Occupancy and probability of detection of the introduced population of *Eleutherodactylus coqui* in Turrialba, Costa Rica.

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SUPPLEMENTARY MATERIAL

Table S1. Site-level covariates used in the occupancy models for the common coqui frog in Costa Rica.

SampUnit	veg_low	veg_med	veg_high	can_cover	brom	leaf_litter	palm	dist_river	dist_origin
1	47.5	53.75	52.5	57.5	0	90	10	20.83	506.8
2	30	22.75	29.5	95.75	1	65	10	21.24	484.62
3	29	14.75	22.5	25	0	21.75	0	38.15	313.12
4	35	22.5	26.75	38.25	0	35	30	9.86	367.79
5	15	40	45	98	0	20	5	5.9	329.04
6	20	40	60	90	1	20	10	20.14	357.46
7	71.5	52.5	51.75	82.75	0	90	3	54.91	443.97
8	13	1	1	70	0	30	2	7.46	320.28
9	10	15	34.75	98.5	0	98	0	52.12	378.67
10	23.5	13	8.5	40	0	2.75	3	97.19	467.03
11	70	70	51.25	58.75	0	60	0	17.82	284.56
12	17.5	16.75	5.5	9.75	1	4.75	8	55.73	373.5
13	15	10	6.75	97.5	0	90	0	16.99	280.86
14	18.75	20	22.5	51.25	1	50	0	4.62	288.81
15	52.5	56.25	57.5	56.25	1	80	15	6.23	206.37
16	33.75	62.5	45.5	53.75	0	40	60	4.38	230.44
17	92.5	36.25	1	0	0	0	0	7.09	241.87
18	47	48.75	53.75	53.75	1	33.75	8	3.64	250.36
19	30	45	35	25	1	30	0	12.78	259.81
20	0	0	5	5	0	0	0	119.84	421.91
21	0	3	3.75	89	1	21.25	0	150.55	440.03
22	0	0	0	0	0	0	0	163.78	363.91
23	0	0	0	0	0	0	0	176.67	427.67
24	0	0	35	43.75	0	5	0	211.33	306.66
25	0	0	0	0	0	0	0	74.64	446.9
26	0	3	22	5	1	5	0	227.7	290.62
27	2	3	6	34	1	35	0	146.14	360.69
28	5	10	16.25	21.5	0	0	0	207.51	148.66
29	0	0	0	63.75	0	3	0	136.56	167.74
30	10	30	30	10	0	50	0	153.41	131.67
31	10	40	20	10	0	40	0	89.07	190.43
32	26.25	21.25	5	0	0	6	0	143.45	432.03
33	70.75	7.5	0	0	0	0	0	75.51	122.28
34	56.25	11.25	0	0	0	0	0	57.78	141.64
35	9.25	13.25	13.25	46.25	0	16.25	1	17.73	226.5
36	1	0	8	93.75	0	76.25	0	69.96	314.22
37	0	0	0	0	0	0	0	14.96	417.95
38	5	0	0	0	0	0	0	138.84	452.25
39	21.25	0	0	0	0	0	0	63.06	370.29

40	38.75	40	18	90.75	0	91.25	10.25	82.7	385.39
41	3	2.5	3	37.25	1	0	3	137.29	313.02
42	0.25	1	9.25	8.25	0	2	0	157.45	271.84
43	14.5	15.25	1	21	0	10.5	0	216.07	230.71
44	3.5	5	25	17.5	1	5	0	273.6	433.04
45	4.5	8	8.5	33.75	0	0	0	294.19	329.66
46	8.75	27.5	30	51.25	1	40	8	284.41	195.5
47	30	31.2	7.5	11.5	0	15	0	265.43	82.28
48	2.5	1.5	2	0	0	0	3	219.29	260.04
49	6.25	3	48.75	52.5	0	0	0	205.62	89.37
50	2.25	2.75	3.5	3.5	0	0	0	156.25	298.21
51	0	2	3.5	3.5	0	0	0	66.86	331.14
52	86	7.5	7.5	7.5	0	0	0	34.01	372.1
53	1	1	1	1	0	0	0	59.58	314.13
54	39.5	9.5	7.5	67.5	0	60	2	34.99	414.96
55	0	20	0	0	0	0	0	139.76	70.88
56	2.75	2	3	3	1	0	0	99.95	290.61
57	0	0	0	0	0	0	0	84.22	193.78
58	1.25	13.75	42.5	42.5	0	15	0	144.14	148.25
59	9.5	4.75	6.75	9.5	0	0	0	225.54	28.19
60	63.75	52.5	63.75	87	0	93	40	29.9	233.46
61	44	7.25	1	0	0	0	0	54.62	192.53
62	8.75	10	6.2	6.2	0	1.75	2.5	7.18	298.52
63	10	2	2	0	0	0	0	10.02	429.42
64	1.25	5	27.5	27.5	0	10	20	2.28	453.46
65	1.5	3.5	8.75	8.75	1	0	0	7.69	381.77
66	61.25	39.75	20.75	90	0	67.5	26.25	11.74	307.42
67	41.25	43.75	41.75	98.75	0	96.25	10	18.3	324.72
68	65	69	76.25	67.5	0	76.25	5.75	36.38	496.61
69	28.7	34.75	40.5	75.25	0	87	21	64.14	497.82
70	70	57.25	48	48.75	1	60	17	66.52	534.79
71	32	14.25	19.25	58.75	0	85	4	21.59	576.8
72	7	0	0	0	0	0	0	328.54	83.89
73	40.75	20	7.5	0	1	0	2	247.57	0.09
74	46	45	30	10	1	5	5	310.26	85.66
75	10.5	10	7.5	0	0	30	5	213.28	92.94
76	1	0	0	0	0	0	0	83.56	185.74
77	5	3	0	0	0	5	0	117.53	131.27
78	4.75	5.5	9.25	18.5	1	4	3	285.51	139.28
79	18.5	17.5	12.5	20.5	1	25	40	255.35	60.47
80	4.5	1.5	4	4.5	0	2	0	212.34	17.64
81	10	29.75	8.25	1.25	0	2	35	212.53	59.21
82	28.75	32	11	8.75	1	20	5	156.45	101.34

83	6	9	1	0	0	0	4	144.27	122.43
84	43.75	54.75	58.75	15	0	20	0	5.42	256.18
85	19.5	24.25	8.75	0	0	5	0	48.24	255.33
86	1	1	1	1	0	1	1	240.83	51.44
87	35	40	5	0	0	2	2	41.76	293.59
88	5	8	4	0	1	2	0	215.85	45.81
89	28	30.5	16.25	3.25	0	30	0	105.02	496.8
90	1	2	1	0	0	0	3	242.42	182.73
91	43.25	33.75	23.75	38.75	0	35	5	24.42	421.79
92	46.25	12.5	0	0	0	50	2	1.81	250.47

Table S2. Detection history of the common coqui frog during seven surveys.

SampUnit	survey1	survey2	survey3	survey4	survey5	survey6	survey6	survey7
1	-	0	0	0	0	0	0	0
2	-	0	0	0	0	0	0	0
3	-	0	0	0	0	0	0	0
4	-	0	0	0	0	0	0	0
5	-	0	0	0	0	0	0	0
6	-	0	0	1	1	1	1	0
7	-	0	0	0	0	0	0	0
8	-	0	0	0	0	0	0	0
9	-	0	0	0	0	0	0	0
10	-	0	0	0	0	0	0	0
11	-	0	0	0	0	0	0	0
12	-	0	0	0	0	0	0	0
13	-	0	0	0	0	0	0	0
14	-	0	0	1	1	1	1	1
15	-	0	0	1	1	0	0	0
16	-	1	-	1	1	1	1	0
17	-	1	1	1	0	1	0	0
18	-	1	1	1	1	1	1	1
19	-	1	0	0	0	0	0	0
20	-	0	0	0	0	0	0	0
21	-	0	0	0	0	0	0	0
22	-	0	0	0	0	0	0	0
23	-	0	0	0	0	0	0	0
24	-	0	0	0	0	0	0	0
25	-	0	0	0	0	0	0	0
26	-	0	0	0	0	0	0	0
27	-	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0

30	0	0	0	0	0	0	0	0
31	0	0	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0
33	-	0	0	0	0	0	0	0
34	-	0	0	0	0	0	0	0
35	-	0	0	0	0	0	0	0
36	-	0	0	0	0	0	0	0
37	-	0	0	0	0	0	0	0
38	0	0	0	0	0	0	0	0
39	0	0	0	0	0	0	0	0
40	-	0	0	0	0	0	0	0
41	-	0	0	0	0	0	0	0
42	-	0	0	0	0	0	0	0
43	0	0	0	0	0	0	0	0
44	0	-	0	0	0	0	0	0
45	0	-	0	0	0	0	0	0
46	0	-	0	0	0	0	0	0
47	0	-	0	0	1	1	1	1
48	0	-	0	0	0	0	0	0
49	1	1	1	1	1	1	1	1
50	0	-	0	0	0	0	0	0
51	0	-	0	0	0	0	0	0
52	0	0	0	0	0	0	0	0
53	0	-	0	0	0	0	0	0
54	0	-	0	0	0	0	0	0
55	0	0	0	0	0	0	0	0
56	0	-	0	0	0	0	0	0
57	0	-	0	0	0	0	0	0
58	0	-	0	0	0	0	0	0
59	0	-	0	0	0	0	0	0
60	-	1	-	1	1	0	0	0
61	0	0	0	0	0	0	0	0
62	0	-	0	0	1	1	0	0
63	0	0	0	0	0	0	0	0
64	0	0	0	0	0	0	0	0
65	0	0	0	0	0	0	0	0
66	-	0	0	0	1	1	0	0
67	-	0	1	0	0	0	0	0
68	-	0	0	0	0	0	0	0
69	-	0	0	0	0	0	0	0
70	-	0	0	0	0	0	0	0
71	-	0	0	0	0	0	0	0
72	-	1	-	-	-	-	1	0

73	-	1	-	-	-	-	1	1
74	-	1	-	-	-	-	1	1
75	-	0	-	-	-	-	0	0
76	-	0	-	-	-	-	0	0
77	-	0	-	-	-	-	0	0
78	-	-	-	1	1	1	1	1
79	-	-	1	1	1	1	1	1
80	-	-	1	1	0	0	1	1
81	-	-	1	1	1	1	1	1
82	-	-	1	1	1	1	1	1
83	-	-	1	1	1	1	1	1
84	-	-	-	1	1	1	1	1
85	-	-	-	1	1	0	0	0
86	-	-	1	1	0	0	0	0
87	-	-	1	1	1	1	0	0
88	-	-	1	1	-	1	0	1
89	-	-	1	1	1	1	1	0
90	-	-	-	1	0	1	0	0
91	-	-	0	0	0	-	0	0
92	-	-	1	1	1	1	1	1

Table S3. Observation-level environmental covariates: relative humidity (hum) in percentage units.

SampUnit	survey1	survey2	survey3	survey4	survey5	survey6	survey7	survey8
1	-	65	65	66	42	50	45	38
2	-	69	62	65	45	46	39	40
3	-	66	63	67	47	36	40	41
4	-	66	64	64	52	40	51	42
5	-	65	65	56	50	39	40	40
6	-	65	65	66	52	40	39	46
7	-	71.5	42	62	54	41	32	45
8	-	71	42	45	55	42	38	38
9	-	44	46	57	59	50	40	39
10	-	52	39	62	44	48	52	52
11	-	62	62	65	49	50	49	39
12	-	52	48	52	59	55	45	45
13	-	55	63	65	49	52	45	45
14	-	53	58	43	44	61	51	50
15	-	47	53	45	46	65	50	50
16	-	53	-	55	52	68	49	49
17	-	62	58	55	48	65	49	49
18	-	58	57	45	49	65	48	50

19	-	60	56	47	50	61	50	48
20	-	50	55	56	47	61	52	45
21	-	54	49	53	47	65	45	39
22	-	51	50	53	42	68	46	38
23	-	59	55	53	42	68	46	38
24	-	49	55	60	51	60	48	37
25	-	69	64	65	43	65	49	39
26	-	51	64	59	50	59	50	39
27	-	49	60	60	45	61	51	40
28	72	57	59	41	50	60	40	41
29	75.5	55	58	40	55	40	41	50
30	71	56	58	45	47	45	42	49
31	72	58	59	56	47	56	41	51
32	72	60	52	55	48	55	45	48
33	-	62	58	55	48	65	49	49
34	-	62	52	60	46	64	49	45
35	-	53	58	43	44	61	51	50
36	-	50	59	45	44	62	52	51
37	-	55	55	47	49	63	53	40
38	72	74	50	54	49	50	53	44
39	60	62	51	56	48	58	54	43
40	-	52	48	59	49	60	53	47
41	-	52	48	60	50	50	53	48
42	-	47	50	60	52	51	49	48
43	74	46	51	61	51	55	52	50
44	76	-	55	55	49	62	55	50
45	83	-	57	57	53	59	53	45
46	80.5	-	56	55	54	63	58	50
47	81	-	54	51	50	60	46	48
48	75.5	-	49	56	48	60	46	44
49	76	50	56	52	47	62	46	39
50	77.5	-	52	55	49	65	46	38
51	72	-	48	55	51	68	47	40
52	68.5	72	49	57	49	68	55	42
53	53	-	46	55	52	61	73	41
54	53	-	46	55	52	61	73	41
55	60	63	50	61	48	65	49	49
56	71	-	49	53	49	69	47	35
57	71	-	52	54	54	68	47	36
58	73	-	58	54	49	66	46	38
59	74	-	63	47	40	51	42	40
60	-	43	-	54	52	68	49	50
61	65	68	54	62	48	65	49	49

62	58	-	55	45	46	50	53	40
63	72	69	48	54	54	68	53	42
64	72	68	50	56	50	68	53	43
65	71.5	52	55	47	38	63	53	44
66	-	52	45	44	60	54	48	50
67	-	41	46	52	59	60	50	39
68	-	47	39	42	44	61	48	48
69	-	61	61	59	44	70	50	45
70	-	57	59	64	44	69	61	40
71	-	63	58	65	46	68	55	38
72	-	60	-	-	-	-	39	37
73	-	61	-	-	-	-	52	49
74	-	62	-	-	-	-	40	39
75	-	58	-	-	-	-	51	54
76	-	70	-	-	-	-	45	48
77	-	65	-	-	-	-	56	45
78	-	-	-	41	53	47	40	40
79	-	-	55	46	38	60	38	45
80	-	-	52	49	42	62	42	44
81	-	-	55	58	48	65	43	43
82	-	-	60	59	50	61	46	39
83	-	-	56	54	38	65	46	40
84	-	-	-	55	48	71	53	51
85	-	-	-	67	52	70	51	49
86	-	-	55	46	38	60	38	45
87	-	-	58	57	52	60	53	49
88	-	-	53	52	-	41	50	50
89	-	-	47	42	46	65	53	38
90	-	-	-	47	47	48	50	45
91	-	-	59	62	50	-	56	50
92	-	-	54	45	52	58	53	39

Table S4. Observation-level environmental covariates: air temperature (temp) in Celsius degrees.

SampUnit	survey1	survey2	survey3	survey4	survey5	survey6	survey7	survey8
1	-	23.4	23.2	22.4	25.9	23	24.2	24
2	-	24.2	24	22.5	24.9	23.1	24	24.4
3	-	23.3	24.2	22.6	24	24	23.5	24.5
4	-	23.6	25.4	22.6	23	24.2	24	23.5
5	-	23.4	25	22.4	23	24.2	23.5	23.6
6	-	24	25	23.4	23	23	23	23.4
7	-	24.6	24	23.6	23.6	22.5	23	23.1

8	-	24.2	24	24.3	23.1	22.9	23.1	23
9	-	25	25.4	22.7	22.4	22.4	23.1	24.8
10	-	23.2	25	22.8	23	23	23.4	24.3
11	-	23.1	23	24.1	24	23.1	22	23
12	-	27.3	24.5	23.1	23.5	23.1	22.8	24.8
13	-	24	22.3	24.2	24	23.5	22.8	24
14	-	22.5	22.6	23.4	23	24	22.9	24.5
15	-	22.5	22.6	23	23.1	24	23	22
16	-	24	-	22.6	23.2	24.1	23	21.5
17	-	24.6	26	23.2	23.2	24	22.5	22
18	-	24	24.4	25.2	23.5	23.9	22.2	23.5
19	-	24.6	25.5	26.1	23.6	24	22.4	22.5
20	-	24.4	24	23.6	23.8	24	22.5	23
21	-	23.6	23.5	23.6	22.9	23.5	22.3	21.9
22	-	24.8	23.4	23.4	23	23.1	22.4	22.5
23	-	23.6	24	23.4	23	23.1	22.4	22.5
24	-	24.7	24	23.2	22.5	23.6	23	22.8
25	-	23.8	23.6	24.5	22.4	23.5	23.4	22.4
26	-	24.8	23.6	23.2	22.4	23.5	23.5	22.5
27	-	24	23.7	23.2	22.8	23.1	23	22.6
28	21.7	24	23.1	26	22.5	23.1	23	22
29	21.8	24.2	23.4	25.7	23.6	23	23	21
30	21.8	23.8	23.1	24.3	24	23	23	21
31	22	22.9	23.5	22.4	24	23	23.2	20.2
32	26	24.5	23.1	23.1	23.5	23.1	23.8	20.4
33	-	24.6	26	23.2	23.2	24	22.5	22
34	-	24	24.4	25.2	23.5	23.9	22.2	23.5
35	-	22.5	22.6	23.4	23	24	22.9	24.5
36	-	24.4	23	23.4	23	24	23	24.2
37	-	25.9	22.4	24	23.1	24.2	22.6	24.5
38	21.6	24.1	25.1	23.8	23.4	25.1	22.4	23
39	22.4	24	23	23.6	23.6	22.8	22.4	22.4
40	-	24.2	23.1	23.6	22.9	22.7	22.8	23.5
41	-	25.2	23.1	23.2	23	23.1	22.9	23.5
42	-	25.2	23.2	24.2	23.4	23.1	22	23
43	22.45	25.1	23	24.4	22.3	23	21.8	22.9
44	22.4	-	23	24	24.3	24	21.7	22.9
45	22.1	-	23.1	23.8	24	23	21.6	22.4
46	21.6	-	23.4	24.1	24	22.7	21.5	22.9
47	21.4	-	24	24.4	23.5	22.8	22	22
48	21.5	-	24.5	24.1	24	23.6	23.7	21.8
49	21.4	25	25	24.1	24.8	23.1	24.2	23
50	22.32	-	24.2	24.1	24.3	23.6	23.4	23.1

51	22.45	-	26	23.8	24.1	22.5	22.5	23.4
52	25.75	23.7	25.5	24	24.1	22.5	22.1	23.5
53	25	-	25.1	24	24.1	23.2	23.6	22.5
54	25	-	24	24	23.6	23.5	23	22.1
55	22	23.9	23.8	22	23.2	24	22.5	22
56	22.25	-	25	23.9	24.1	22.6	22.2	21.9
57	22.6	-	25.4	23.8	24.2	22.3	23.2	22
58	21.9	-	24.5	24	23.8	22.6	23.2	22.4
59	22	-	26	23.7	25.1	23	24.2	22.8
60	-	23.5	-	23.2	23.2	24.1	23	22.5
61	23.15	23	24.8	23.5	23.2	24	22.5	22
62	22.8	-	24.8	24	24.2	23.5	22.4	23
63	22.2	24.2	24.2	24.7	24	22.3	22.3	22.4
64	22.65	24	25.3	26.7	24.2	22.6	22.4	22.5
65	22.5	24.4	22.4	24	23	24.2	22.6	22.6
66	-	25.6	24.2	24.8	22.2	22.5	21.2	22
67	-	28.7	26.6	23.6	22.4	23	21.5	24
68	-	24	26	26.6	23	23	21.6	23
69	-	24.5	23.1	22.8	24	24.1	24	23
70	-	23.3	23.5	22.5	24.7	23	23	23.1
71	-	23	23.4	22.6	23.8	23.5	24	23.1
72	-	20	-	-	-	-	20.4	20.2
73	-	19.8	-	-	-	-	20.7	19.7
74	-	20.5	-	-	-	-	18.9	21.3
75	-	20	-	-	-	-	19	20.2
76	-	20	-	-	-	-	19	20.3
77	-	21	-	-	-	-	19	20.1
78	-	-	-	26	23.6	24.7	24	23.2
79	-	-	25	24.8	25.8	23.7	24.3	24
80	-	-	24.6	24	24.8	23.4	24.1	24.1
81	-	-	24	24.2	24.7	23	23.9	23.5
82	-	-	23	24.1	23.6	22.5	23.3	23.1
83	-	-	25.1	23.8	23.8	22.6	23.1	24.2
84	-	-	-	23.7	24	22.7	22.5	24.4
85	-	-	-	23	24.1	22.4	22.4	23.8
86	-	-	25	24.8	25.8	23.7	24.3	24
87	-	-	24.5	24	24	23	22.8	24
88	-	-	24.2	25.2	-	26	22.4	23.5
89	-	-	25	24	23.8	22.3	23	23.6
90	-	-	-	25.2	22.7	24	22	23.5
91	-	-	25	24	23	-	21.3	23
92	-	-	25.3	23.3	23.5	22.6	24	23

Table S5. Observation-level environmental covariates: illuminated percentage of the moon (moon).

SampUnit	survey1	survey2	survey3	survey4	survey5	survey6	survey6	survey7
1	-	70.6	35.2	44.1	99.8	0.1	73	19.5
2	-	70.6	35.2	44.1	99.8	0.1	73	19.5
3	-	70.6	35.2	44.1	99.8	0.1	73	19.5
4	-	70.6	35.2	44.1	99.8	0.1	73	19.5
5	-	70.6	35.2	44.1	99.8	0.1	73	19.5
6	-	70.6	35.2	44.1	99.8	0.1	73	19.5
7	-	70.6	35.2	44.1	99.8	0.1	73	19.5
8	-	70.6	35.2	44.1	99.8	0.1	73	19.5
9	-	70.6	35.2	44.1	99.8	0.1	73	19.5
10	-	70.6	35.2	44.1	99.8	0.1	73	19.5
11	-	70.6	35.2	44.1	99.8	0.1	73	19.5
12	-	70.6	35.2	44.1	99.8	0.1	73	19.5
13	-	70.6	35.2	44.1	99.8	0.1	73	19.5
14	-	70.6	35.2	44.1	99.8	0.1	73	19.5
15	-	70.6	35.2	44.1	99.8	0.1	73	19.5
16	-	70.6	-	44.1	99.8	0.1	73	19.5
17	-	70.6	35.2	44.1	99.8	0.1	73	19.5
18	-	70.6	35.2	44.1	99.8	0.1	73	19.5
19	-	70.6	35.2	44.1	99.8	0.1	73	19.5
20	-	70.6	35.2	44.1	99.8	0.1	73	19.5
21	-	70.6	35.2	44.1	99.8	0.1	73	19.5
22	-	70.6	35.2	44.1	99.8	0.1	73	19.5
23	-	80	25.8	54.5	99.8	2.7	82.6	12.3
24	-	80	25.8	54.5	99.8	2.7	82.6	12.3
25	-	80	25.8	54.5	99.8	2.7	82.6	12.3
26	-	80	25.8	54.5	99.8	2.7	82.6	12.3
27	-	80	25.8	54.5	99.8	2.7	82.6	12.3
28	9.4	80	25.8	54.5	99.8	2.7	82.6	12.3
29	9.4	80	25.8	54.5	99.8	2.7	82.6	12.3
30	9.4	80	25.8	54.5	99.8	2.7	82.6	12.3
31	9.4	80	25.8	54.5	99.8	2.7	82.6	12.3
32	9.4	80	35.2	54.5	99.8	2.7	82.6	12.3
33	-	80	35.2	54.5	99.8	2.7	82.6	12.3
34	-	80	35.2	54.5	99.8	2.7	82.6	12.3
35	-	80	35.2	54.5	99.8	2.7	82.6	12.3
36	-	80	35.2	54.5	99.8	2.7	82.6	12.3
37	-	80	35.2	54.5	99.8	2.7	82.6	12.3
38	9.4	80	35.2	54.5	99.8	2.7	82.6	12.3
39	9.4	80	25.8	54.5	99.8	2.7	82.6	12.3
40	-	80	25.8	54.5	99.8	2.7	82.6	12.3

41	-	80	25.8	54.5	99.8	2.7	82.6	12.3
42	-	80	25.8	54.5	99.8	2.7	82.6	12.3
43	9.4	80	25.8	54.5	99.8	2.7	82.6	12.3
44	9.4	-	25.8	54.5	99.8	2.7	82.6	12.3
45	9.4	-	25.8	44.1	99.8	2.7	82.6	12.3
46	9.4	-	25.8	44.1	99.8	2.7	82.6	12.3
47	9.4	-	25.8	44.1	99.8	2.7	82.6	12.3
48	9.4	-	25.8	44.1	99.8	2.7	82.6	12.3
49	9.4	80	25.8	44.1	99.3	0.1	73	12.3
50	9.4	-	25.8	54.5	99.3	0.1	73	12.3
51	9.4	-	25.8	54.5	99.3	0.1	73	12.3
52	9.4	80	25.8	54.5	99.3	0.1	73	12.3
53	9.4	-	25.8	54.5	99.3	0.1	73	12.3
54	9.4	-	25.8	54.5	99.3	0.1	73	12.3
55	9.4	80	25.8	54.5	99.3	2.7	82.6	12.3
56	9.4	-	25.8	54.5	99.3	2.7	82.6	12.3
57	9.4	-	25.8	54.5	99.3	2.7	82.6	12.3
58	9.4	-	25.8	54.5	99.3	2.7	82.6	12.3
59	9.4	-	25.8	54.5	99.3	2.7	82.6	12.3
60	-	80	-	54.5	99.3	2.7	82.6	12.3
61	9.4	80	25.8	54.5	99.3	2.7	82.6	12.3
62	9.4	-	35.2	54.5	99.3	2.7	82.6	12.3
63	9.4	80	35.2	54.5	99.3	2.7	82.6	12.3
64	9.4	80	35.2	54.5	99.3	2.7	82.6	12.3
65	9.4	80	35.2	54.5	99.3	2.7	82.6	12.3
66	-	80	35.2	54.5	99.3	2.7	82.6	12.3
67	-	80	35.2	54.5	99.3	2.7	82.6	12.3
68	-	80	35.2	54.5	99.3	2.7	82.6	12.3
69	-	80	17.6	65	99.3	6.7	82.6	6.4
70	-	80	17.6	65	99.3	6.7	82.6	6.4
71	-	80	17.6	65	99.3	6.7	82.6	6.4
72	-	70.6	-	-	-	-	90.4	0.2
73	-	70.6	-	-	-	-	90.4	0.2
74	-	70.6	-	-	-	-	90.4	0.2
75	-	70.6	-	-	-	-	90.4	0.2
76	-	70.6	-	-	-	-	90.4	0.2
77	-	70.6	-	-	-	-	90.4	0.2
78	-	-	-	65	99.3	6.7	82.6	6.4
79	-	-	17.6	65	99.3	6.7	82.6	6.4
80	-	-	17.6	65	99.3	6.7	82.6	6.4
81	-	-	17.6	65	99.3	6.7	82.6	6.4
82	-	-	17.6	65	99.3	6.7	82.6	6.4
83	-	-	17.6	65	99.3	6.7	82.6	6.4

84	-	-	-	65	99.3	6.7	82.6	6.4
85	-	-	-	65	99.3	6.7	82.6	6.4
86	-	-	17.6	65	99.3	6.7	82.6	6.4
87	-	-	17.6	65	99.3	6.7	82.6	6.4
88	-	-	17.6	65	-	6.7	82.6	6.4
89	-	-	17.6	65	99.3	6.7	82.6	6.4
90	-	-	-	65	99.3	6.7	82.6	6.4
91	-	-	17.6	65	99.3	-	82.6	6.4
92	-	-	17.6	65	99.3	6.7	82.6	6.4

Supplementary material S6. R code script for the Occupancy models, probability of detection and importance of variables

```
# Occupancy and probability of detection of the introduced population of Eleutherodactylus coqui in Turrialba, Costa Rica

# Barrantes et al. 2022.


library(unmarked)

library(gridExtra)

library(grid)

library(ggplot2)

library(ggalt)

library(MuMIn)

library(corrplot)

library(dplyr)

library(AICcmodavg)


# Define directory where the data is located

path <- "C:/Path/ToYourFolder" # set the local path where the data is located

setwd(path)

set.seed(120)
```

```
#-------------------------------------------------------------

#  Loading data

#-------------------------------------------------------------

# Detection history

DetHist <- read.csv("Detection_history.csv", header = TRUE, row.names = "SampUnit",
na.strings = "-", sep = ";")


# Site-level covariates

SiteCov <- read.csv("Site_covariates.csv", header = TRUE, na.strings = "-")


# Scaling variables, except factors

SiteCov$brom <- as.factor(SiteCov$brom)

SiteCov[,-which(names(SiteCov) == "brom")]  <- scale(SiteCov[,-which(names(SiteCov)
== "brom")])


# Observation-level covariates

ObsCov1 <- read.csv("ObsCov_temp.csv", header = TRUE, na.strings = "-", row.names =
"SampUnit", sep = ";")

ObsCov2 <- read.csv("ObsCov_hum.csv", header = TRUE, na.strings = "-", row.names =
"SampUnit", sep = ";")

ObsCov3 <- read.csv("ObsCov_moon.csv", header = TRUE, na.strings = "-", row.names =
"SampUnit", sep = ";")


# Combining and converting data into unmarkedFrame format

obs <- list( ObsCov1 = ObsCov1, ObsCov2 = ObsCov2, ObsCov3 = ObsCov3)

umf <- unmarkedFrameOccu(y = DetHist, siteCovs = SiteCov, obsCovs = obs)


#-----------------------------------------

# Define full model and null model

#-----------------------------------------
```

```
# Full model
mFull<- occu(~ ObsCov1 + ObsCov2 + ObsCov3 ~ veg_low + veg_med + veg_high + can_cover + brom + leaf_litter + palm + dist_river + dist_origin, data = umf)


# Null model
mNull <- occu(~1 ~1, data = umf)


#----------------------------------------
# Checking correlation between site covariates
#----------------------------------------


siteCorrelation <- cor(SiteCov[ , -which(names(SiteCov) == "brom")])
corrplot::corrplot(siteCorrelation)
siteCorrelation <- as.data.frame(siteCorrelation)


varcorrelated = data.frame(Var1 = NA, Var2 = NA, cor = NA)
countrow = 0
for (numcolumn in 1:ncol(siteCorrelation)) {
  for (numrow in 1:nrow(siteCorrelation)) {
    #Correlation greater than 0.6
  if(abs(siteCorrelation[numrow, numcolumn]) > 0.6){
    countrow = countrow + 1
    varcorrelated[countrow, ] <- c(rownames(siteCorrelation)[numrow], colnames(siteCorrelation)[numcolumn], siteCorrelation[numrow, numcolumn])
  }
  }
}
varcorrelated <- varcorrelated[-c(which(varcorrelated$Var1 == varcorrelated$Var2)),]
```

```
varcorrelated <- varcorrelated[!duplicated(varcorrelated$cor),]

print(varcorrelated) #Veg_low, veg_med and veg_high are correlated, also can_cover and leaf_litter


# Checking if the model improves when dropping out one variable

# Vegetation

dropout_veglow <- occu(~ ObsCov1 + ObsCov2 + ObsCov3 ~  veg_med + veg_high + can_cover + brom + leaf_litter + palm + dist_river + dist_origin, data = umf)


dropout_vegmed <- occu(~ ObsCov1 + ObsCov2 + ObsCov3 ~ veg_low + veg_high + can_cover + brom + leaf_litter + palm + dist_river + dist_origin, data = umf)


dropout_veghigh <- occu(~ ObsCov1 + ObsCov2 + ObsCov3 ~ veg_low + veg_med + can_cover + brom + leaf_litter + palm + dist_river + dist_origin, data = umf)


dlist <- list(dropout_veglow = dropout_veglow, dropout_vegmed = dropout_vegmed, dropout_veghigh = dropout_veghigh, fullmodel = mFull, nullmodel = mNull)

modSel(fitList(fits = dlist))# The fit is better when removing veg_high


# Updating full model without veg_med

mFull<- occu(~ ObsCov1 + ObsCov2 + ObsCov3 ~ veg_low + veg_med + can_cover + brom + leaf_litter + palm + dist_river + dist_origin, data = umf)

# veg_low and veg_med are still correlated


# Checking if the fit improves when removing one of these

dropout_veglow <- occu(~ ObsCov1 + ObsCov2 + ObsCov3 ~ veg_med + can_cover + brom + leaf_litter + palm + dist_river + dist_origin, data = umf)

dropout_vegmed <- occu(~ ObsCov1 + ObsCov2 + ObsCov3 ~ veg_low + can_cover + brom + leaf_litter + palm + dist_river + dist_origin, data = umf)

dlist <- list(dropout_veglow = dropout_veglow, dropout_vegmed = dropout_vegmed, fullmodel = mFull, nullmodel = mNull)
```

```
modSel(fitList(fits = dlist)) # The fit improved when dropping out veg_low


# Updating full model without veg_low

mFull<- occu(~ ObsCov1 + ObsCov2 + ObsCov3 ~ veg_med + can_cover + brom + leaf_litter + palm + dist_river + dist_origin, data = umf)


# Leaf_litter and can_cover are still correlated, checking which one should be removed

dropout_leaf_litter <- occu(~ ObsCov1 + ObsCov2 + ObsCov3 ~ veg_med + can_cover + brom + palm + dist_river + dist_origin, data = umf)

dropout_can_cover <- occu(~ ObsCov1 + ObsCov2 + ObsCov3 ~ veg_med + brom + leaf_litter + palm + dist_river + dist_origin, data = umf)

dlist <- list(dropout_leaf_litter = dropout_leaf_litter, dropout_can_cover = dropout_can_cover, fullmodel = mFull, nullmodel = mNull)

modSel(fitList(fits = dlist)) # The fit improved when removing leaf_litter


# Updating full model removing leaf_litter

mFull<- occu(~ ObsCov1 + ObsCov2 + ObsCov3 ~ veg_med + can_cover + brom + palm + dist_river + dist_origin, data = umf)


# Now we don't have any correlated site variables


# Temperature and Humidity are correlated

# Checking if the fit improves when removing one of these:

dropout_cov1 <- occu(~ ObsCov2 + ObsCov3 ~ veg_med + can_cover + brom + palm + dist_river + dist_origin, data = umf)

dropout_cov2 <- occu(~ ObsCov1 + ObsCov3 ~ veg_med + can_cover + brom + palm + dist_river + dist_origin, data = umf)

dlist <- list(dropout_cov1 = dropout_cov1, dropout_cov2 = dropout_cov2, fullmodel = mFull, nullmodel = mNull)

modSel(fitList(fits = dlist)) # Fit is better when removing ObsCov2 (Humidity)
```

```
# Updating Full model:
mFull<- occu(~ ObsCov1 + ObsCov3 ~ veg_med + can_cover + brom + palm + dist_river + dist_origin, data = umf)
# Now we don't have any correlated variables


# Testing goodness-of-fit of the final model
occ_gof <- mb.gof.test(mFull, nsim = 1000, plot.hist = FALSE)
# Hide the chisq table to give simpler output
occ_gof$chisq.table <- NULL
print(occ_gof)


#------------------------------------------------------------
# Model selection
#------------------------------------------------------------


# Checking what combination of variables gives the best fit
# dredge function test all possible combinations
All_combinations <- dredge(mFull, beta = "none", evaluate = T, rank = AIC, trace = 2)


# Extracting the set of models with a delta AIC less than 2
best_models <- get.models(All_combinations, delta < 2)
best_models_list <- fitList(best_models)
modSel(best_models_list)
length(best_models) # list of 19 models


# Getting information from all models
table_models <- as.data.frame(aictab(best_models))
model_formula <- list()
for (model in 1:19) {
```

```
  model_formula[[model]] <- best_models[[model]]@formula
}
table_models$Modnames <- paste(model_formula)
table_models # all 19 models are similar, we will use a averaging model


# Save table
write.csv(table_models, "table_models.csv", row.names = FALSE)
# Averaging model using all 19 models with dAIC < 2
avgmodel <- model.avg(best_models)
summary(avgmodel)


# Relative importance of the estimated parameters
imp <- MuMIn::sw(All_combinations)
importance_table <- data.frame(importance = imp, covariates = names(imp))
importance_table <- dplyr::filter(importance_table, grepl('psi', importance_table$covariates))
importance_table$covariates <- gsub(pattern = "psi\\(|)", replacement = "", x = importance_table[, 2])


# Importance plot
importance_plot <- ggplot(importance_table, aes(y = reorder(covariates, importance), x = importance)) + geom_lollipop(point.colour = "steelblue", point.size = 2, horizontal = TRUE) + xlab("Relative importance") + ylab("Covariable") + theme(text = element_text(colour = "black", family = "Arial"), axis.title.y = element_blank(), axis.text = element_text(colour = "black", size = 10, family = "Arial"), axis.title.x = element_text(size = 10, family = "Arial"))
importance_plot# Print plot


# Save plot
jpeg("plot_imp.jpg", res = 400, width = 16, height = 8, units = "cm")
importance_plot
```

```
dev.off()


#---------------------------------------------------------------

#   Detection probability estimate

#---------------------------------------------------------------

# Detection probability using averaged model and mean values of observation-level variables

detprob <- predict(avgmodel, type = "det", newdata = data.frame(ObsCov1 = mean(colMeans(ObsCov1, na.rm = TRUE)), ObsCov3 = mean(colMeans(ObsCov3, na.rm = TRUE)))) %>%  as.data.frame() %>% mutate(lower = (fit - (se.fit*1.96)), upper = (fit + (se.fit*1.96)))

detprob


#---------------------------------------------------------------

#   Plot model

#---------------------------------------------------------------

# Building function for plotting

pred.var <- function(var, modData, model) {

  factors <- sapply(modData, is.factor)

  const <- data.frame()

  for (ncolum in 1:ncol(modData)) {

    columndata = modData[ , ncolum]

    if(is.factor(columndata)){

      a = columndata[1]

    }else{

      a = mean(columndata)

    }

    const[1, ncolum] <- a

  }

  names(const) <- names(modData)
```

```
  if(var %in% names(modData[factors])){
    secuencia <- levels(modData[ , which(names(modData) == var)])
  }else{
    secuencia <- seq(min(modData[[var]]), max(modData[[var]]), length = nrow(modData))
  }
  const <- cbind(const, secuencia)
  const[[var]] <- secuencia
  num.col = which(colnames(const) == "secuencia")
  df <- const[ , -num.col]
  psi_var <- predict(model, newdata = df, se.fit = TRUE, type = "state")
  psi_var[["values"]] <- secuencia
  psi_var[["variable"]] <- var
  return(as.data.frame(psi_var))
}

# Get the data to graph each variable
# ignore warnings
v1 <- pred.var("brom", SiteCov, avgmodel)
v2 <- pred.var("can_cover", SiteCov, avgmodel)
v3 <- pred.var("dist_origin", SiteCov, avgmodel)
v4 <- pred.var("dist_river", SiteCov, avgmodel)
v5 <- pred.var("palm", SiteCov, avgmodel)
v6 <- pred.var("veg_med", SiteCov, avgmodel)

# Define the structure
fontsize <- 10  #font size
# v1
p_info <- ggplot(data = v1, aes(values, fit))
```

```
plot1 <- p_info + geom_errorbar(aes(ymin = (fit - (se.fit*1.96)), ymax = (fit +
(se.fit*1.96))), width = 0.1) + geom_point(aes(y = fit), size = 3) + theme_bw() +
xlab(p_info[["data"]][["variable"]][1]) + ylim(0,1) + theme(text = element_text(colour =
"black"), axis.title.y = element_blank(), axis.text = element_text(colour = "black", size =
fontsize), axis.title.x = element_text(size = fontsize))

# v2

p_info <- ggplot(data = v2, aes(values, fit))

plot2 <- p_info + geom_ribbon(aes(ymin = (fit - (se.fit*1.96)), ymax = (fit + (se.fit*1.96))),
fill = "grey70") + geom_line(aes(y = fit)) + theme_bw() +
xlab(p_info[["data"]][["variable"]][1]) + theme(text = element_text(colour = "black"),
axis.title.y = element_blank(), axis.text = element_text(colour = "black", size = fontsize),
axis.title.x = element_text(size = fontsize))

# v3

p_info <- ggplot(data = v3, aes(values, fit))

plot3 <- p_info + geom_ribbon(aes(ymin = (fit - (se.fit*1.96)), ymax = (fit + (se.fit*1.96))),
fill = "grey70") + geom_line(aes(y = fit)) + theme_bw() +
xlab(p_info[["data"]][["variable"]][1]) + theme(text = element_text(colour = "black"),
axis.title.y = element_blank(), axis.text = element_text(colour = "black", size = fontsize),
axis.title.x = element_text(size = fontsize))

# v4

p_info <- ggplot(data = v4, aes(values, fit))

plot4 <- p_info + geom_ribbon(aes(ymin = (fit - (se.fit*1.96)), ymax = (fit + (se.fit*1.96))),
fill = "grey70") + geom_line(aes(y = fit)) + theme_bw() +
xlab(p_info[["data"]][["variable"]][1]) + theme(text = element_text(colour = "black"),
axis.title.y = element_blank(), axis.text = element_text(colour = "black", size = fontsize),
axis.title.x = element_text(size = fontsize))

# v5

p_info <- ggplot(data = v5, aes(values, fit))

plot5 <- p_info + geom_ribbon(aes(ymin = (fit - (se.fit*1.96)), ymax = (fit + (se.fit*1.96))),
fill = "grey70") + geom_line(aes(y = fit)) + theme_bw() +
xlab(p_info[["data"]][["variable"]][1]) + theme(text = element_text(colour = "black"),
axis.title.y = element_blank(), axis.text = element_text(colour = "black", size = fontsize),
axis.title.x = element_text(size = fontsize))

# v6

p_info <- ggplot(data = v6, aes(values, fit))
```

```
plot6 <- p_info + geom_ribbon(aes(ymin = (fit - (se.fit*1.96)), ymax = (fit + (se.fit*1.96))), fill = "grey70") + geom_line(aes(y = fit)) + theme_bw() + xlab(p_info[["data"]][["variable"]][1]) + theme(text = element_text(colour = "black"), axis.title.y = element_blank(), axis.text = element_text(colour = "black", size = fontsize), axis.title.x = element_text(size = fontsize))

# Organize the 6 plots in a single graph

grid.arrange(plot1, plot2, plot3, plot4, plot5, plot6, ncol=2, left = textGrob("Selection probability", rot = 90))

# Save graphic

jpeg("selectionprob.jpg", res = 400, width = 16, height = 13, units = "cm")

grid.arrange(plot1, plot2, plot3, plot4, plot5, plot6, ncol = 2, left = textGrob("Selection probability", gp = gpar(fontsize = fontsize), rot = 90))

dev.off()
```