Supplementary Material: Learning Tri-modal Embeddings for Zero-Shot Soundscape Mapping

BMVC 2023 Submission # 813

In this supplemental material, we present a demonstration of the zero-shot soundscape mapping capability offered by our proposed framework, GeoCLAP. Specifically, we showcase the soundscape maps created by querying our best performing model with diverse sound-related textual prompts. Furthermore, in a video demonstration accompanying this material, we highlight the satellite image to audio retrieval capability of GeoCLAP.

1 Zero-Shot Soundscape Mapping

Following the same methodology from Section 5.3 in the main paper, we constructed a soundscape map of England. We selected three prompts: *This is a sound of car horn; This is a sound of chirping birds; This is a sound of animal farm*. We downloaded sentinel2-cloudless images for England, each with dimension 256×256. Then, using cosine similarity scores between image and text embeddings, we created a dense soundscape map for the region. All visualizations were created using Q-GIS.

As observed in Figure 1, there is a strong correlation between sound categories and relevant land-cover classes. As expected, the soundscape map reveals that urban areas in England, such as the region around London, are highly associated with the sound category *car horn* indicated by the colour blue in Figure 1 (a). On the other hand, less populated areas with crops exhibit a notable association with the sound category *animal farm*. An intriguing observation is that around built-up areas in England, a combination of both *car horn* and *chirping birds* sound is observed, as indicated by purple-coloured regions in soundscape. This suggests that despite human activities in these regions, birds still inhabit them.

Soundscapes can be viewed as composite pseudo-colour maps representing a desired set of sound categories, as shown in Figure 1. However, if one is specifically interested in a single sound category, the GeoCLAP model can be queried with a textual prompt corresponding to that particular sound category, as demonstrated in Figure 2. Furthermore, visualizing soundscapes for smaller geographic regions, as showcased in Figure 3 and 4, can provide a better understanding of sound-related concepts learned by the model.

The results shown in Figure 3 indicate high similarity between the prompt: *This is a sound of a manufacturing factory* and a sub-region that likely contains structures resembling manufacturing factories. Similarly, in Figure 4, areas associated with water bodies exhibit a high similarity with the prompt: *This is a sound of a flowing river.* These findings demonstrate that the embedding space of GeoCLAP possesses an understanding of high-level sound-related concepts within geographic regions.

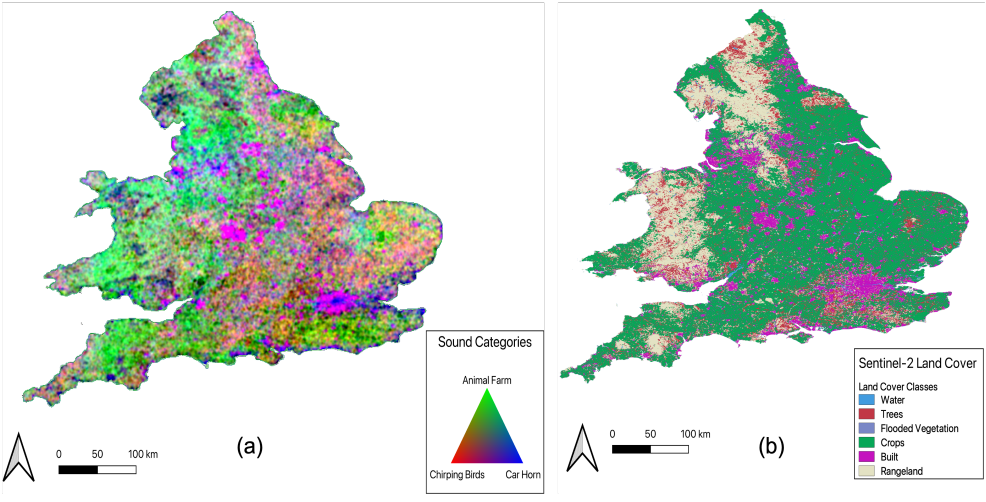

Figure 1: Comparison of (a) Soundscape map of England with (b) *ESRI's sentinel-2 land cover classes*. The soundscape map was created by querying GeoCLAP with textual prompts for three sound categories: *car horn*, *chirping birds*, and *animal farm*. Best viewed in colour.

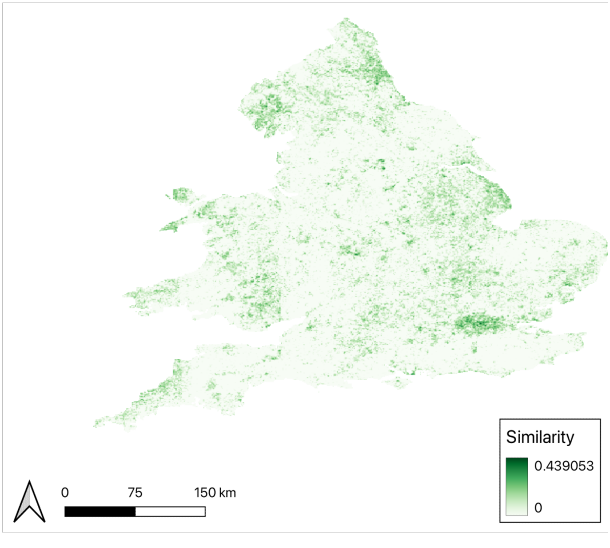

Figure 2: Soundscape map of England created by querying GeoCLAP with a textual prompt: *This is a sound of church bells*.

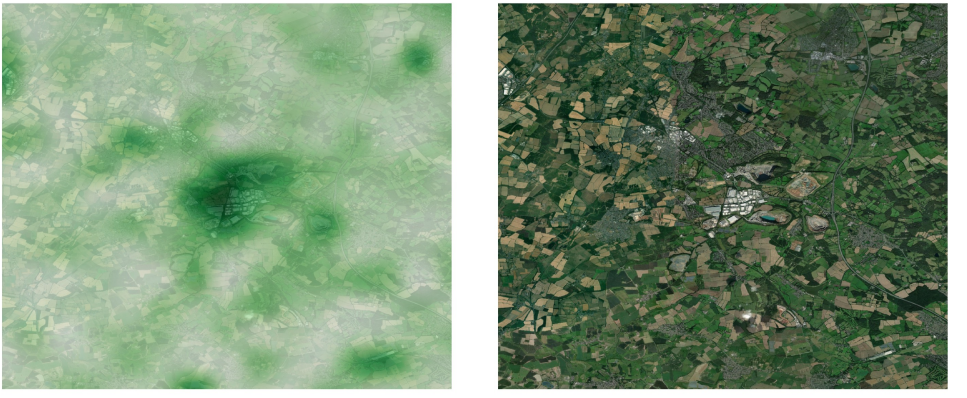

Figure 3: Soundscape map of a small region (a) along with the reference overhead image (b). Soundscape created for the textual prompt: *This is a sound of manufacturing factory*. (green: more probable, white: less probable).

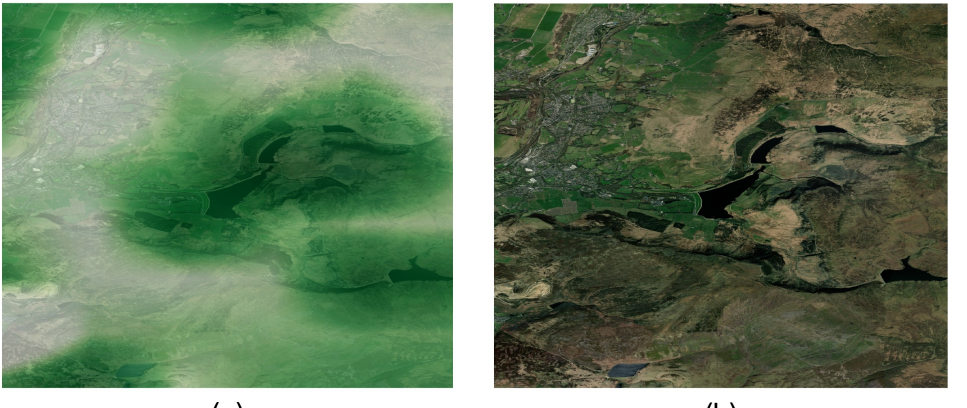

Figure 4: Soundscape map of a small region (a) along with the reference overhead image (b). Soundscape created for the textual prompt: *This is a sound of flowing river*. (green: more probable, white: less probable).