We would like to thank all the reviewers for their selfless reviews and astute comments about our work. We sincerely think that these comments will improve the quality of our paper's presentation. We provide a brief point by point reply to the concerns raised, while abridging the reviewers' concerns due to page constraint.

Reviewer 1:

Point 1. about finiteness of N: This is an interesting point. For finite N, we note that the empirical CDF is a bounded random variable. So Hoeffding or any sub-Gaussian random variable tail inequality will result in a sharp concentration around the mean (true CDF) for finite N. Owing to space and deadline constraints, we will consider this in a future version of our work.

Point 2. about Theorem 2: In (5), (16) and (20) the $\max$ is over x and s. Therefore, only the second term in the right hand side of (5) is dependent on s. In Theorem 2 we take the supremum over s which results in (16) and (20).

Point 3. about experiments and value of N: In our trials, as noted by the reviewer, N is indeed days. It is indeed shy of infinity. However, we do see "closeness" between the empirical CDFs obtained by fixed sensors readings and mobile sensor readings. This was the point of experiments. We expect this agreement to get better with larger N.

Reviewer 2:

Point 1. about renewal process model: The renewal model is realistic in the following scenarios: (i) if the mobile vehicle is nearly on uniform speed with slight variation in the speed (jitter); and (ii) if the sensing time intervals are programmed to record on a (temporal) renewal process. We will add the above points to clarify the renewal process model used. We believe that inter-sample intervals *can be* modeled as autoregressive process, but it is beyond the scope of our current work.

Point 2. about experimental study: Owing to space constraints, we abridged this discussion. We will expound more on it if we get a chance to revise our NeurIPS submission.

Point 3. about minor details: We thank the reviewer for suggesting minor changes. We will incorporate them in our final paper.

Reviewer 3:

Points raised in paragraph 2: In spatial sensing setup (such as in smart cities or IoT or climatology), it is desirable to estimate the distribution of spatial fields along a path or in a region; this is our upcoming application. In distribution learning, error between the estimated and the true distribution is an accuracy metric. (On Lipschitz and C^2) We note that a spatial field in C^2 is also Lipschitz and therefore our results will extend to the C^2 setup; and, we need Lipschitz criterion since smoothness of the field seems necessary when measurement locations have small errors. (On NeurIPS and signal processing) We did submit our work to the signal processing/time series area of NeurIPS. We also note that our work presents a data-driven approach (backed by proofs) to distribution learning, which we believe is a good fit for NeurIPS.

Points raised on the lack of clarity in problem formulation: We will be more than happy to rectify any lack of clarity in our paper. While we will give a thorough read, it would benefit us if the reviewer points out the major issue.

On the goal of our paper and lack of fundamental limits: This is a great point. Our paper is a first attempt towards distribution learning with location-unaware sensor. It is a new area of interest, which involves contributions to statistical learning theory, since the distribution of sampling location is not known. As a result, benchmarks/fundamental limits are not available yet. We believe our positive result (i.e., distribution can be learned with higher density of samples) will be of interest to the community. We do wish to unravel fundamental limits as we study this area further.

On the path being closed or a loop: Please note that the begin and end point of the path need not be the same, though in our experiments they were. We will revise our submission to remove any confusion regarding this issue.

On the lack of time-variation in simulated signal: Upon reviewing our paper submission, it does seem that $A_r(s)$, $f_r(s)$ do not vary with time. But, we generated $A_r(s)$, $f_r(s)$ for each renewal process based sampling location $S_{i,j}$ independently (i-th trial, j-th sampling location). This independent realization of $A_r(S_{i,j})$ and $f_r(S_{i,j})$ is modeling the time-variation. In our experiments, the sampling time interval is 1 second, during which the spatial acoustic field modifies to a different value. We will *revise* the simulation section to reflect this very important point.

On mismatch between the title and setting: We think there is no mismatch since apart from our assumptions on Lipschitz property of $X(s,t)$, we are working with a random process in Theorem 1 and Theorem 2. In experiments, the spatial field changes (is not deterministic or fixed) as our mobile sensor moves. In the simulations as well, the field's frequency and amplitude changes to a random value between successive samples. We request the reviewer to check the same. In other words, the spatial field is random and the sampling locations are random too.