We thank all the reviewers for their comments, and acknowledging that our approach is R1: “theoretically well grounded, state-of-the-art using a weakly supervised formulation”. R4: “shows that good mappings can be obtained as long as proper regularizations are incorporated which is valuable. End-to-end weakly supervised deep functional map for both full shape and partial shape matching as a whole is valuable”. In the following, we address major concerns:

Non-linear Effect of Zoomout on accuracy (R1) In Table 1 (main paper), compared to GeomFmap, we obtain better results with zoomout as it refines initial maps better if they do not contain large errors, e.g. due to symmetries (detailed next), which we observe with GeomFmap when trained on Faust and tested on Scape (non-aligned dataset). Also, when the initial maps are good (in range 3-5), refined map is often similar regardless of initial maps.

Weak Supervision (R2,R3) It is necessary due to the presence of symmetries. Since some poses (e.g. the neutral pose) are fully extrinsically symmetric, a PointNet like feature extractor cannot distinguish left/right unless the shapes are aligned, we need *some way* to disambiguate them for correspondence. Therefore some amount of weak supervision, such as rigid alignment, is necessary and also explains performance drop of GeomFmap when tested on Scape(non-aligned)

Ablation, R1,R2: We show below ablation of our method trained on Surreal and tested on Faust and Scape. E3

Losses	All	E1	E2	E3	(E1+E3)	All-not-aligned
Scape	7.5	12	15	9.5	8.2	20
Faust	5.2	11	14	9.0	6.3	8.0

Table 1: Avg. Geodesic error with individual losses with and without alignment when trained with Surreal.

(Laplacian commutativity) is the most important while E2 (Orthonormality) is the least among the three losses. Drastic decrease in performance of our method (All) without weak supervision underlines its importance. The drop is less severe in case of Faust where one axis is already aligned in contrast to Scape that is not aligned at all. Table 3 in the paper also validates the effectiveness of weak supervision on GeomFmap and Unsup FMNet as they are trained on aligned dataset. We will clarify this more in paper.

Sufficient and Minimum Conditions (R3,R4) Our approach does not require Geodesic matrices, as in FMnet and UnSupFmnet, ground truth maps, as in GeomFmap and FMnet, regularizers, such as descriptor preservation in SurfmNet and regularized FMap layer in GeomFMap. Removal of so many components without compromising results motivated us to use this terminology. Furthermore, when we remove these components from the respective works and include our minimum components, we get comparable results, thus proving the redundancy. We always claimed this based on empirical findings. Even in the abstract, we mention “with slight of abuse of notation.” We will tone it down further to avoid any possibility of this being a theoretical condition and pose the in-depth theoretical study as a future work.

Weakness by R2: We believe there is a misunderstanding. In line 44, we claim to achieve state-of-the-art results from point clouds with rigid supervision when compared to Donati et al. that learns it with full *point to point ground truth dense correspondences*. We never claim our approach to be the first one to learn from point clouds. We do not agree with the assessment that contribution on partial shape matching seems out of place in the paper. We believe end-to-end learning pipeline that can handle both partial and full shape matching is a valuable contribution to the community.

Weakness by R3: We need orthonormal C as it promotes locally area preserving correspondences. One can enforce the same with Stiefel manifold but the resulting problem is much harder to optimize and besides, as shown in our partial matching results, does not bring additional accuracy. Note that bijectivity does *not* follow from enforcing commutativity and orthonormality. We will be happy to provide analytical counter examples to prove this. Low no. of Laplacian eigen-basis reduces overfitting and helps generalization as the embedding space decreases and bias/variance trade off kicks in. These may be simple observations but have a significant impact, as our approach with as low as 100 approximately rigidly aligned shapes obtains comparable results to much more expensive methods that require thousands of densely annotated maps. We do not understand what does ‘GeomFmap + unsup. loss + regularizers’ means? Our Unsup. loss only consists of regularizers. Besides, Table 3 contains GeomFmap with a deep descriptor and our unsupervised loss on aligned dataset with name ‘GeomFmap loss+Ours’.

Cuts result/Discussion in supplement, R1 We agree and will include them in the main text. Thank you for suggestion.

Comparison with a different metric, R4: We show the corresponding curves below that are consistent with avg. error.

We thank all reviewers for pointing out typos and will fix them. We addressed all major concerns of R2 and R4 and thus, kindly ask them to **reconsider their ratings based on rebuttal**.