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# Balancing fuel considerations and rare carnivore habitat: an evaluation of risk and reward

*EMC update 16 June 2025*

**Jessica K. Buskirk**, David Lamphear*, Holly Munro, Josh Twining*, John Bailey, and Katie M. Moriarty

Photo: M. Stevens

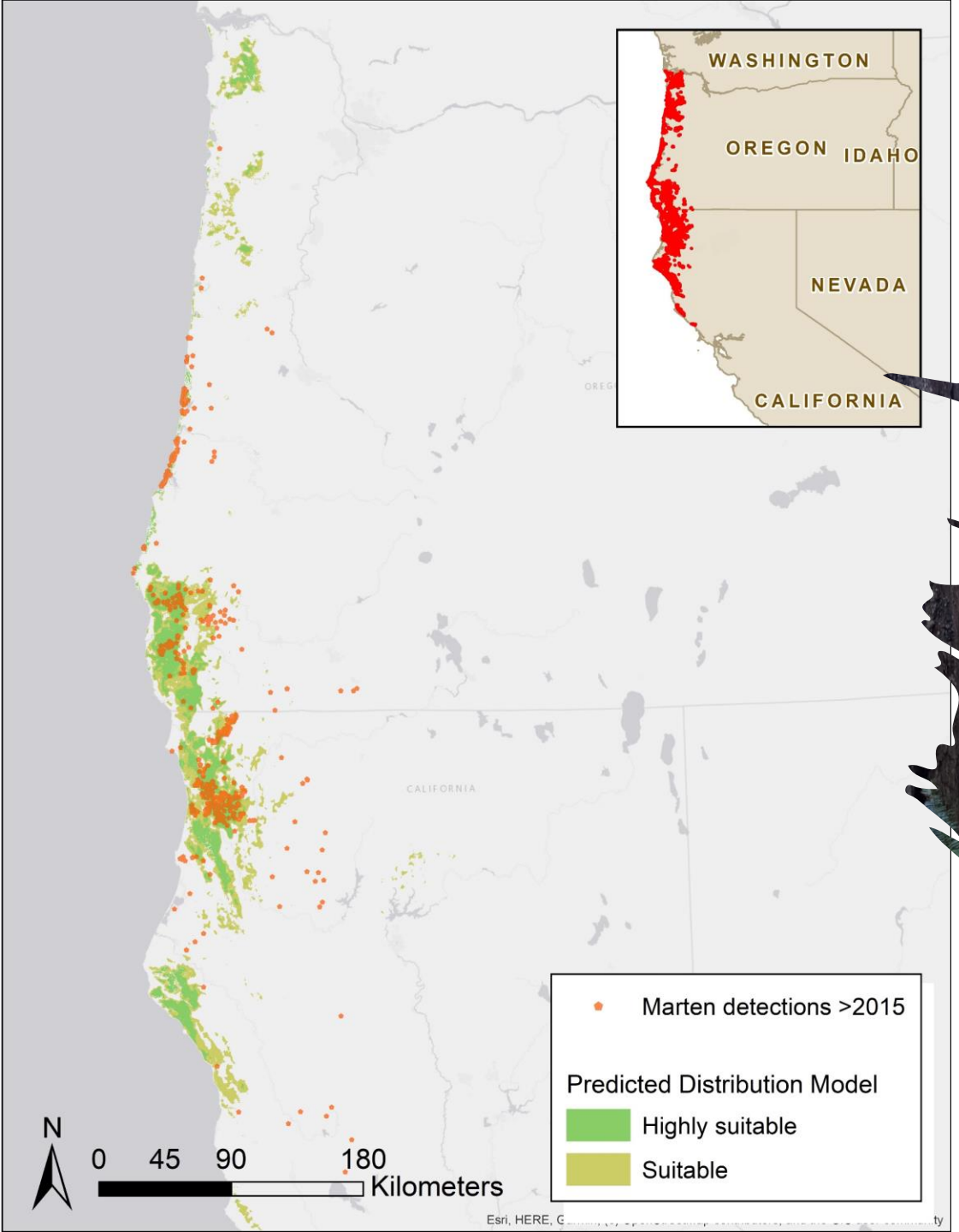
Update: Humboldt marten vegetation data collection on Green Diamond

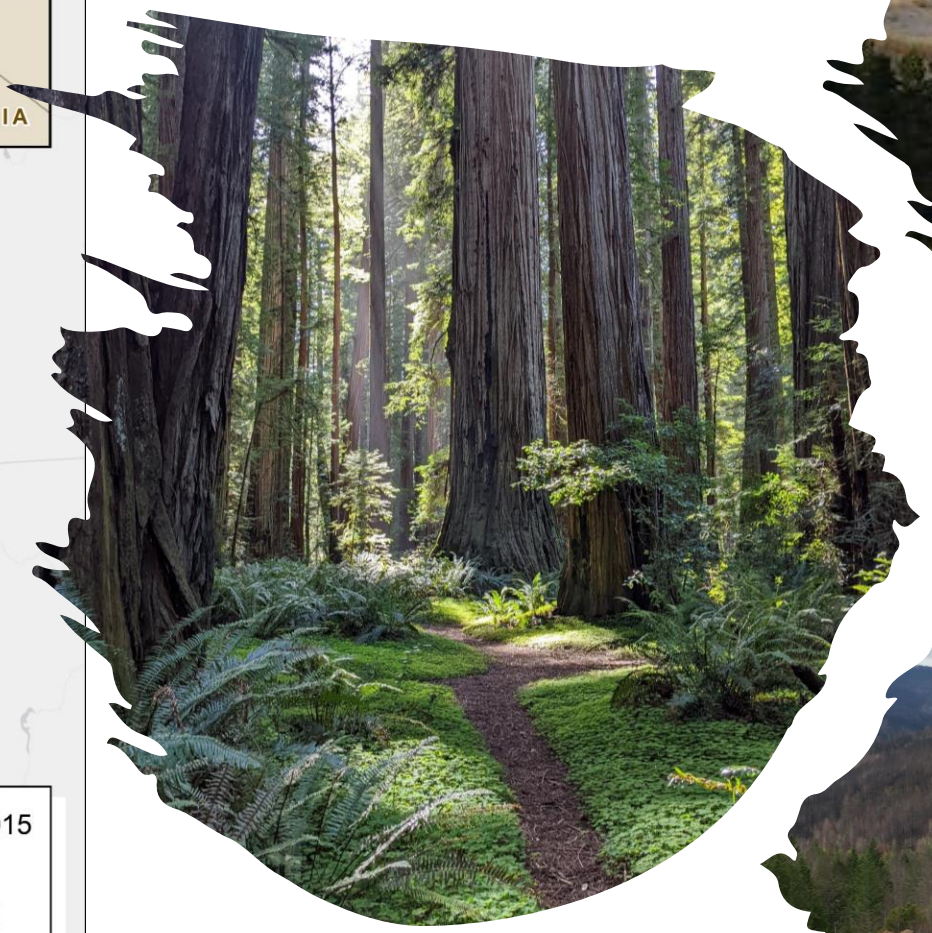
Bonus 1: is it possible to identify shrub characteristics through LiDAR?

Bonus 2: can we use new technology to evaluate fisher use of slash piles?

# The Humboldt marten

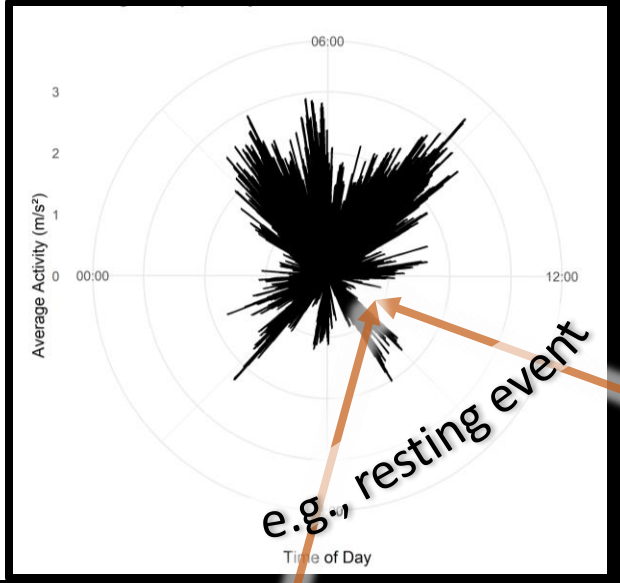
(*Martes caurina humboldtensis*)



Resting areas must provide…

- Safety from predators
- Thermal refuge




e.g., resting event

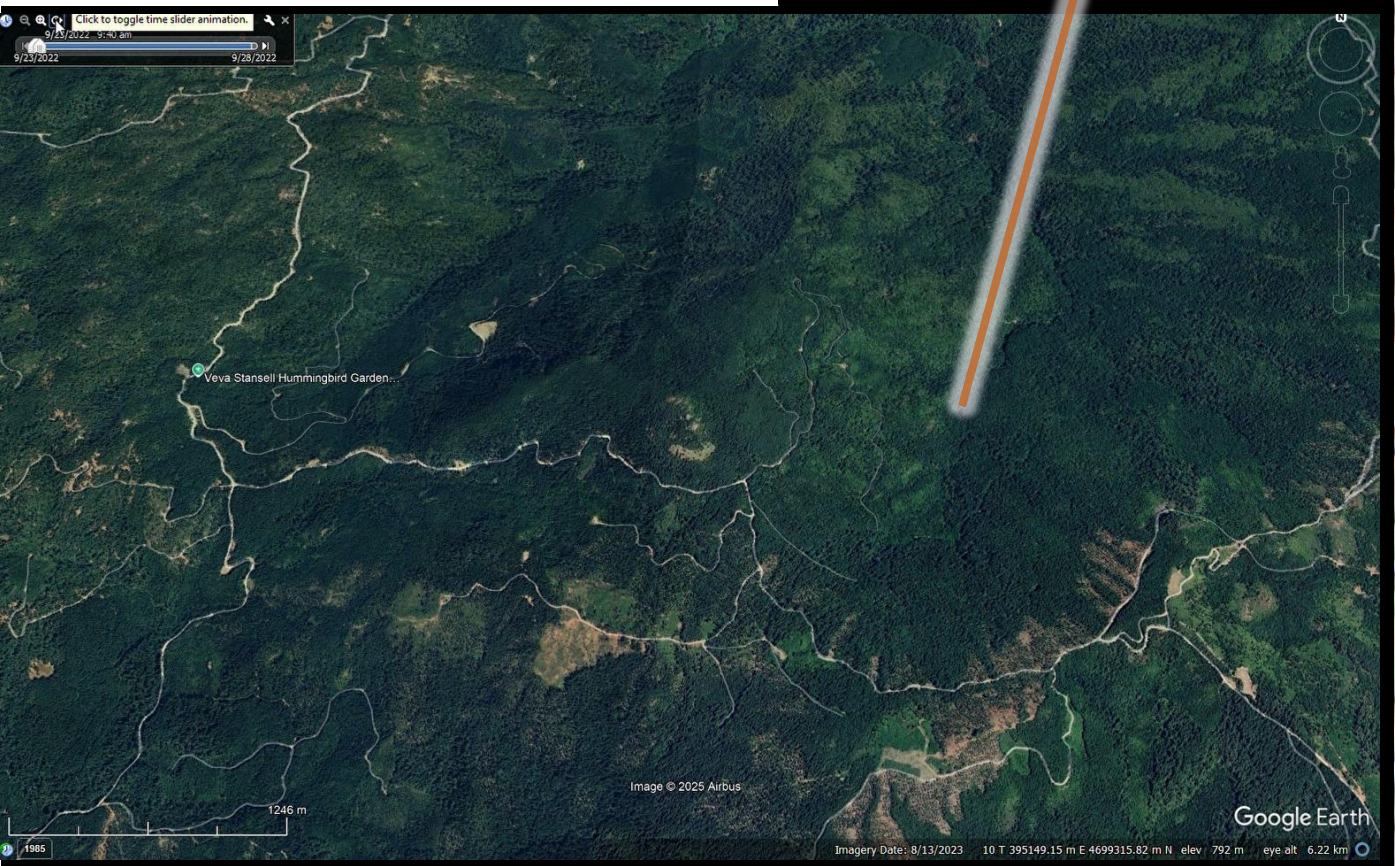
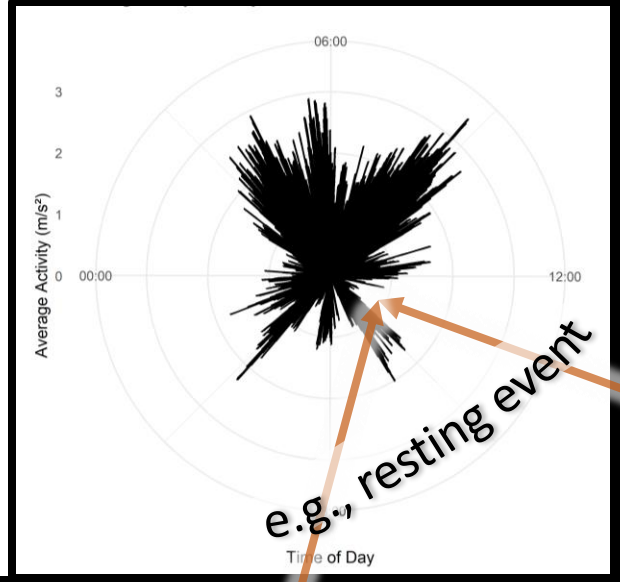



Photo: M. Stevens

Finding these areas is hard!!

- Expensive
- Invasive




e.g., resting event

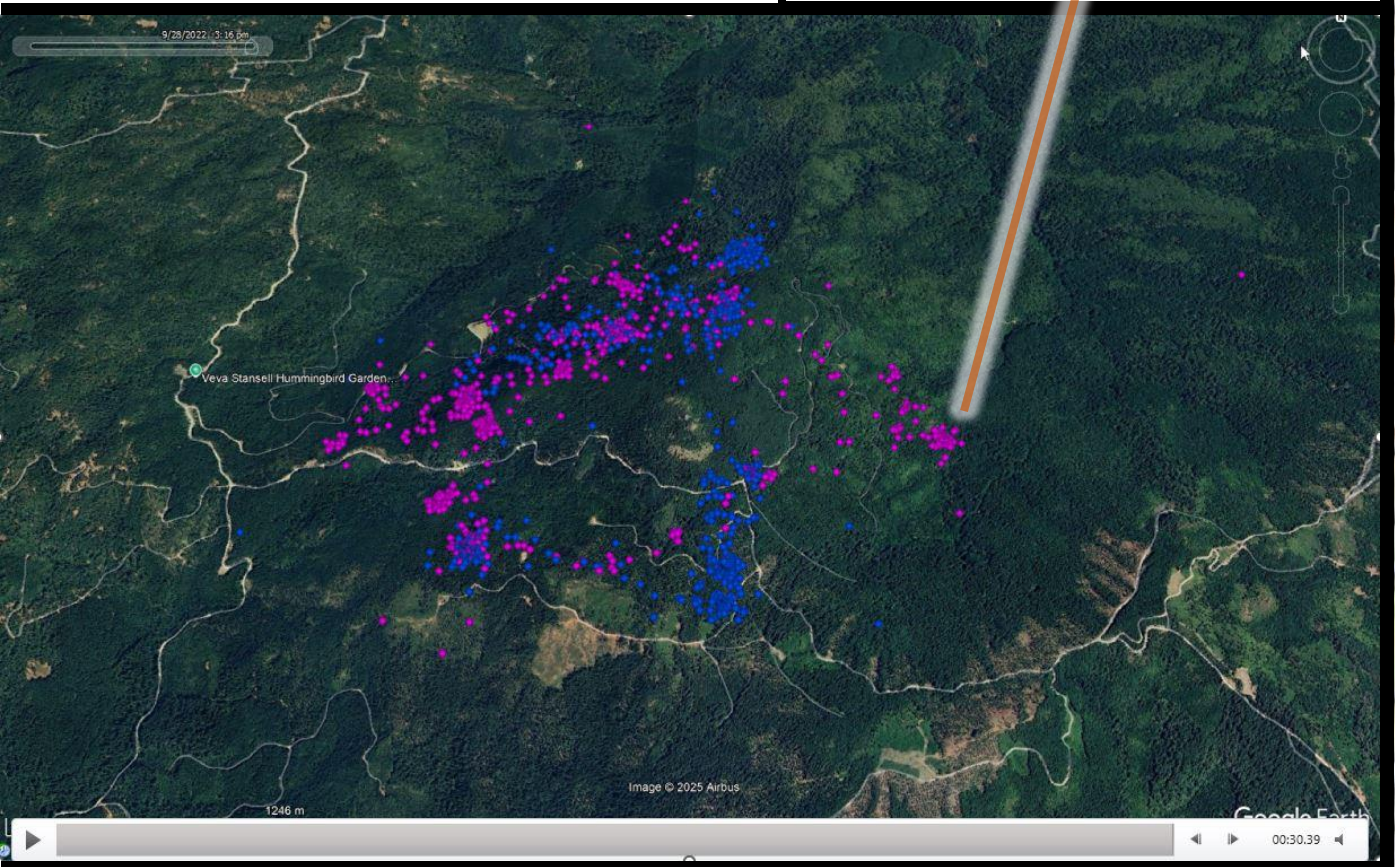



Photo: M. Stevens



Received: 7 October 2022 | Revised: 18 January 2023 | Accepted: 24 January 2023

DOI: 10.1002/jwmg.22388

RESEARCH ARTICLE

THE JOURNAL OF WILDLIFE MANAGEMENT

THE WILDLIFE SOCIETY

# Structural complexity characterizes fine-scale forest conditions used by Pacific martens

Matthew S. Delheimer[1] | Katie M. Moriarty[2] | Holly L. Munro[3] | Desiree A. Early[4] | Keith A. Hamm[4] | Rebecca E. Green[5]

Aimed to address marten vegetation knowledge gap on private California forests by…

- Identifying marten resting areas
- Measuring vegetation conditions at used & random locations

- Spatial GPS collar clusters

Hance et al. Movement Ecology (2021) 9:17
https://doi.org/10.1186/s40462-021-00256-8

Movement Ecology

RESEARCH Open Access

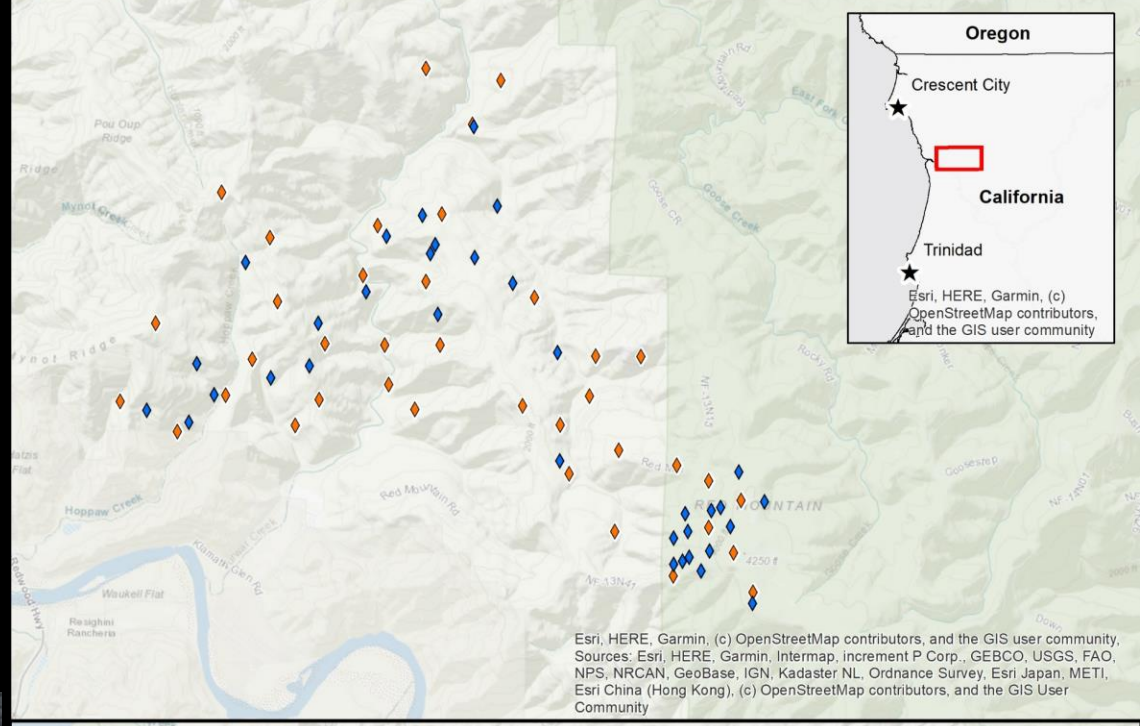
Identifying resting locations of a small elusive forest carnivore using a two-stage model accounting for GPS measurement error and hidden behavioral states

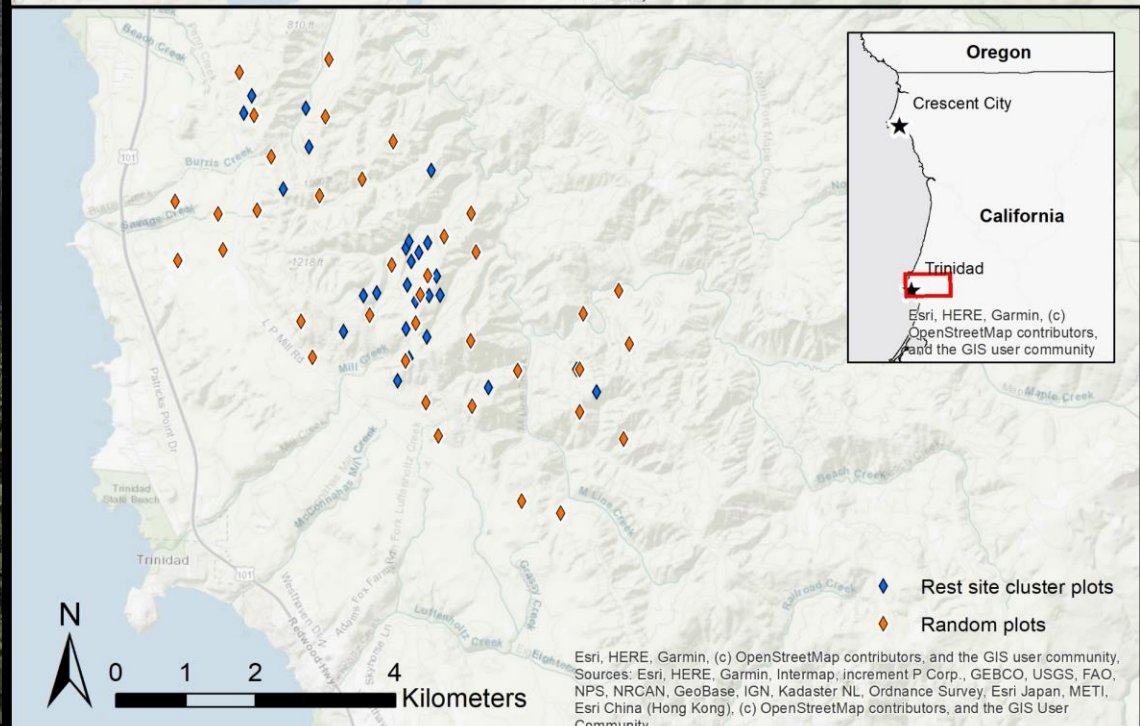
Dalton J. Hance[1*], Katie M. Moriarty[2], Bruce A. Hollen[3] and Russell W. Perry[1]

- Telemetry


- GPS collared 9 martens
- Identified 60 spatial GPS clusters
- With new design, identified 60 stratified random locations

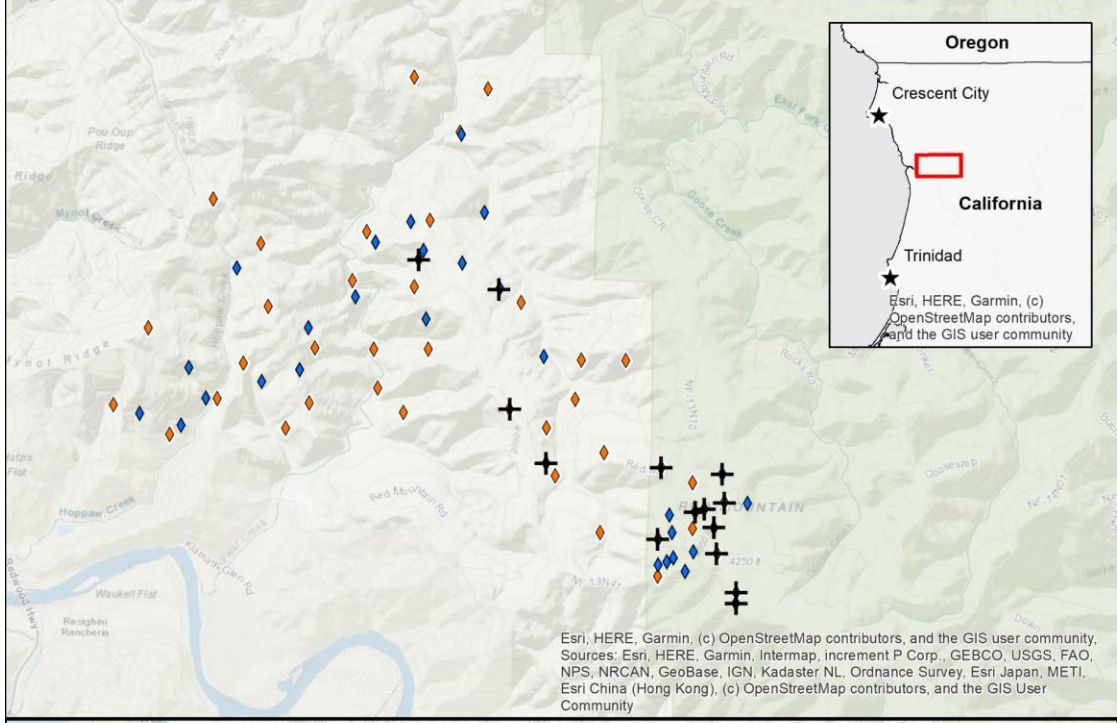

Extant Population Area
Marten Detection (1980-2024)
Non-detection (1997-2024)
State Boundary
County Boundary
Salem
Newport
Eugene
Central Coastal Oregon
Oregon
Pacific Ocean
Coos Bay
Roseburg
Southern Coastal Oregon
Medford
Northern Coastal California
Maple Creek California
California
Eureka
N

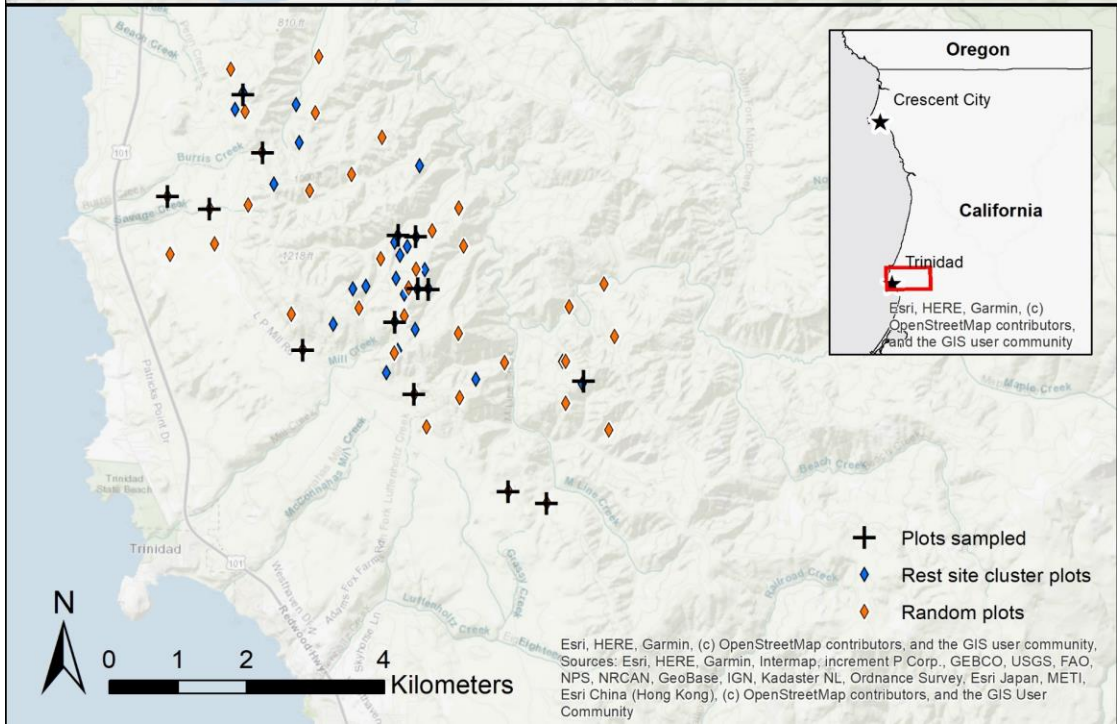

Oregon
Crescent City
California
Trinidad
Esri, HERE, Garmin, (c) OpenStreetMap contributors, and the GIS user community
Esri, HERE, Garmin, (c) OpenStreetMap contributors, and the GIS user community, Sources: Esri, HERE, Garmin, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), (c) OpenStreetMap contributors, and the GIS User Community


Oregon
Crescent City
California
Trinidad
Esri, HERE, Garmin, (c) OpenStreetMap contributors, and the GIS user community
Rest site cluster plots
Random plots
N
0 1 2 4
Kilometers
Esri, HERE, Garmin, (c) OpenStreetMap contributors, and the GIS user community, Sources: Esri, HERE, Garmin, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), (c) OpenStreetMap contributors, and the GIS User Community

# Collected vegetation data at 16 used and 13 random plots

## Crew started June 10, 2025!



*Collecting 40 vegetation metrics, including…*

## Plot metrics

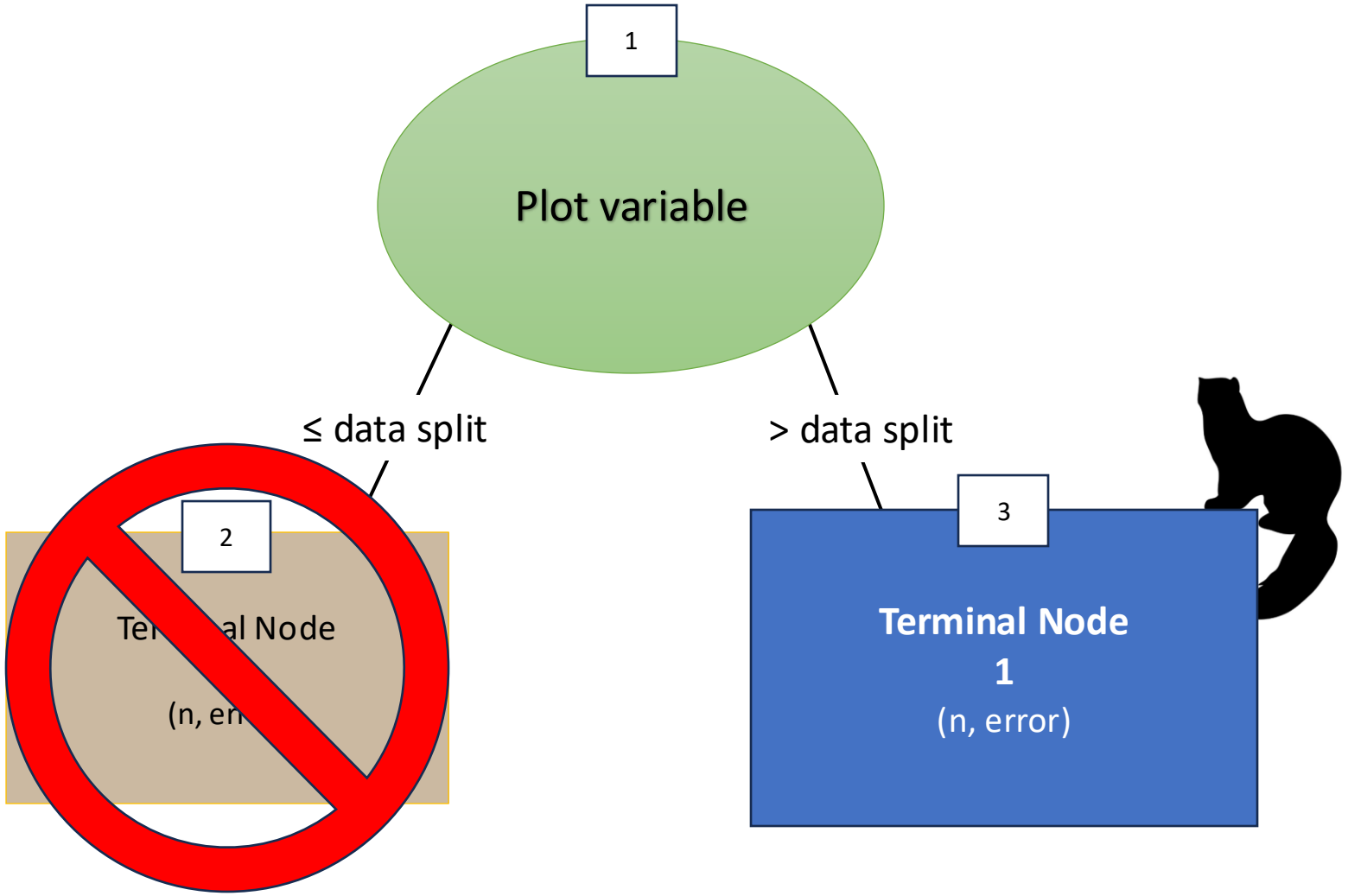
- basal area ($m^2$/ha)
- # live trees & snags
- % shrub cover
- visual obstruction (horizontal cover)
- large material
  - Logs and stumps
  - Slash and rock piles

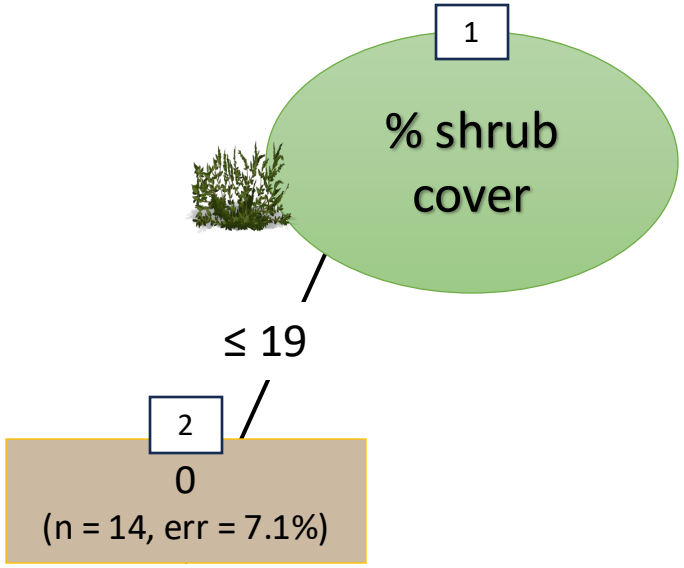
How do I reduce fuel loads while maintaining marten resting habitat conditions here?

# One example from Southern Oregon data

Building decision trees using:

- Plot level vegetation data
- Boosted C5.0 algorithm via recursive partitioning






# Tree # 5

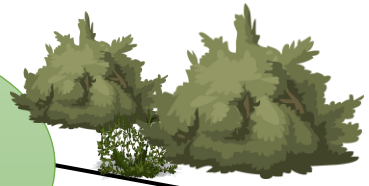
## Lowest error (21.5%)

# Tree # 5

## Lowest error (21.5%)

1

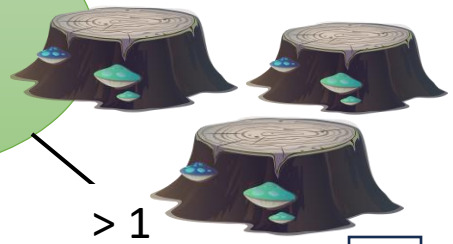
% shrub cover



> 19

3

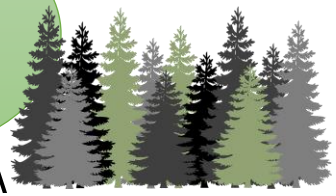
# large stumps



> 1

9

Tree basal area ($m^2$/ha)



> 16

11

**1**

(n = 49, err = 24.5%)

≤ 19

2

0

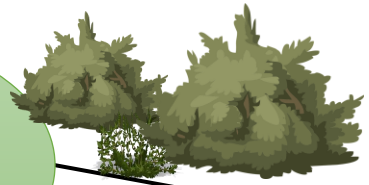
(n = 14, err = 7.1%)

# Tree # 5

## Lowest error (21.5%)

1

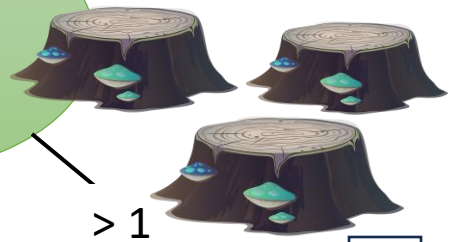
% shrub cover



> 19

3

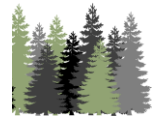
# large stumps



> 1

9

Tree basal area ($m^2$/ha)



≤ 16

10

0

(n = 11, err = 27.3%)

> 16

11

1

(n = 49, err = 24.5%)

≤ 19

2

0

(n = 14, err = 7.1%)

# Tree # 5

## Lowest error (21.5%)

1

% shrub cover

> 19

≤ 19

2

0

(n = 14, err = 7.1%)

3

# large stumps

≤ 1

> 1

4

% fruiting shrub cover

≤ 33

9

Tree basal area ($m^2$/ha)

≤ 16

> 16

5

Variation in % shrub cover

≤ 23

10

0

(n = 11, err = 27.3%)

11

1

(n = 49, err = 24.5%)

6

**1**

(n = 22, err = 27.3%

# Tree # 5

## Lowest error (21.5%)

1
% shrub cover
≤ 19
> 19

2
0
(n = 14, err = 7.1%)

3
# large stumps
≤ 1
> 1

4
% fruiting shrub cover
≤ 33
> 23

5
Variation in % shrub cover
≤ 23
> 23

6
1
(n = 22, err = 27.3%)

7
0
(n = 17, err = 23.5%)

9
Tree basal area ($m^2$/ha)
≤ 16
> 16

10
0
(n = 11, err = 27.3%)

11
1
(n = 49, err = 24.5%)

# Tree # 5

## Lowest error (21.5%)

1 % shrub cover

≤ 19

2
0
(n = 14, err = 7.1%)

> 19

3 # large stumps

≤ 1

4 % fruiting shrub cover

≤ 33

5 Variation in % shrub cover

≤ 23

6
1
(n = 22, err = 27.3%)

> 23

7
0
(n = 17, err = 23.5%)

> 33

8
0
(n = 8, err = 0.0%)

> 1

9 Tree basal area ($m^2$/ha)

≤ 16

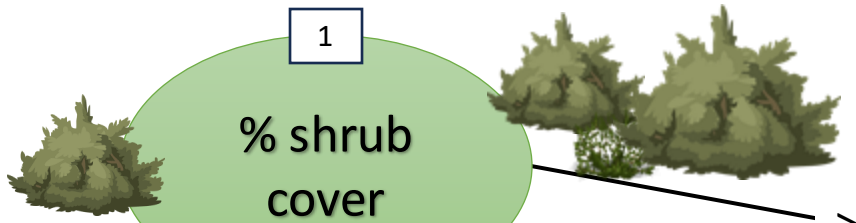
10
0
(n = 11, err = 27.3%)

> 16

11
1
(n = 49, err = 24.5%)

# Tree # 5

## Lowest error (21.5%)



1

% shrub cover

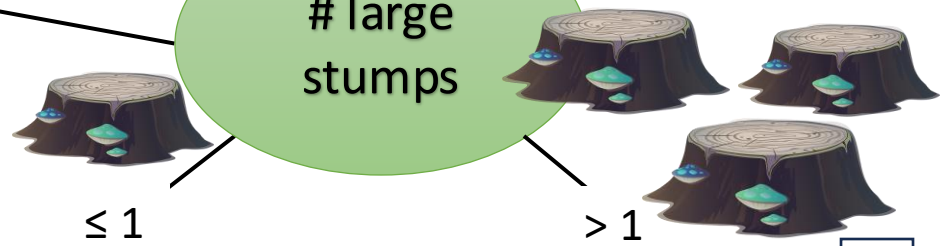
> 19

≤ 19

2

0

(n = 14, err = 7.1%)

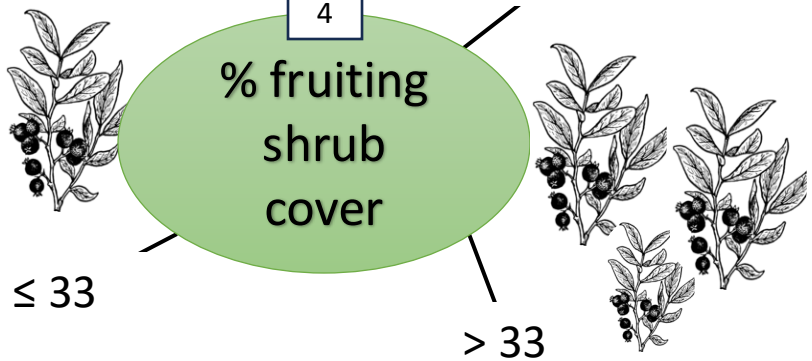


3

# large stumps

≤ 1

> 1



4

% fruiting shrub cover

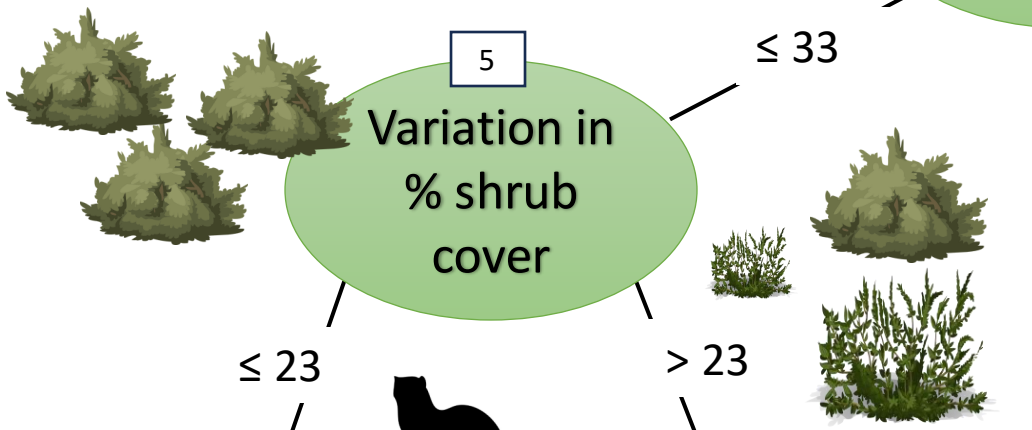
≤ 33

> 33

8

0

(n = 8, err = 0.0%)



5

Variation in % shrub cover

≤ 23

> 23

6

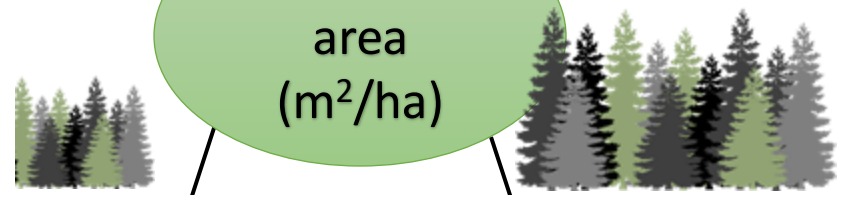
**1**

(n = 22, err = 27.3%)

7

0

(n = 17, err = 23.5%)



9

Tree basal area ($m^2$/ha)

≤ 16

> 16

10

0

(n = 11, err = 27.3%)

11

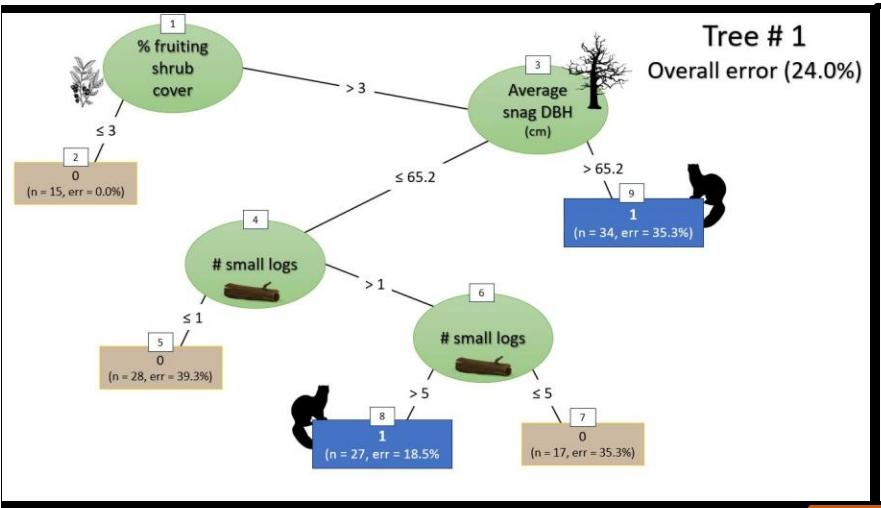
**1**

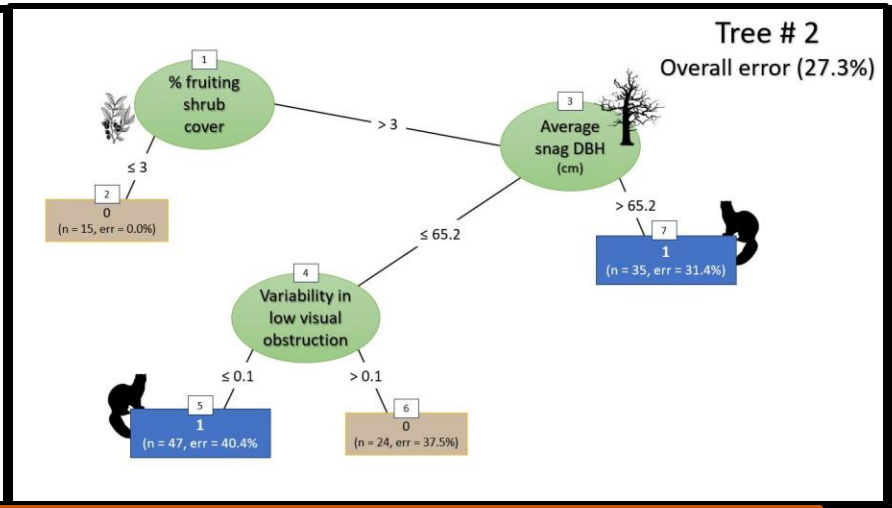
(n = 49, err = 24.5%)

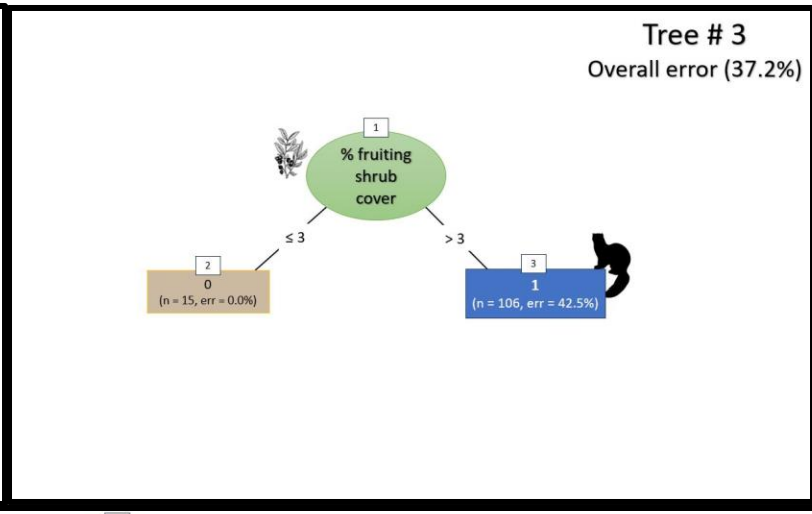
Example from **Southern Oregon**

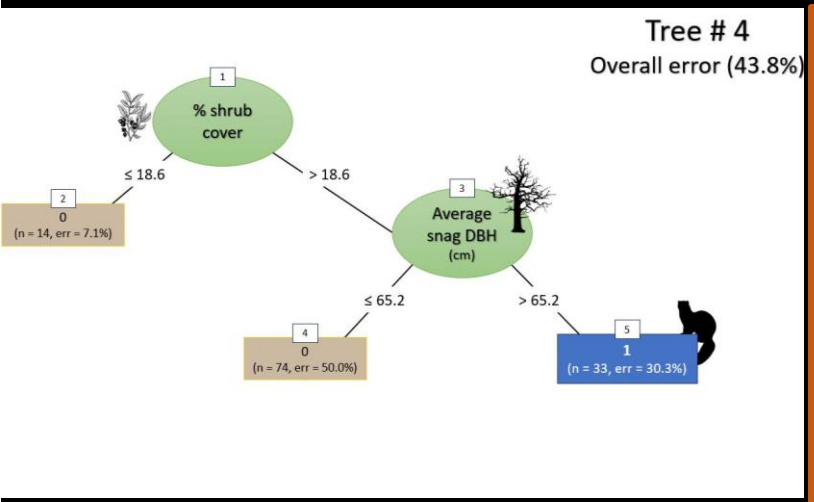
Retained 22/40 variables for final modeling

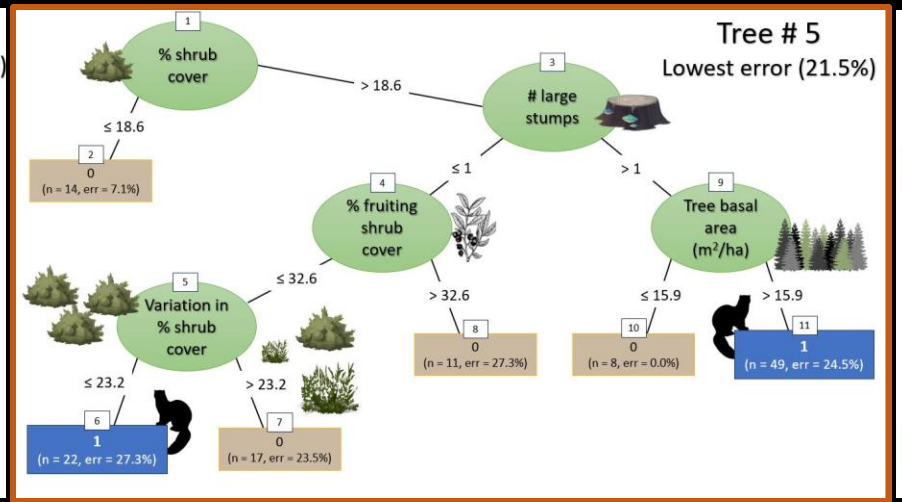
11/22 variables appeared in **6 final trees**

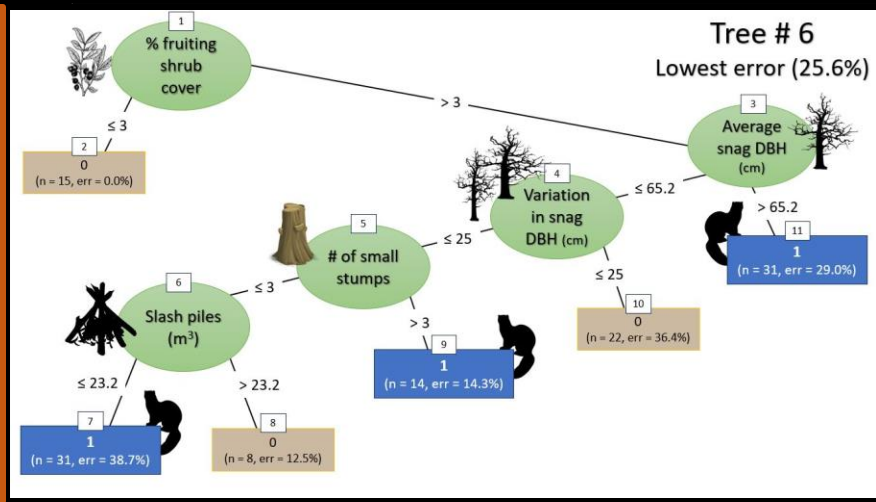


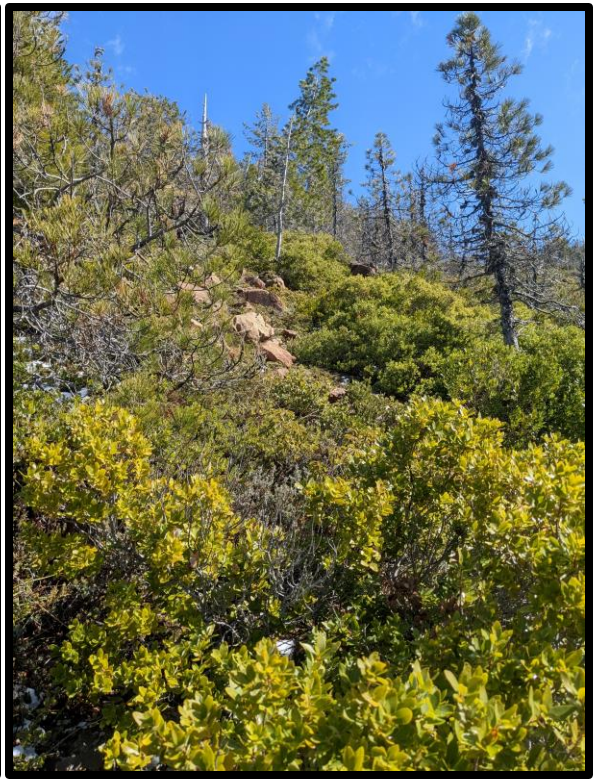



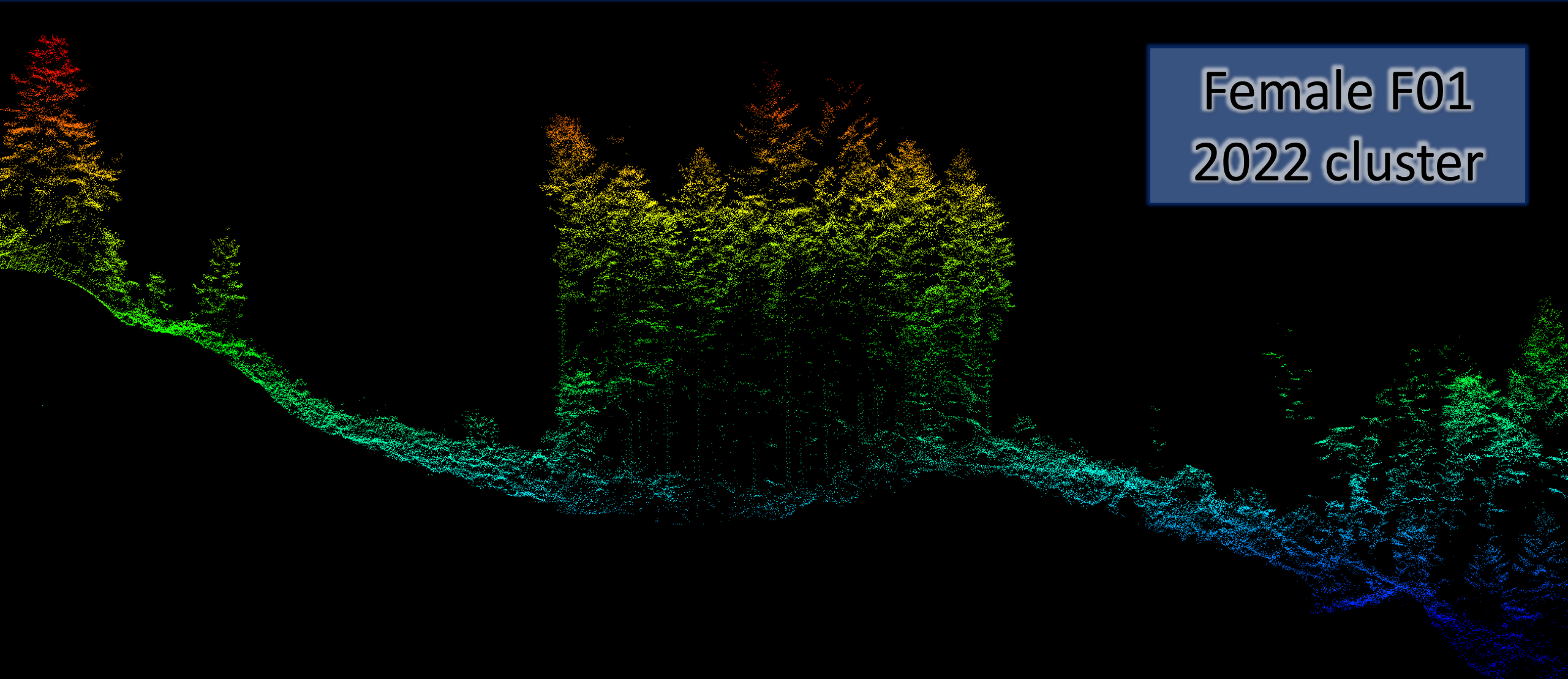
# Southern Oregon marten resting conditions:*

| >18.6% shrub cover | >3% fruiting shrub cover | >65.2 cm DBH snags |
|---|---|---|
|  |  |  |

*when used in context of decision trees



# Bonus 1: Using detailed field-based plot measurements to calibrate LiDAR

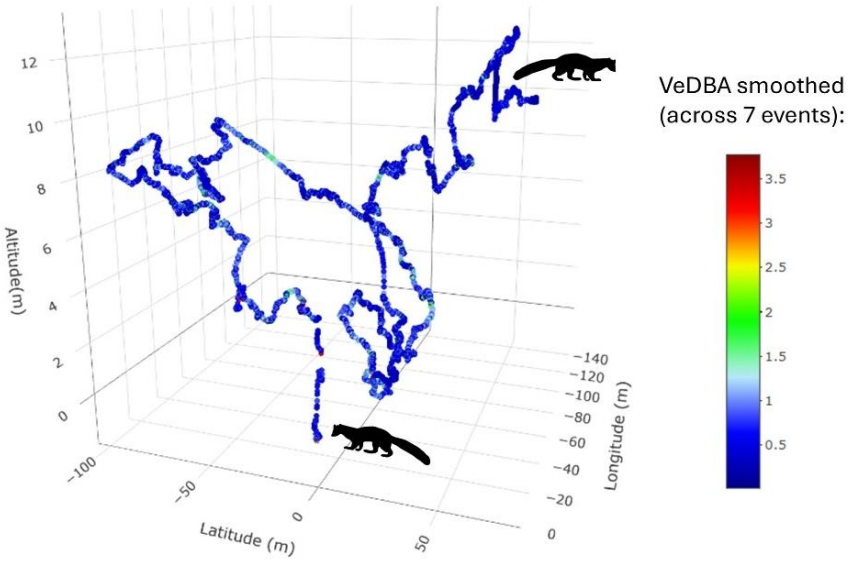


Female F01
2022 cluster

# Bonus 1: Using detailed field-based plot measurements to calibrate LiDAR

Female F01
2023 cluster

# Bonus 2: Can new technology elucidate fisher use of slash piles?




Swansea University
Prifysgol Abertawe

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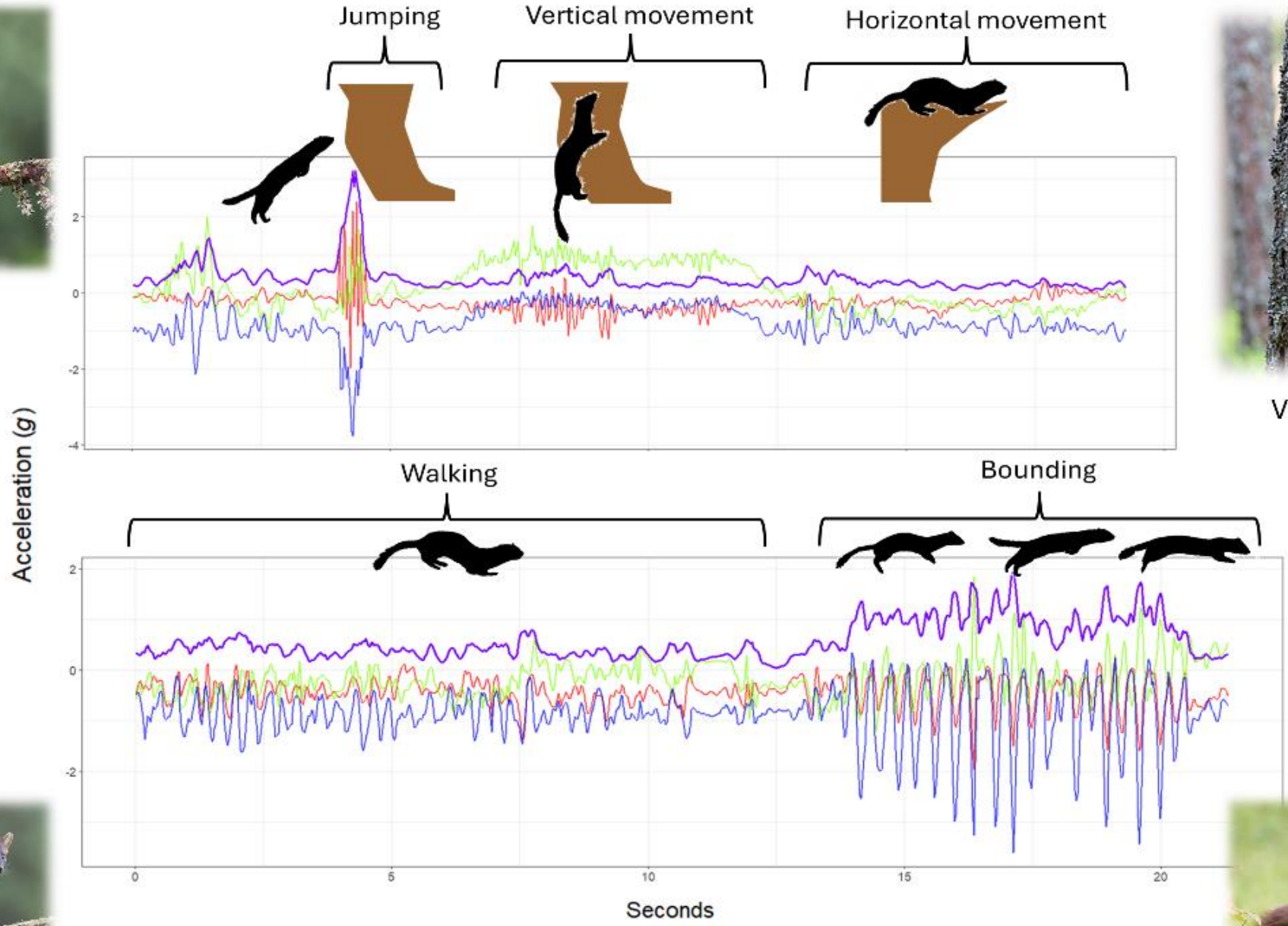
Oregon State University

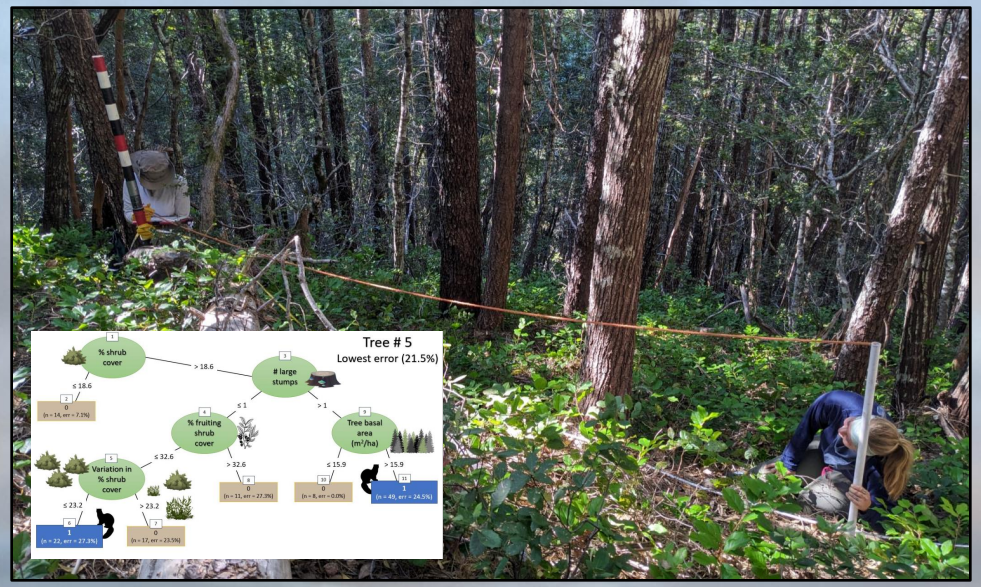
Jumping

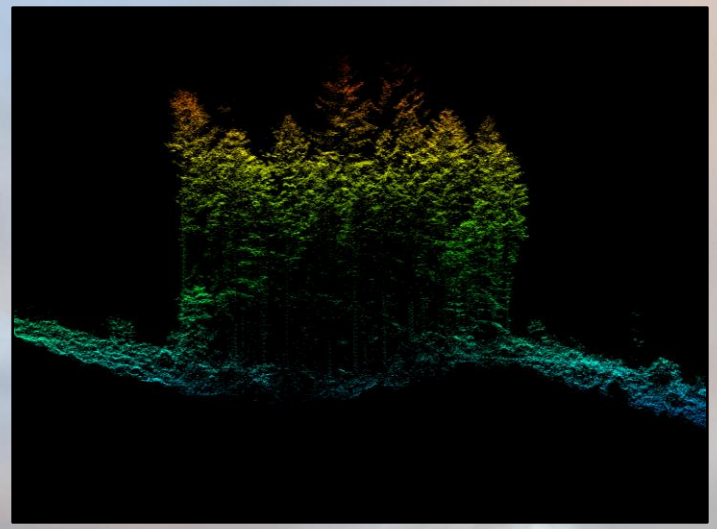
Vertical movement

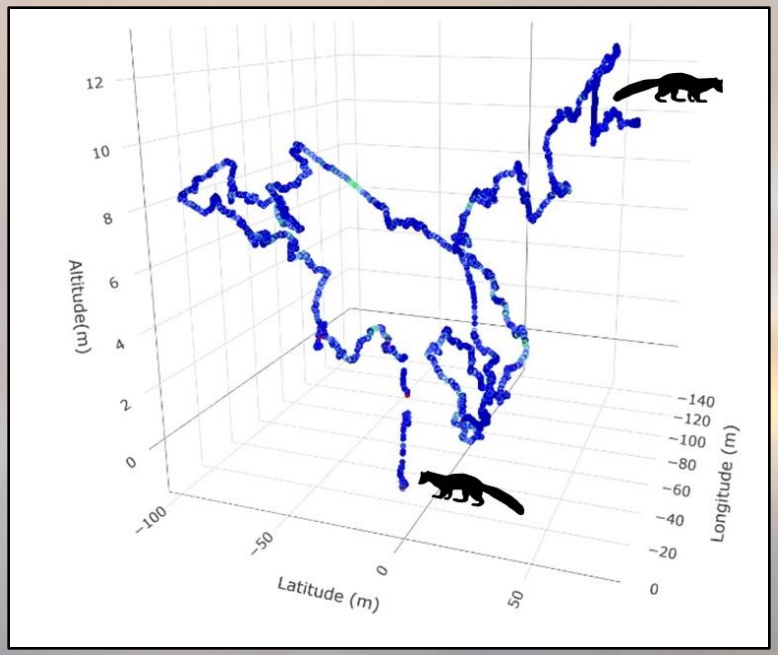
Walking

Bounding




Tree # 5
Lowest error (21.5%)
% shrub cover
# large stumps
% fruiting shrub cover
Tree basal area (m²/ha)
Variation in % shrub cover
≤ 18.6
> 18.6
≤ 1
> 1
≤ 32.6
> 32.6
≤ 15.9
> 15.9
≤ 23.2
> 23.2




Altitude(m)
Latitude (m)
Longitude (m)
12
10
8
6
4
2
0
−100
−50
0
50
−140
−120
−100
−80
−60
−40
−20
0

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# Thank you!!!

Effectiveness Monitoring Committee

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OSU
Oregon State University

GREEN DIAMOND RESOURCE COMPANY

# Tree # 1

Overall error (24.0%)

1

% fruiting shrub cover

≤ 3

2

0

(n = 15, err = 0.0%)

> 3

3

Average snag DBH (cm)

≤ 65.2

4

# small logs

≤ 1

5

0

(n = 28, err = 39.3%)

> 1

6

# small logs

> 5

8

1

(n = 27, err = 18.5%

≤ 5

7

0

(n = 17, err = 35.3%)

> 65.2

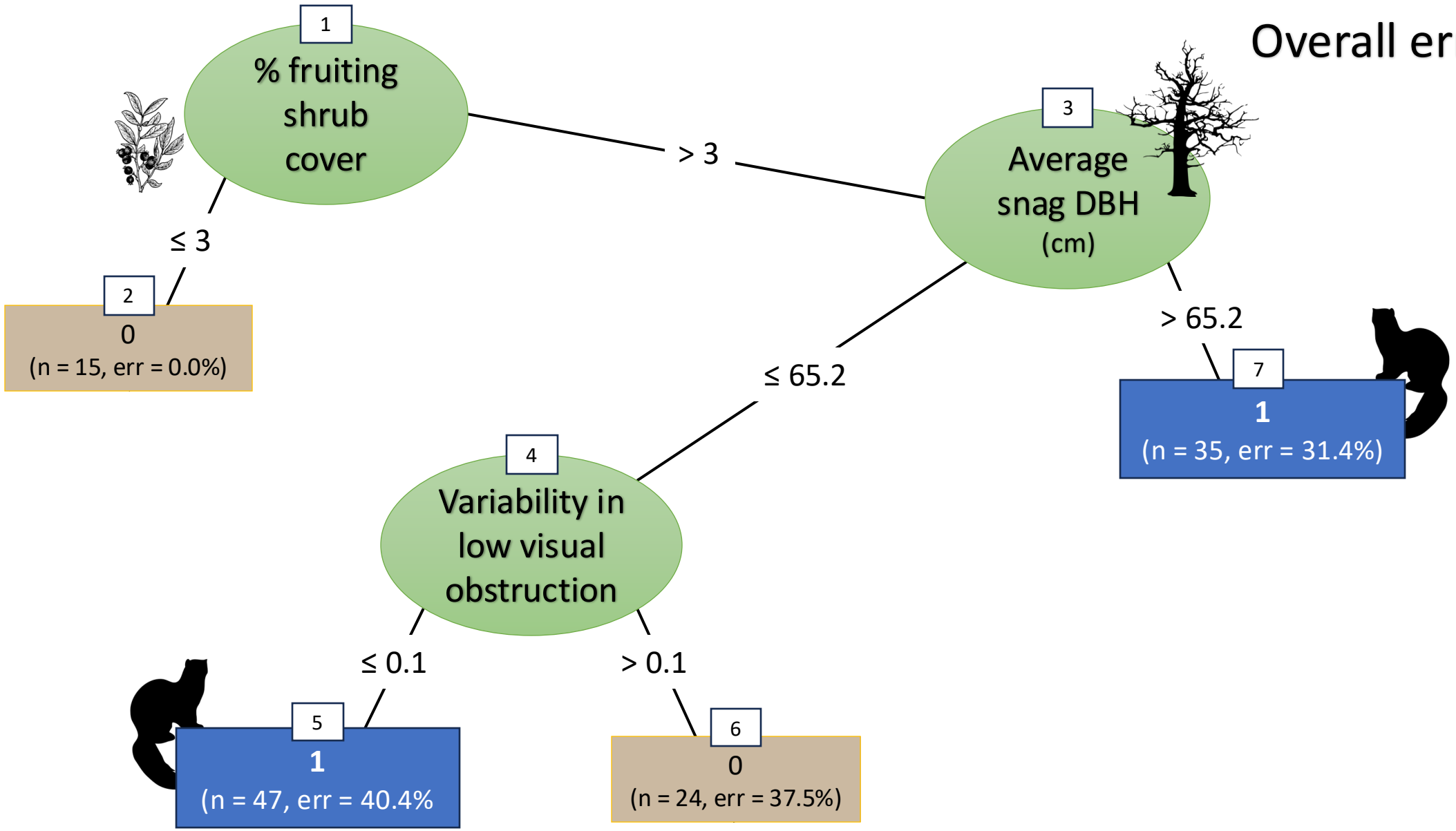
9

1

(n = 34, err = 35.3%)

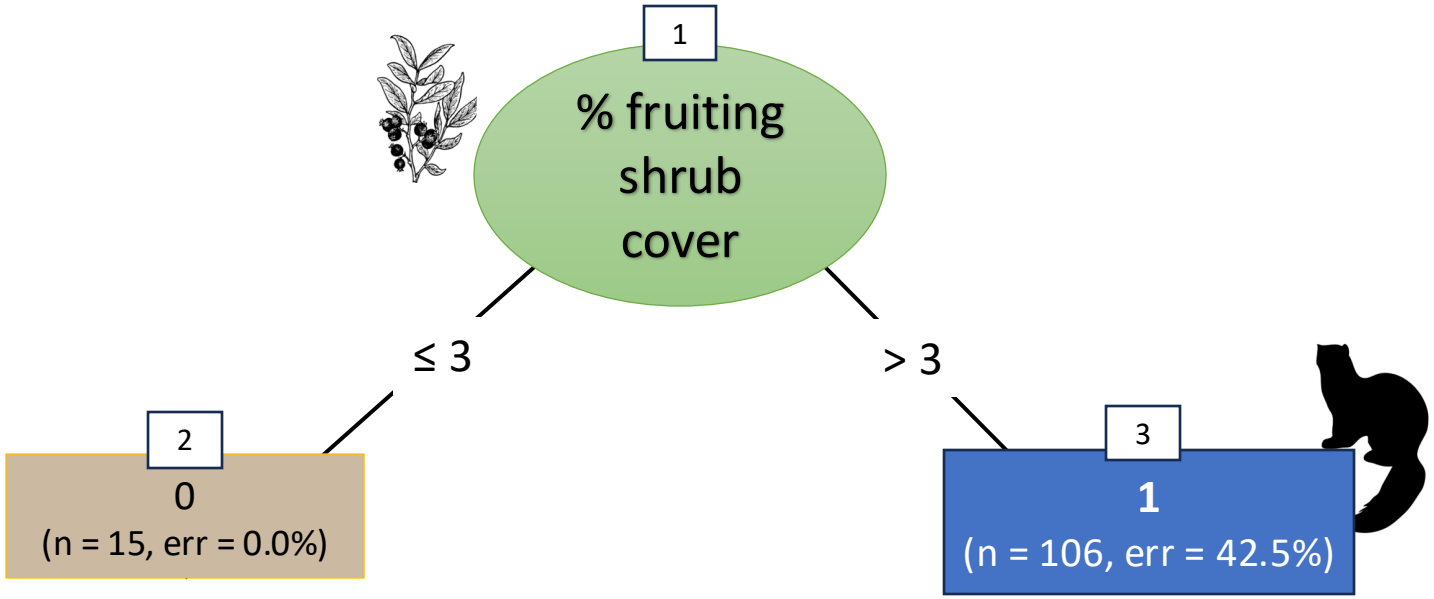
# Tree # 2

Overall error (27.3%)



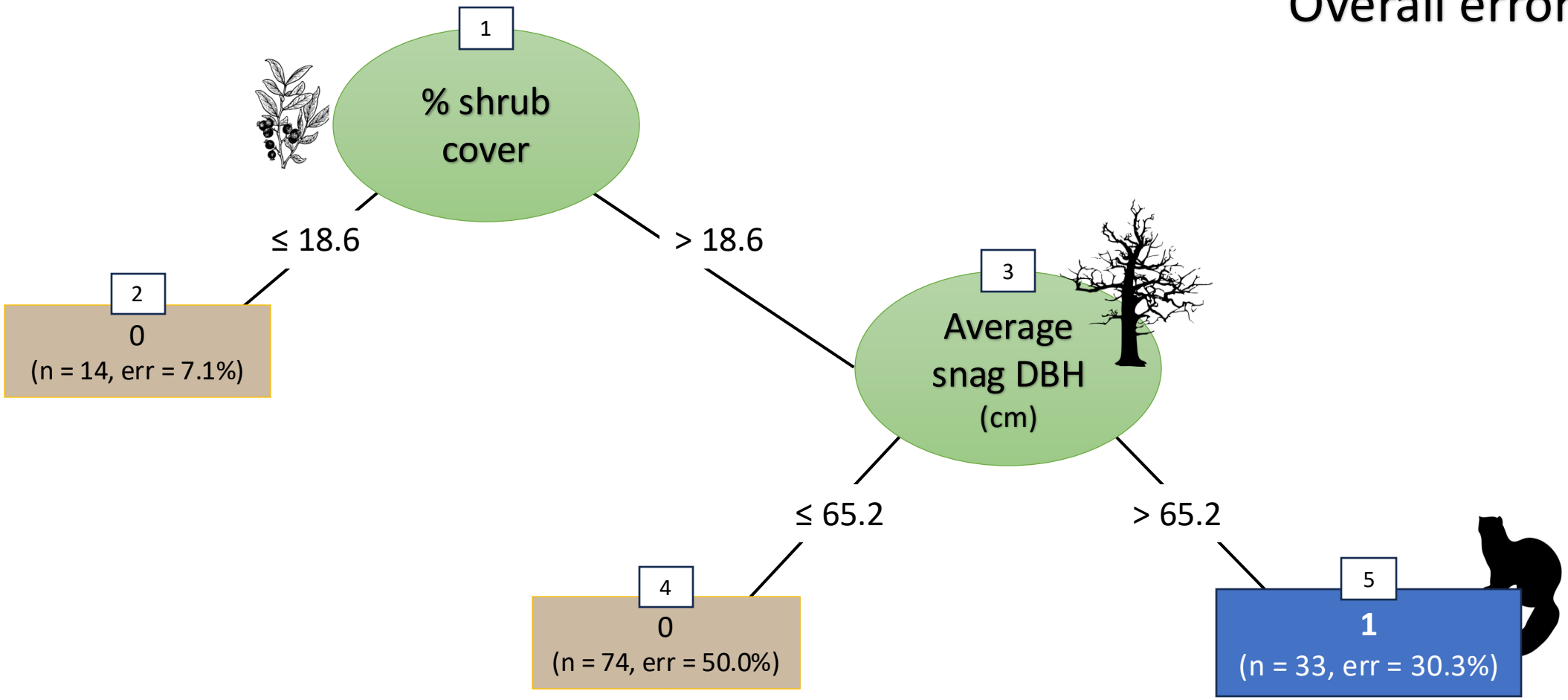
# Tree # 3

## Overall error (37.2%)



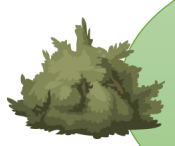
# Tree # 4

## Overall error (43.8%)



# Tree # 5

## Overall error (21.5%)



1

% shrub cover

≤ 18.6

> 18.6

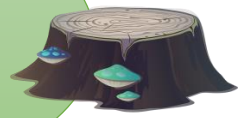
2

0

(n = 14, err = 7.1%)

3

# large stumps



≤ 1

> 1

4

% fruiting shrub cover

≤ 32.6

> 32.6

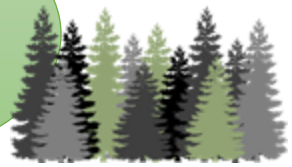
8

0

(n = 8, err = 0.0%)

9

Tree basal area ($m^2$/ha)



≤ 15.9

> 15.9

10

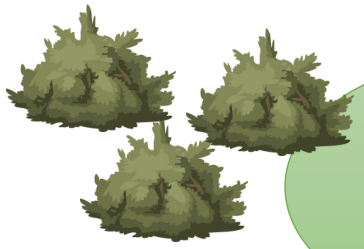
0

(n = 11, err = 27.3%)

11

**1**

(n = 49, err = 24.5%)



5

Variation in % shrub cover

≤ 23.2

> 23.2

6

**1**

(n = 22, err = 27.3%)

7

0

(n = 17, err = 23.5%)

# Tree # 6

## Lowest error (25.6%)

1
% fruiting shrub cover

≤ 3

2
0
(n = 15, err = 0.0%)

> 3

3
Average snag DBH (cm)

≤ 65.2

4
Variation in snag DBH (cm)

> 65.2

11
1
(n = 31, err = 29.0%)

≤ 25

5
# of small stumps

> 25

10
0
(n = 22, err = 36.4%)

≤ 3

6
Slash piles ($m^3$)

> 3

9
1
(n = 14, err = 14.3%)

≤ 23.2

7
1
(n = 31, err = 38.7%)

> 23.2

8
0
(n = 8, err = 12.5%)