Inference of successional patterns from land cover maps

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Introduction

Caribou populations decline mainly driven by habitat loss and fragmentation, which affects available winter forage (mainly lichen).

Lichen abundance recovers slowly to pre-disturbance levels (> 40 years after disturbance) [1].

It is therefore critical to predict future developments of lichen-rich caribou winter habitat for recovery planning.

We want to build a state and transition simulation model to forecast dynamics of suitable winter habitat in caribou landscapes.

Problem is the limited availability of chronosequence data that allow us to identify patterns of vegetation succession and estimate transition probabilities that are needed for the model.

We here propose a solution to use available land cover maps, and fire history data, to identify changes in the spatiotemporal arrangement of land cover classes (LCCs) within these maps.

and try to answer the question:

Can we deduce patterns of vegetation dynamics from the analysis of the spatiotemporal arrangement of classes in land cover maps?

We hypothesise that changes in the pattern of aggregation of LCCs over time can reveal successional pathways.

Methods

In our study area, covering the taiga plains in the Northwest Territories, west of Great Slave Lake (Fig 1A).

we use the Land Cover Map of Canada 2005 (Fig 1B), which is produced from 0.25km spatial resolution MODIS data [2]. This map distinguishes between 39 land cover classes, and between classes with and without lichen. The 15 most abundant classes are described in Table 1.

and fire history data from 1965 to 2004 [3] (Fig 1C), which allows us to identify areas that burned once, are reburned and have not been burned in areas where there was no record of fire history < 1965 (control) (Fig 1D).

to create a chronosequence we create 5-year age groups

First, we extract proportions for each LCC within age group, reburned and control areas,

and compare proportions to identify the development of class abundance over time.

Second, we characterize spatial associations of LCCs using join count statistics (JCS) and test whether the occurrence of categories at spatially adjacent locations can be accounted for by randomness alone [4,5,6,7,8].

We then calculate join counts, using the queen's move to consider each cell's 8 direct neighbours, or less in case cells border empty cells, e.g. at fire boundaries (Fig. 2.). Weights are based on remaining links; i.e. 1/7 for each link in Fig. 2.

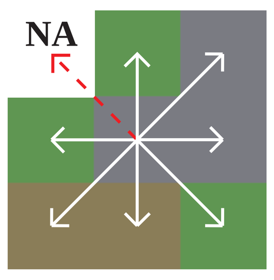


Figure 2. Queen's move.

and z-values are calculated and plotted, to assess the level of aggregation of LCC-pairs (significance at p=0.05, $-1.645 > z \geq 1.645$).

A change in spatial pattern over time, could indicate that class-to-class transitions take place.

All analyses were performed using R [9].

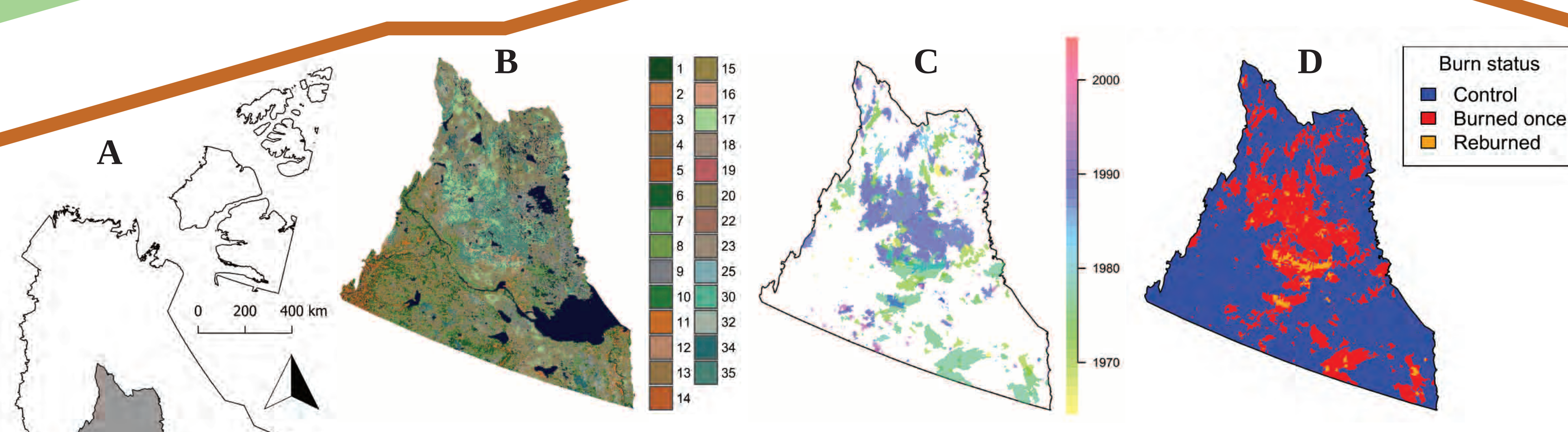


Figure 1. **A.** Map of the Northwest Territories with the study area in grey; **B.** Land cover classes in the study area; **C.** Fire history 1965-2004; **D.** Areas that are burned once, reburned and control. All maps are in Lambert conformal conic projection.

Table 1. Description of the 15 most abundant LCCs; composition and density of canopy, understory vegetation or other class-differentiating characteristics.

(6) conifer; medium density (40-60%); moss-shrub	(12) deciduous; medium density (40-60%); young regenerating	(18) herb-shrub-bare
(7) conifer; medium density (40-60%); lichen-shrub	(13) mixed conifer-deciduous; low to medium density (25-60%); irregular canopy	(20) conifer; sparse density (<25%); herb-shrub-moss
(8) conifer; low density (25-40%); moss-shrub	(15) mixed conifer-deciduous; low regenerating	(32) lichen-spruce bog; sparse density (<25%)
(9) conifer; low density (25-40%); lichen (rock)	(16) high-low shrub dominated; dry to wet areas	(34) recent burns; areas burned within the last ~5 years
(10) wet conifer bogs; low density (25-40%); shrub-herb-lichen-moss	(17) grassland; herbaceous (non-woody) vegetation; tree or shrub cover (<10%)	(35) old burns; areas burned within the last ~10 years

Results

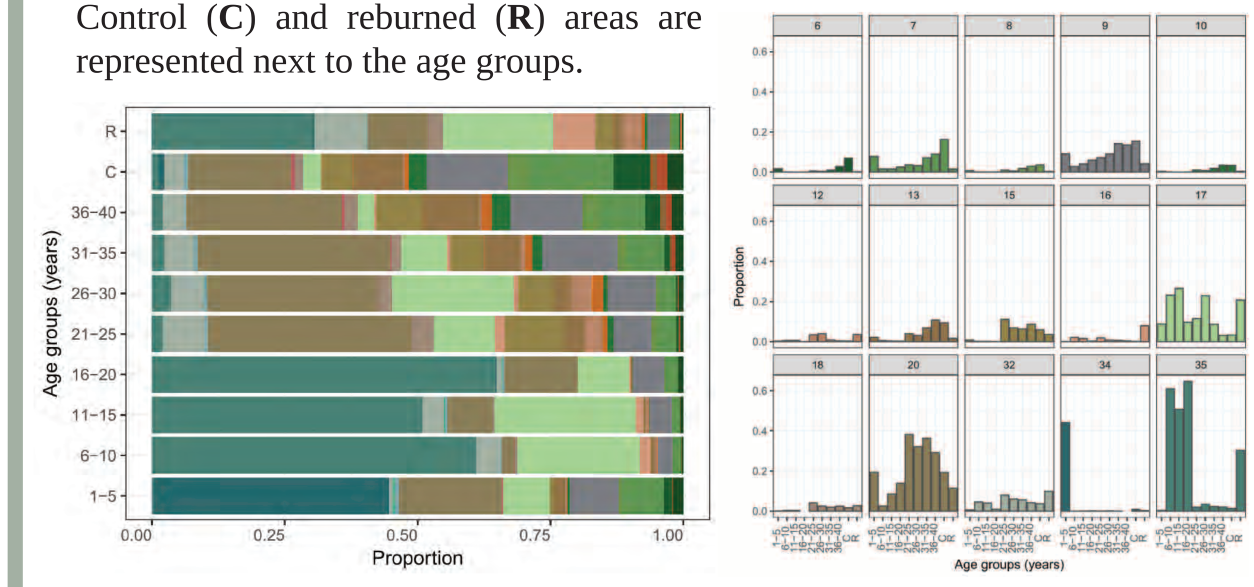
LCC-proportions show temporal trends (Fig. 3), where some LCCs increase over time while others decrease. LCCs 34 and 35 dominate in the young age groups, while 20, 17, 15 and 32 dominate in the mid-range, but show a gradual decline while 6, 7, 9, 10 and 13 increase and become dominant in later stages. These are primary indicators of transitions.

Z-values reveal spatiotemporal patterns of aggregation (Fig. 4)

- Positive values (blue dots) indicate that classes aggregate more than can be expected to be a result of randomness, i.e. the spatial pattern is clustered.
- Null values (black dots) indicate that the spatial pattern is random.
- Negative values (red dots) indicate that classes aggregate less.

indicating presence of class-transitions works as follows. Transition partners are expected to aggregate in early stages of the transition, after which they slowly disaggregate, when one of the two classes takes over.

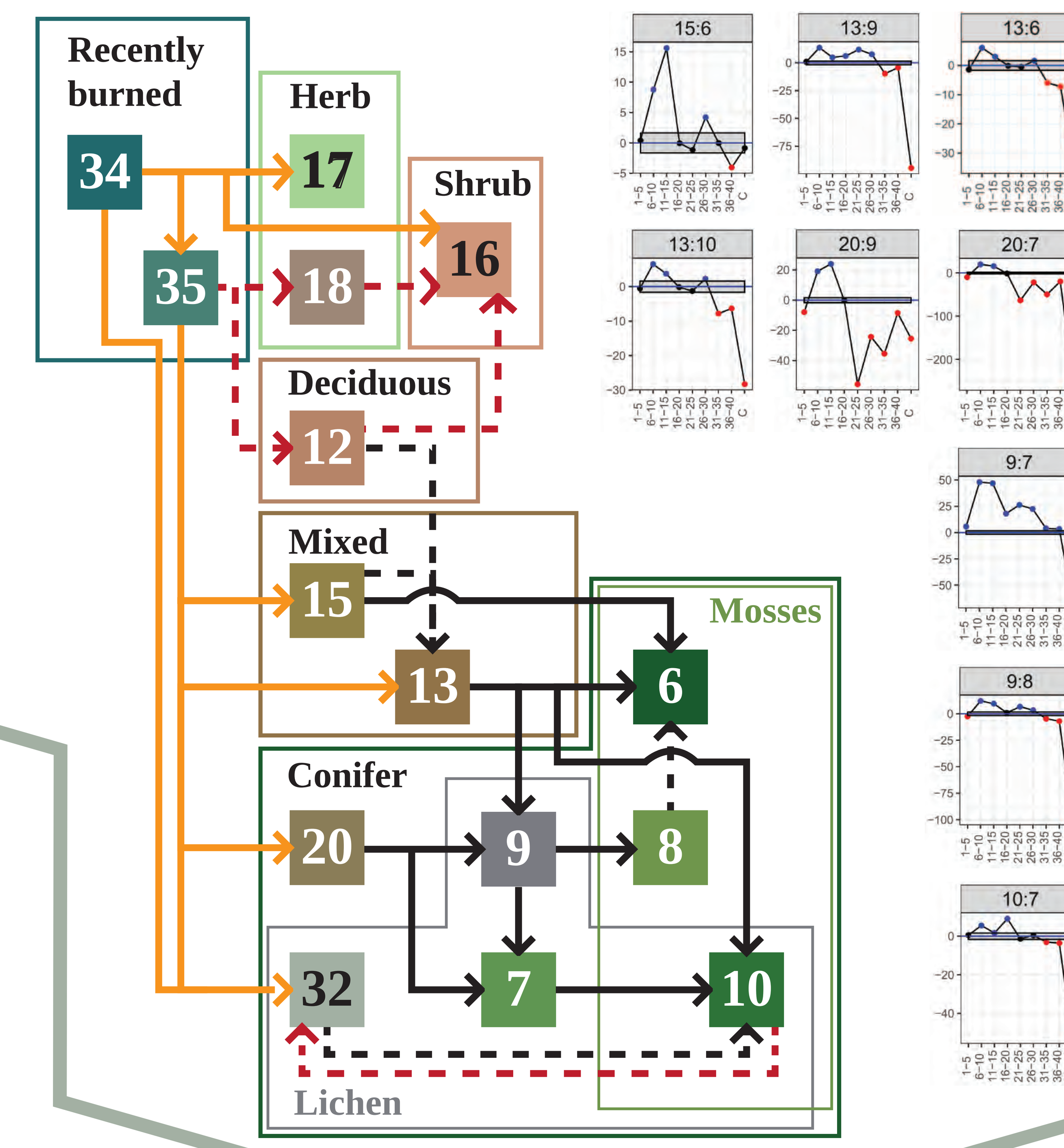
Figure 3. **Left.** Stacked LCC-proportions per age group. **Right.** Selection of most abundant classes, showing the development of LCC-proportions per class. Control (**C**) and reburned (**R**) areas are represented next to the age groups.



Using this principle and the observed patterns we constructed a conceptual diagram of successional pathways where potential support for transitions are visualized (Fig.4).

- **Orange arrows** show links which were impossible to assess using spatial associations, due to the arbitrary nature in which recently burned classes, 34 and 35, were assigned. These links are purely based on the class descriptions and temporal trends of LCC-proportions.
- **Black dashed arrows** show links which are based on the class descriptions, temporal trends only.
- **Black solid arrows** are like dashed arrows, but also have shown strong changes in the pattern of aggregation.
- **Red dashed arrows** show links between classes that showed a high association with reburned areas. These classes generally show high pairwise spatial associations (not shown here), which supports this idea.

Figure 4. Conceptual diagram of successional patterns and spatial association of most important LCC-pairs.



Discussion and conclusion

Observations of age-groups 1-5 and 16-20 are possibly biased due to the small area burned during these periods. This seems to correspond with the general sensitivity of JCS to the density, shape and connectivity of individual examined areas [10].

Future analyses should include:

- **Compositional statistics.**
- **Checking of alternative explanations of the observed spatial patterns** in order to confirm these results.
- **Calculation of transition probabilities**.
- **Application of the H Moran statistic** [11], to deal with the possible lack of stationarity within the study area, which could cause the join count statistic to lose its robustness [6].

Although not conclusive these results show a promising use of JCS to aid in drawing inference of successional patterns from land cover maps.

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