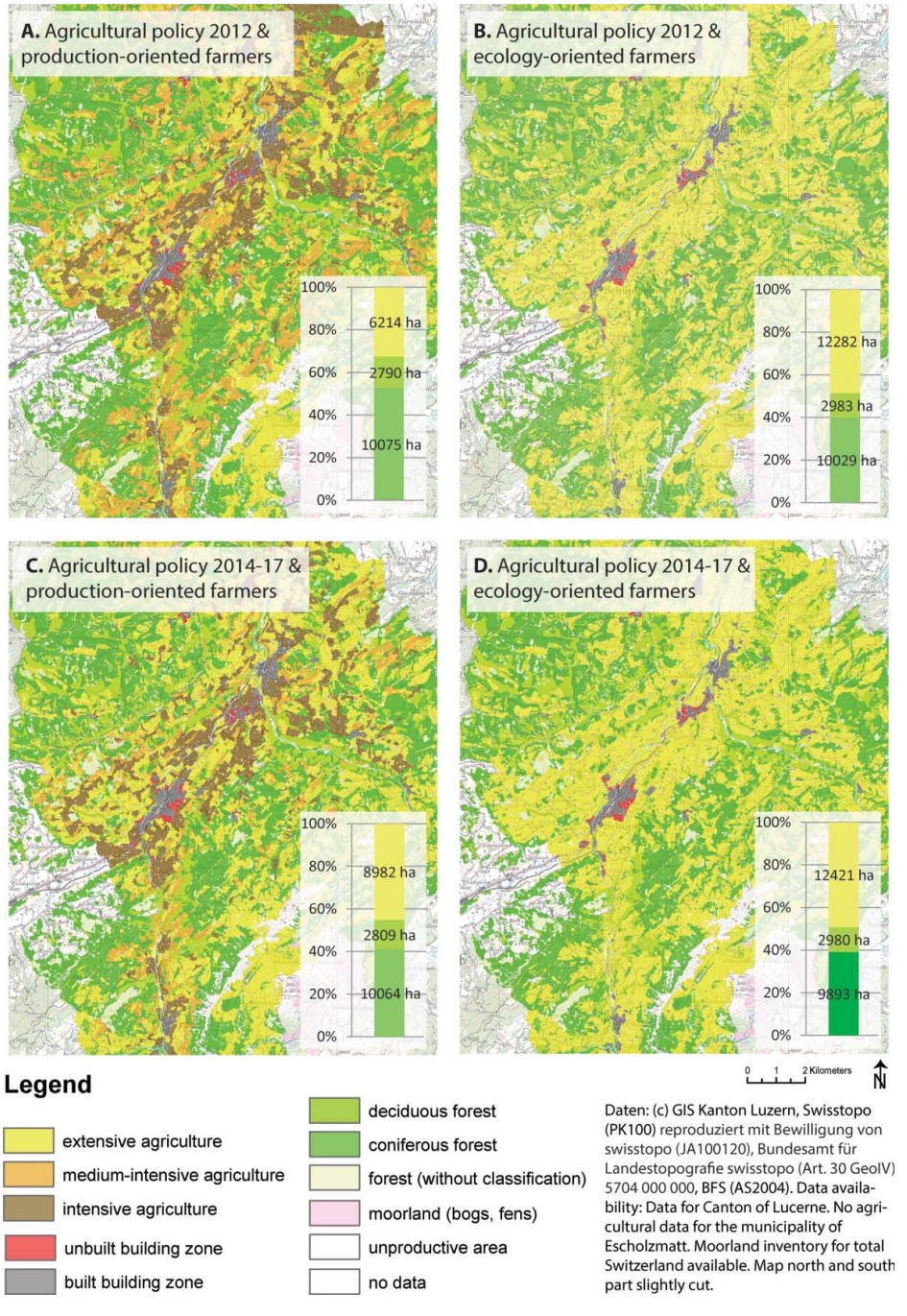


Figure 4. Land-use scenarios for the two different policy schemes and the two different local actor characteristics. The bar plots show the main land-use categories. See online color version for full interpretation.

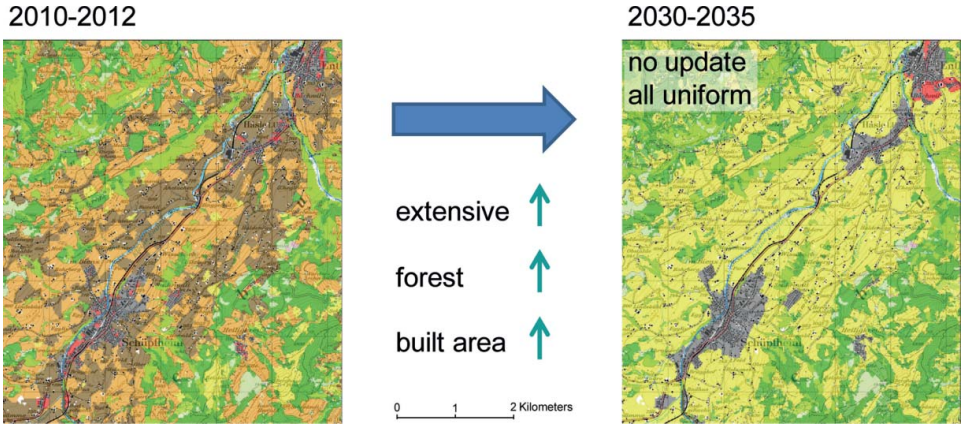


Figure 5. Land-use development without any specification (updating) of driving factors (input nodes provided in a uniform distribution). In the expert-based version, we identify three LUC trends: (a) more extensive agriculture; (b) more forested areas; (c) and more built settlement area. See online color version for full interpretation.

under AP2012 driving factors, there are more cells displayed in Figure 6(d) than in Figure 6(b). In Figure 6(a) (comparing policy- with ecology-oriented actors), most of the cells show differences in the probability of occurrence between 6% and 10%. In Figure 6(c) (comparing policy- with production-oriented local actors), productive farmers seem to counteract the policy trend of extensification. Hence, fewer plots are extensively used in this combination of factors.

This spatially explicit comparison allows us to quantify the effects of different policies and different actors on LUC. Figure 7 shows for each of the maps (and the four additional comparisons including the no update-scenarios) the relative number of cells (y-axis) depicted in the same categories as in the legend of Figure 6. In other words, we summarize the cells in the map and categorize them according to the legend categories. These five categories display the respective differences in probability of land-use occurrence. We again identify the 0%−10% difference induced by the policy change (Figures 7(g) and 7(h) and 6(a) and 6(c)).

In the AP2012-fixed comparison (Figure 7(a)), for 55.9% of the cells, the likelihood of finding a cell in an extensive state is 20%−30% higher in 2030 when comparing ecology- and production-oriented farmers. Hence, the probability of occurrence of cells with more extensive production will strongly depend on the intentions of actors in the case study (e.g., identification with 'federal ecological aims and programs'). Likewise, in the comparison conducted for AP14-17, for 41.7% of the cells, the likelihood of finding a cell in an extensive state in 2030 is higher by 30%−40% for ecology-oriented farmers than for production-oriented farmers (probability of occurrence, Figure 7(b)).

Comparing the modeled output for ecology-oriented and production-oriented actors with the baseline map (Figure 7(c)−(f)), we find that differences are smaller than comparing the effects of two extreme actor characteristics on LUC (Figure 7(a) and 7(b)). Both actor types have a similar effect in terms of probability difference − both have the majority of the data points in the 10−20 percent-class in terms of differences in probabilities of land-use occurrence, but one takes effect in the direction of more ecology-oriented cultivation and the other in more production-oriented cultivation. In other words, local actor characteristics are important and may overrule policy as a driving force of LUC.

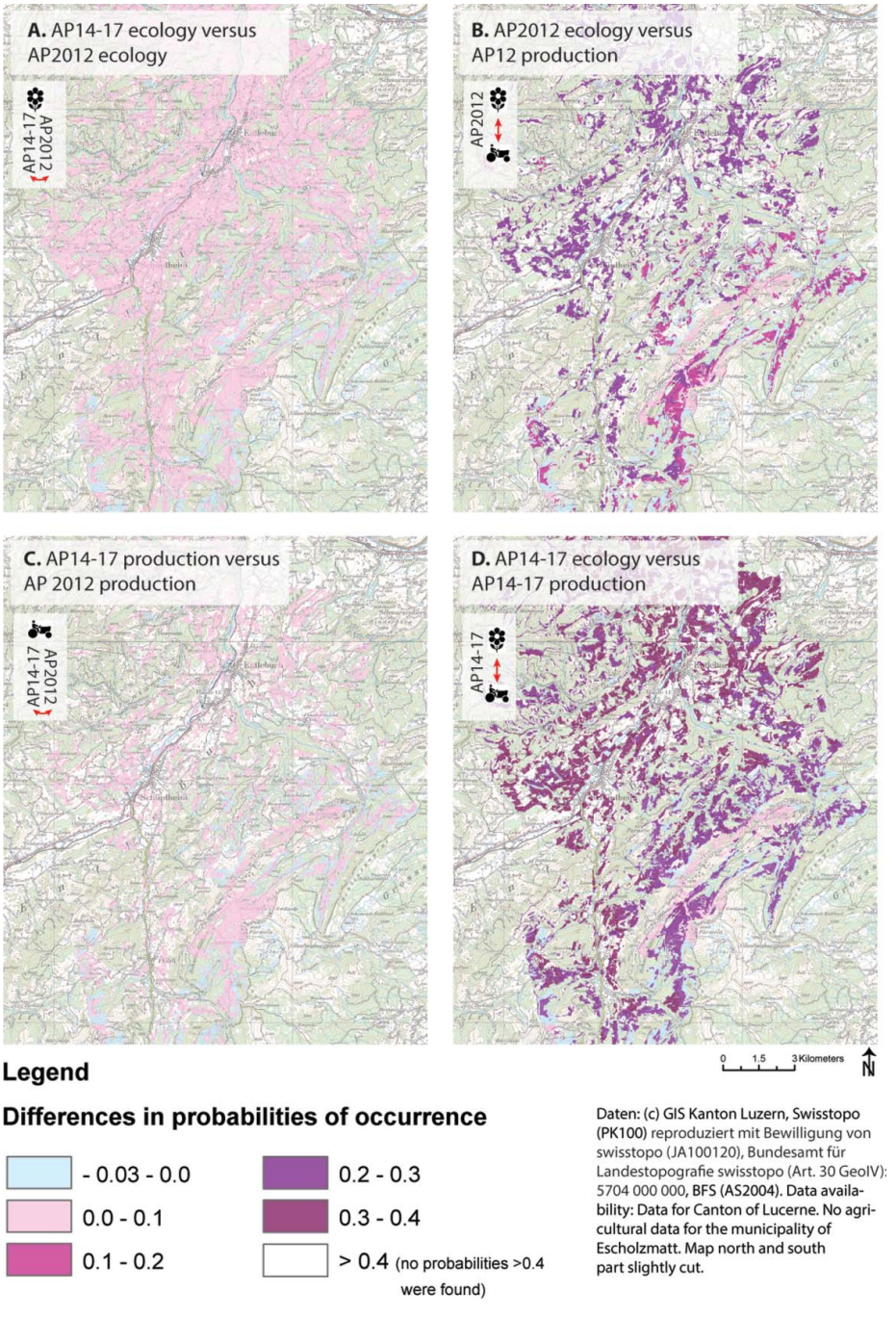


Figure 6. Differences in probabilities of land-use occurrence in four scenarios for the land-use category 'extensive agriculture'. Key: 'AP' = agricultural policy; 'production' = updated with production-oriented farmer characteristics; 'ecology' = updated with ecology-orientated farmer characteristics. See online color version for full interpretation.

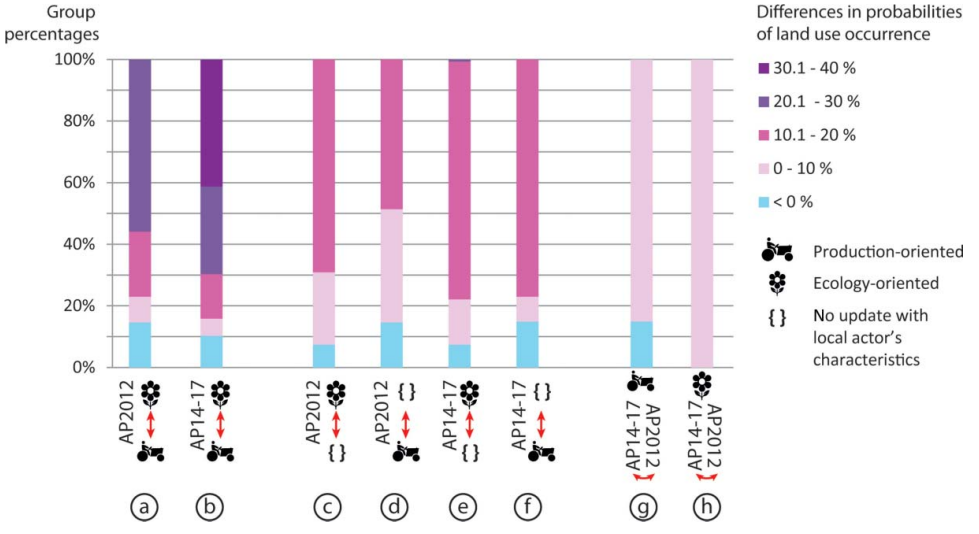


Figure 7. Categorized differences in probability of land-use occurrence for eight scenario comparisons, focusing on extensively used agricultural plots. The comparison of AP14-17 without local actor characteristics updating with production-oriented local actors has fewer identical land uses. Thus, we have fewer cells available for analysis. See online color version for full interpretation.

The question of the spatial variability of the probabilities of occurrences for the different LUCs is also addressed in Figure 6, where the patchy structure reflects the different actor characteristics. A spatial trend is evident: the local actor characteristics in the northern part differ by around 30% and in the south-east by around 20% in terms of probability of land-use occurrence. This trend is likely due largely to spatially explicit input variables such as 'slope' and 'distance to farm' as well as to spatially explicit input from the questionnaire, e.g., 'education of farmers' and 'federal ecological aims and programs'. We observe, e.g., that local actors in the northern part tend to have higher education levels and be more supportive of federal ecological programs and aims (see Figure 4.1(A and B) in Appendix 4 with the update file for 'education' and 'federal ecological aims and programs'). Another reason for the spatial variability is that today's land use influences the probabilities of occurrence. The probability difference in 2030 is significantly different if cells are sampled and compared according to their land use at the start of the simulation (p-value < 0.01 in a two-sample Kolmogorov−Smirnov test).

In order to show path dependency of LUC, we monitored the land use of specific plots through time and the probability of occurrence of particular types of use (Table 3). We intentionally chose cells starting with the three different agricultural land uses (extensive, medium-intensive, and intensive) and focused on two scenarios with different local actor characteristics (production- and ecology-oriented farmers) and the same policy scheme (AP14-17).

We found a faster change to extensive land use with ecology-oriented actors, i.e., the inherent LUC trend in the model is accelerated. If the model trend and actors' intentions are competitive, LUC from intensive to more extensive is slowed down by local actor influence.

Table 3. Land-use category and respective probability of occurrence (following a modeled cell over time). Land-use categories: '1': extensive agriculture; '2': medium-intensive agriculture; '3': intensive agriculture.

Cell / Scenario	2012	2017	2022	2030	2035	Comments
Map coordinates: 646,375.927 | 202,322.746 Meters						
Land-use: AP14-17, ecology-oriented	1	1	1	1	1	Probability falls slowly
Probabilities: AP14-17, ecology-oriented	100 %	88 %	82 %	78 %	76 %	
Land-use: AP14-17, production-oriented	1	1	1	1	1	Probability falls faster
Probabilities: AP14-17, production-oriented	100 %	76 %	62 %	53 %	47 %	
Map coordinates: 646,066.761 | 202,278.693 Meters						
Land-use: AP14-17, ecology-oriented	2	1	1	1	1	Ecology-oriented makes probability of extensive use more likely
Probabilities: AP14-17, ecology-oriented	100 %	46 %	60 %	65 %	66 %	
Land-use: AP14-17, production-oriented	2	2	2	1	1	Sharp decline in probability
Probabilities: AP14-17, production-oriented	100 %	54 %	38 %	32 %	33 %	
Map coordinates: 646,101.686 | 202,478.719 Meters						
Land-use: AP14-17, ecology-oriented	3	2	1	1	1	Tendency towards extensive land use
Probabilities: AP14-17, ecology-oriented	100 %	47 %	45 %	60 %	68 %	
Land-use: AP14-17, production-oriented	3	3	3	3	3	Trend vs. actors is depicted as falling probability
Probabilities: AP14-17, production-oriented	100 %	66 %	50 %	42 %	37 %	

Probabilities rounded. The analyzed cells are not in the most frequent (with respect to number of cells in Figure 7), but found in the second most frequent category where 20 to 30 % of the differences between ecology- and production oriented farmers occur.

4. Discussion

The use of BNs to understand the influence of local actor characteristics on LUC has provided two main findings: (1) local actor characteristics have a substantial influence on LUC and this influence can be quantified using spatially explicit data; and (2) the probabilities of occurrence of a certain LUC modeled with BN provide insights into processes inherent in LUC. Following changes in probabilities of occurrence over time allow a better understanding at which locations we are confronted with uncertain LUC situations.

The influence of local actor characteristics can be visualized in the output maps. As soon as local actor characteristics are integrated in the BN, the baseline model output is enhanced with the complex pattern of local actors' decision-making. Thus, LUC seems to be more influenced by local actor characteristics than by policy schemes. These findings suggest that: (1) the participatory integration of local actors is crucial in studying LUC and in spatial and landscape planning; and (2) the attitudes, beliefs, and motivations of farmers may substantially change LUC. This is supportive of user-centered policy analysis approaches (e.g., Gerber *et al.* 2009). According to the results of these analyses, LUC is always highly dependent on actors as they are always the decision-makers. However, from a policy-making point of view, a change in agricultural policy should imply a change in a farmer's way of production. Our results underline that both farmers and implemented policies are, to a certain degree, steering whether LU is changing toward more extensive or more intensive agriculture. In our case study area, both of these driving factors are present at the same time: we find farmers with productivity-oriented self-concepts and production-oriented farms even though the policy trend was set in the opposite direction (Swiss Federal Council 1998; cf. Burton and Wilson 2006).

Swiss agricultural policy is mainly implemented through ecological and general direct payments. All payments have a common ecological basis that every farmer has to adhere to if he wants to benefit from these payments (proof of ecological performance). Regarding the implementation of the direct payments in the modeling framework, we made a simplification in two aspects: (1) changing payment schemes may alter farmers' intention and behavior – this possible adaptation of local actor variables was not applied in our model because the relationship is not yet clear (cf. Burton and Wilson 2006); and (2) the difference between ecological and general direct payments is not as strict in the new agricultural policy (AP14-17) as it was before (Table 2). For example, official documents no longer make this distinction. Nevertheless, we implemented these two sides as influencing factors in the model.

The question of how to integrate local actor characteristics in a spatially explicit manner requires more investigation. In this study, we implemented only two variables ('education' and 'federal ecological aims and programs') in this manner, but larger and spatially denser samples would allow statistical analyses such as regressions to determine the influence of single variables on LUC intentions. Alternatively, local actor characteristics could be interpolated with spatial-statistical methods to generate an interpolated surface for the variables. Grêt-Regamey and Crespo (2011) and Crespo and Grêt-Regamey (2012) describe ways estimating the weight influence factors have on house rents in a spatially explicit manner through an inverse modeling approach. Another way to integrate local actor characteristics would be to use psychology-based questionnaires to improve confidence in the results (Kaiser 1998; Kaiser *et al*. 1999).

The attitudinal variables we studied were operationalized by three to five Likert items. However, these attitudinal variables were complex, and responses to questions tended to approach the mean, which may be an effect of insufficiently detailed questions or simply a general problem in questionnaire-based surveys (error of central tendency). A reverse procedure would be possible in which questionnaires filled in by local land-use actors (e.g., managers and owners) would be used for the parameterization of the BN (Meyer *et al*. 2014), and spatial specificity would be introduced by expert judgments (Grêt-Regamey *et al*. 2013) or other (questionnaire) data. Other ways of obtaining data on local actor characteristics such as interviews could produce better characterizations of complex local actor characteristics, especially in small case study areas where potential sample sizes are also small (cf. Johnson and Christensen 2007). Alternatively, focusing on geodata types, land-use data at the plot level (vector data) instead of grid cells (raster data) could be analyzed. However, grid cells are easier to use technically and, in certain cases, land-use cells divide the plots and allow a fine-grained representation of biophysical characteristics. Farmers, moreover, decide about land use on an even more detailed level than evident in the plots available as geodata.

While BLUMAP is able to simulate LUC change on single parcels, it is not yet able to simulate changing farm situations such as land redistribution after farm abandonment. Furthermore, possible feedbacks in the land-use system are included only through the transfer of land-use probabilities from one time step to another (from node land-use t1 back to node land-use t0 after a decision period).

Feedbacks are a factor that has to be considered cautiously, because in BNs, we cannot address them. BLUMAP can be categorized as a trend-based expert model (cf. Koomen, Koekoek, and Dijk 2011) that can transparently communicate ongoing LUC. There are certain cells for which the probability of occurrence of the most probable land

use is rising constantly over time because the main driving factors (biophysical limitations, policy, and local actor characteristics) tend toward the same direction. We also find cells that show a flattening of the discrete probability distribution over the land-use categories (Celio, Koellner, and Grêt-Regamey 2014). We therefore hypothesize that these cells will help to identify the model frontier in terms of the time horizon, e.g., at a certain point in time, the model will predict a land-use category that has only a marginally higher probability of occurrence than the land-use category ranked second at the same location. This, however, will only apply if the variable settings over time are assumed to be constant.

The validation of such probability measures could be one of the next steps. The quantitative and qualitative procedures for validation of the land-use scenarios were described in another context (Celio, Brunner, and Grêt-Regamey 2012; Celio, Koellner, and Grêt-Regamey 2014). These procedures require the inclusion of local actors and the policy implementing administration. Such a transdisciplinary process still needs to be developed for this version of BLUMAP, which would allow for an in-depth validation of this model. Hamilton, Pollino, and Jakeman (2015) present a possible methodological blueprint for such a transdisciplinary process by applying a data-driven mode of model evaluation using different data sources, including expert-elicited and data-based conditional probabilities for BN parameterization. Despite its limitations, BLUMAP helps reveal subjective factors involved in land-use decision-making in order to make assumptions explicit. This subjectivist approach is valuable because it translates expert judgments into a form that can be analyzed (Goldstein 2006). Once the validation procedure and its results are accepted, the same analysis and the subsequent validation procedure can be used for other land-use categories. A more frequentist (objective) perspective would quantify the influence of local actors on LUC processes, e.g., with logit functions to regress landscape characteristics onto farmer types or to compare farm types and the density of land-use processes (Bakker and van Doorn 2009; Carmona *et al*. 2010).

5. Conclusions

Using BLUMAP, as parameterized here, it has been possible to show that local actor characteristics strongly influence LUC (even more than policy changes do). The spatially explicit BN presented here allows the integration of local actor characteristics to better understand their effect on LUC in a spatially explicit manner. Such approaches can support policy-makers, especially when designing implementation processes for agricultural policies.

We have shown how the probability of land-use occurrence change over time and that potential LUC is more likely if policy and local actor variables are working against each other. Taking local actors, i.e., farmers, on board when designing new policies, e.g., through advanced training programs, could be supported by the approach presented here, leading to a reduction in diverging efforts of farmers and legislators for their preferred LUC.

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No potential conflict of interest was reported by the authors.

Supplemental data

Supplemental data for this article can be accessed http://dx.doi.org/10.1080/09640568.2015.1120713.

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