Combining multi-view UAV photogrammetry, thermal imaging, and computer vision can derive cost-effective ecological indicators for habitat assessment

Supplementary Materials

S1. Dataset details

Table S1. The details of the datasets used in this study.

	Coordinates	Locations	Areas	Images	Flight area
Straightwater WMA	-97.232600, 40.869200	Seward, NE	0.947 km^2	754	0.11 km^2
Smith WPA	-97.976900, 40.437500	Clay, NE	2.052 km^2	787	0.12 km^2
Johnson WPA	-99.328900, 40.556800	Phelps, NE	2.348 km^2	753	0.11 km^2

S2. MV-data structure

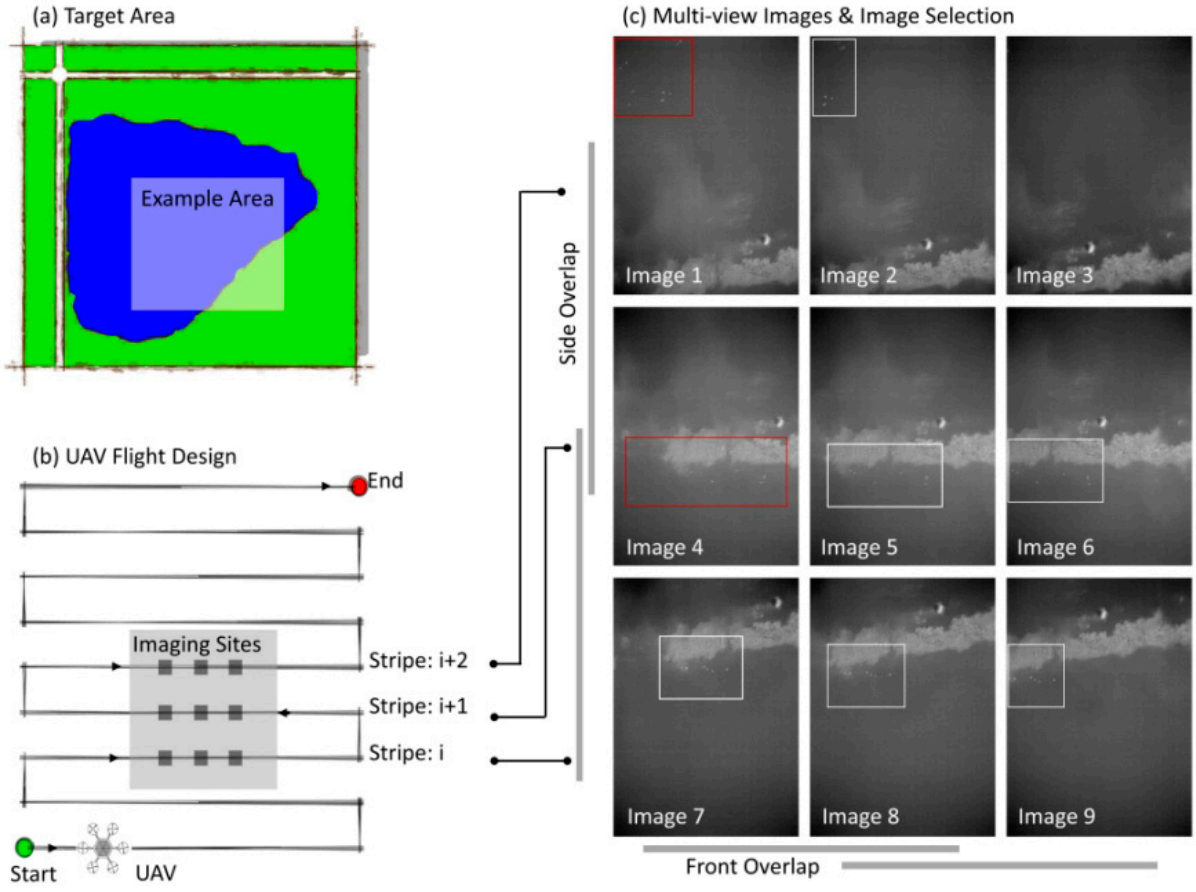


Figure S1. MV-data structure.

S3. Hardware for AutoML implementation

All the training and testing works were based on a GeForce RTX 3060 (Nvidia, Santa Clara, California), a GPU with 7.5 computing capability, and executed in MATLAB 2023a.

S4. Model fine-tuning

Table S2. Data organizing for practical tests and fine-tuning process. With the same training setting, the fine-tuning process only took minutes with respect to the pre-trained base model.

Usages	Detector	Labeled Wildlife	Training Time
Base model	Detector SW	660 (in 128 images)	30 min
Fine-tuning	Detector SW	34 (in 4 images)	3 min
Fine-tuning	Detector SM	150 (in 2 images)	3 min
Fine-tuning	Detector JS	55 (in 4 images)	3 min

S5. Metric calculations

The relation among precision, recall, and F1 are specified by Eqs. (S1–S3), respectively, as follows:

$$P_i = TP_i/(TP_i + FP_i), \quad (S1)$$

$$R_i = TP_i/(TP_i + FN_i), \quad (S2)$$

$$F1_i = 2(P_i * R_i)/(P_i + R_i), \quad (S3)$$

where P_i, R_i and $F1_i$ are the precision, recall and F1 of the i-th test image respectively; TP_i, FP_i, and FN_i are the number of TP, FP, and FN in the i-th test image, respectively.

S6. Detailed results

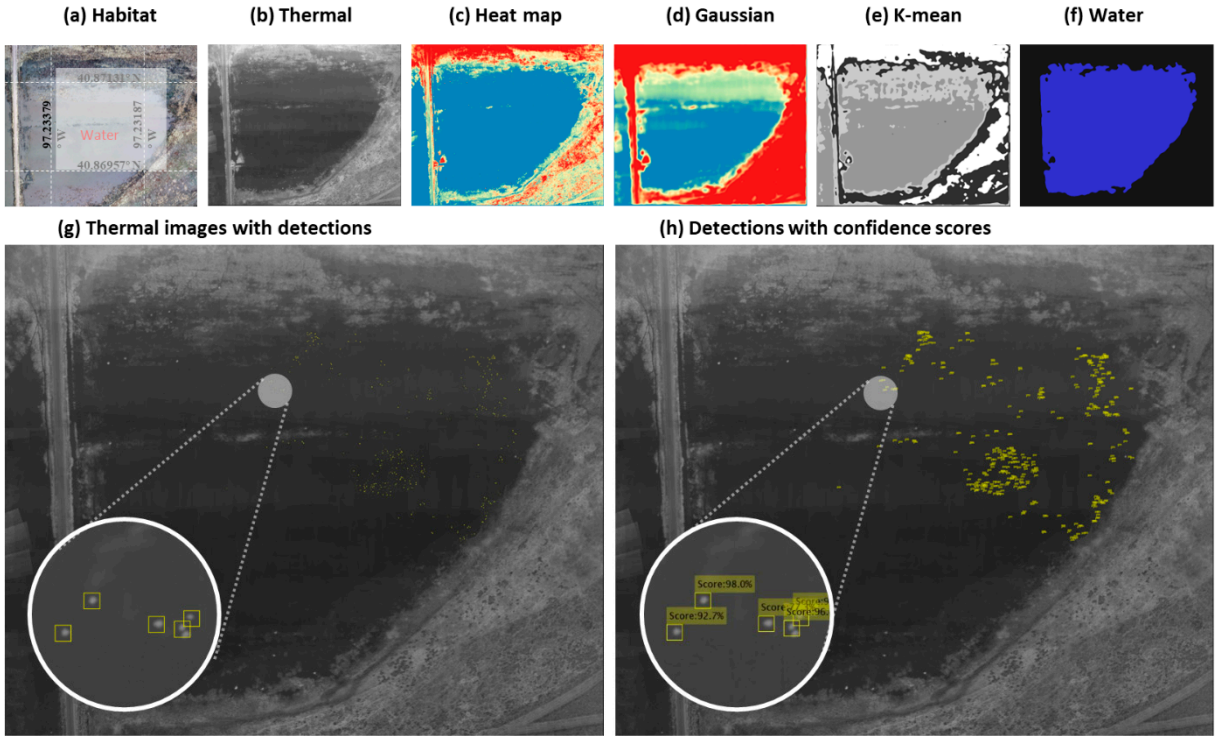


Figure S2. Wildlife detection & Water segmentation for Straightwater WMA.

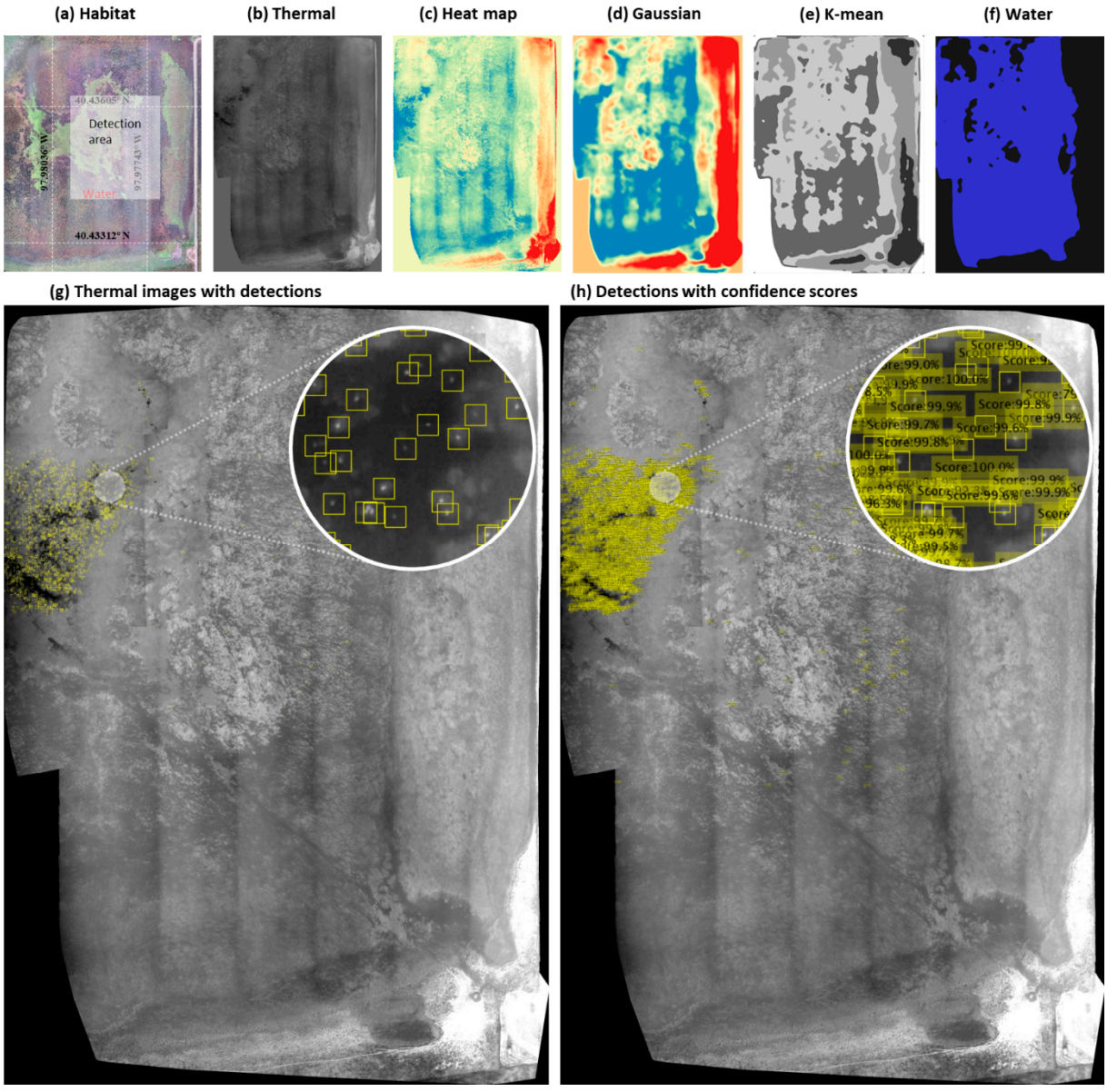


Figure S3. Wildlife detection & Water segmentation for Smith WPA.

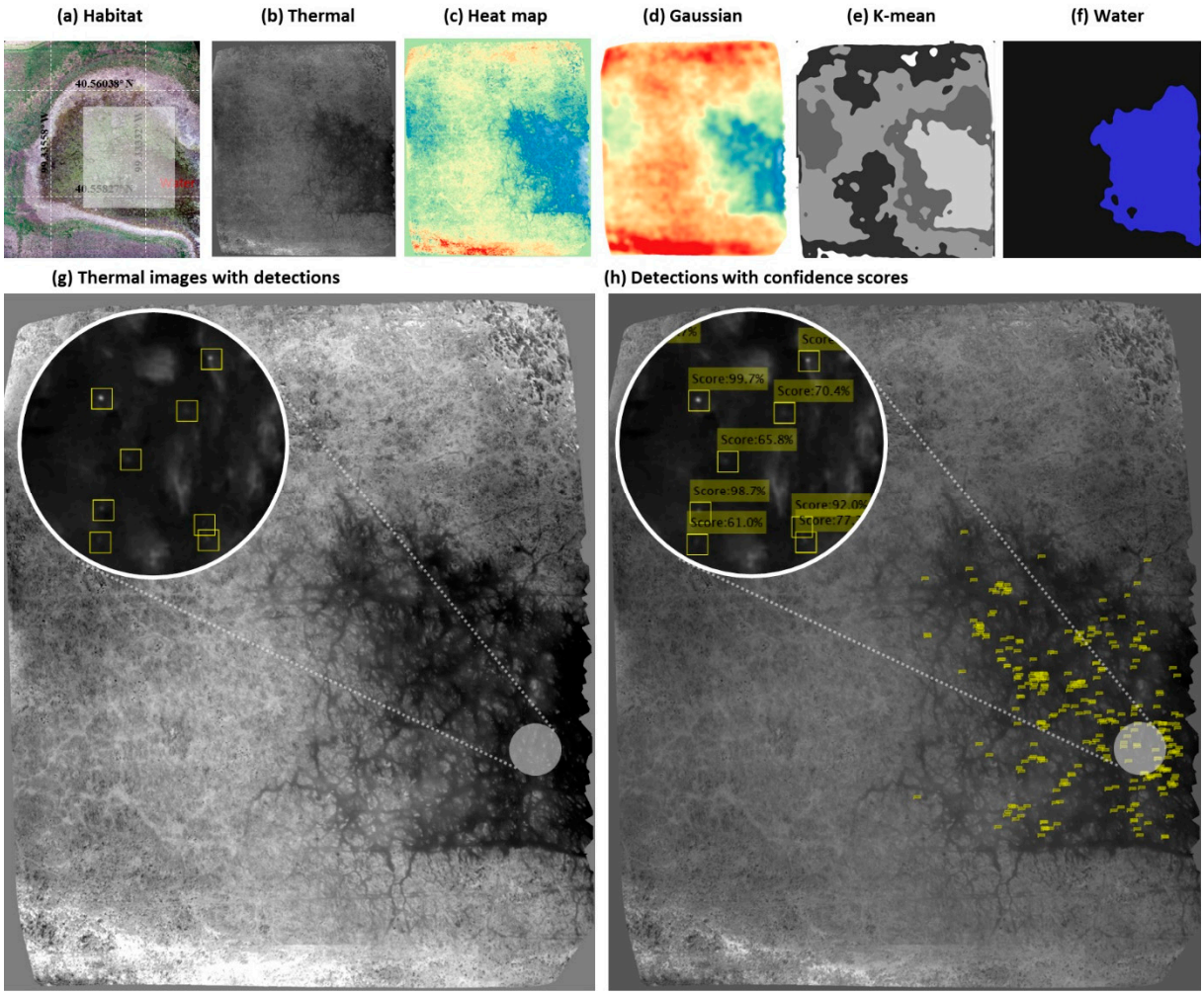


Figure S4. Wildlife detection & Water segmentation for Johnson WPA.

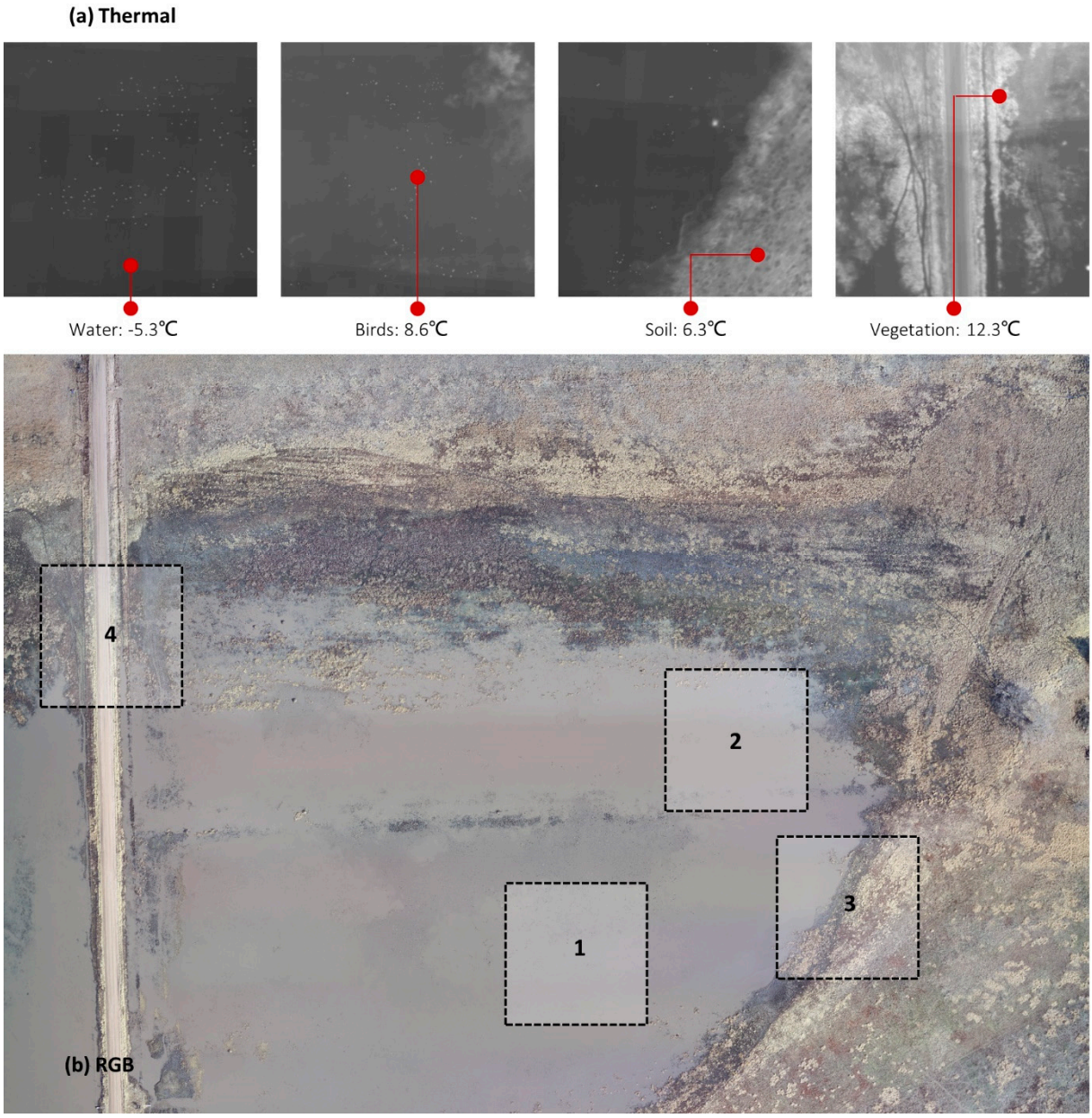


Figure S5. Thermal signatures by different land covers.