

Additional file 1: Supplementary Figures

STopover captures spatial colocalization and interaction in the tumor microenvironment using topological analysis in spatial transcriptomics data

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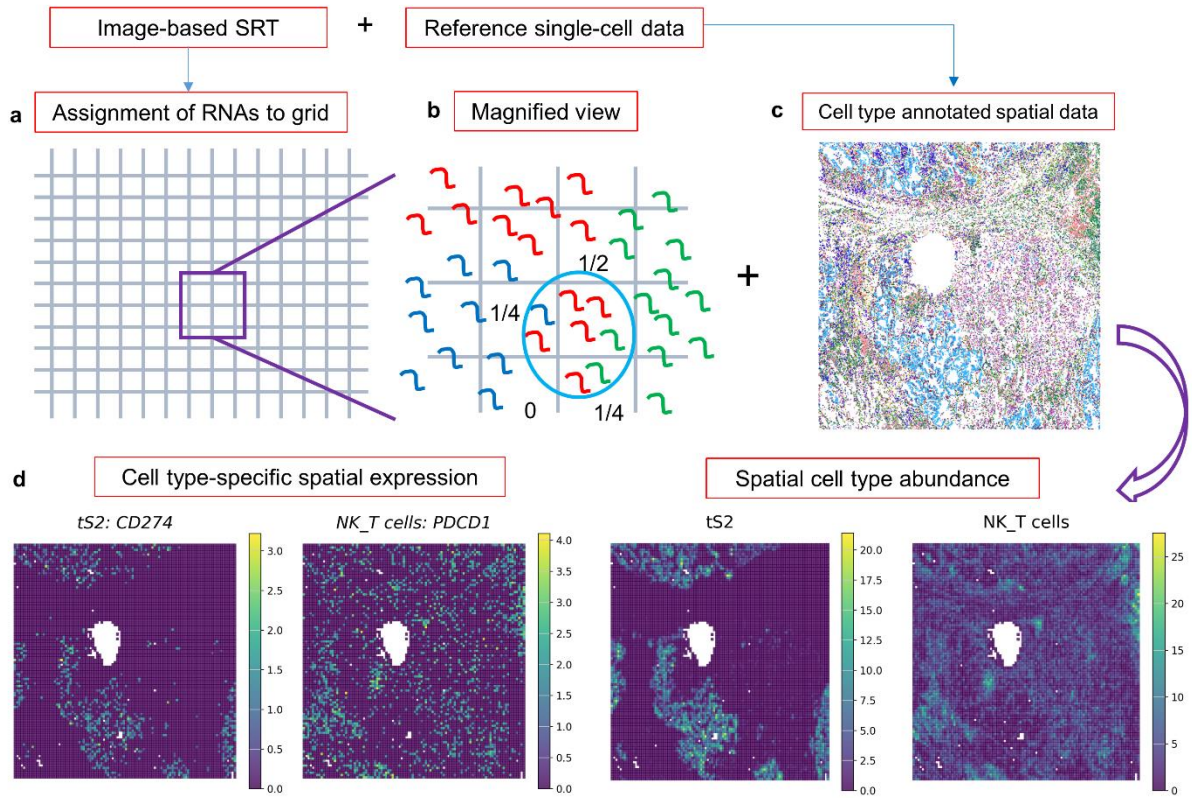
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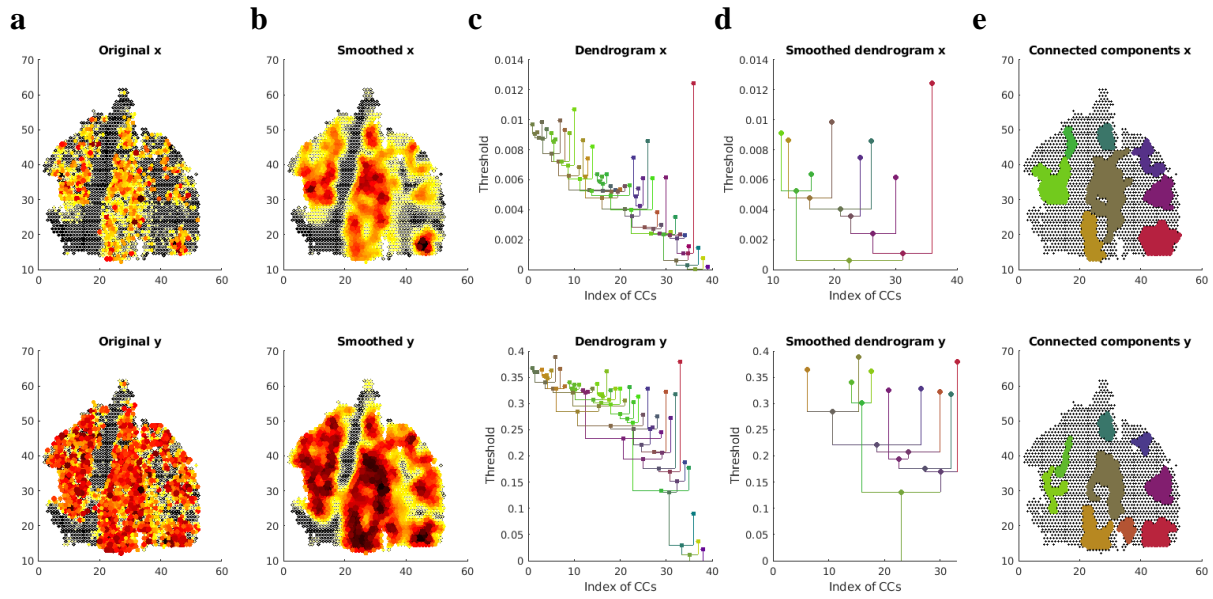
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Supplementary Fig. 1. Schematic image for converting image-based SRT to grid-based data

(a) The entire field of view in the image-based SRT is divided into grids (in the case of the CosMx SMI platform, 100 by 100 grids are applied), allowing for adjustment of the spatial resolution to be similar to the Visium spatial transcriptomic dataset. **(b)** Then, RNA transcripts are assigned to the grids, and the fraction of a particular cell in a grid is calculated based on the total number of RNAs belonging to the cell in each grid that the cell covers. **(c)** Next, reference single-cell RNA-seq data is utilized to annotate the cells segmented in the image-based SRT. **(d)** By summing up the fractions of cells corresponding to a specific cell type, a spatial map of cell type abundance can be acquired. Also, cell type-specific spatial expression can be calculated by extracting RNAs belonging to a specific cell type.



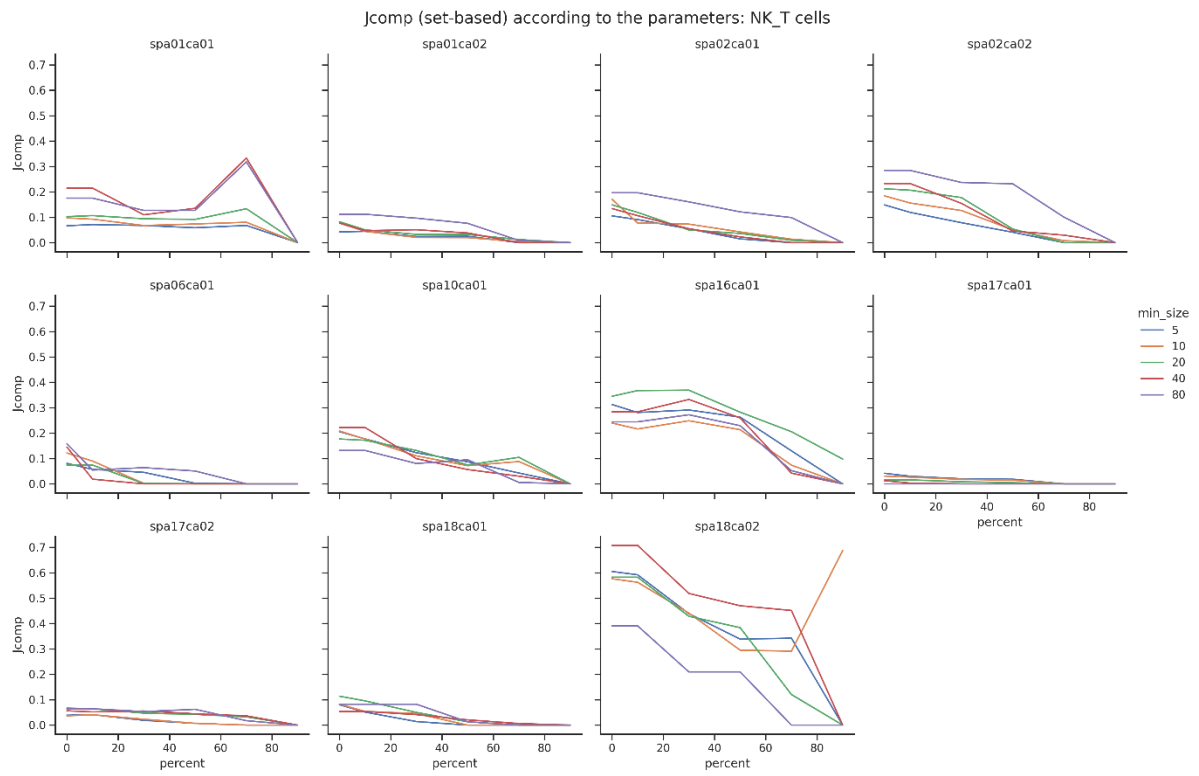
Supplementary Fig. 2. Extracting CCs by Morse filtration and dendrogram smoothing in Visium dataset.

An example of extracting connected components (CCs) from a spatial map of feature x (tS2) and feature y (NK/T cells), which is the core algorithm of STopover. The utilized Visium dataset is one of the PD-L1 high tissues (spa18ca02). **(a, b)** First, the original spatial maps of the features are smoothed by applying a Gaussian filter with a full-width half maximum (FWHM) of 2.5 times the unit distance between the center of the spots. **(c)** Then, the CCs of both features are discovered based on the spatial distance between spots by gradually lowering the feature values from the highest possible threshold value to the lowest value. **(d)** The resulting CCs, expressed as dendrograms, are smoothed based on the minimum size of the CCs and the persistence of each CC during the threshold lowering. **(e)** Finally, reconfigured CCs, represented by the uppermost bars of the dendrograms, are considered to be locally activated regions of the feature x and y.

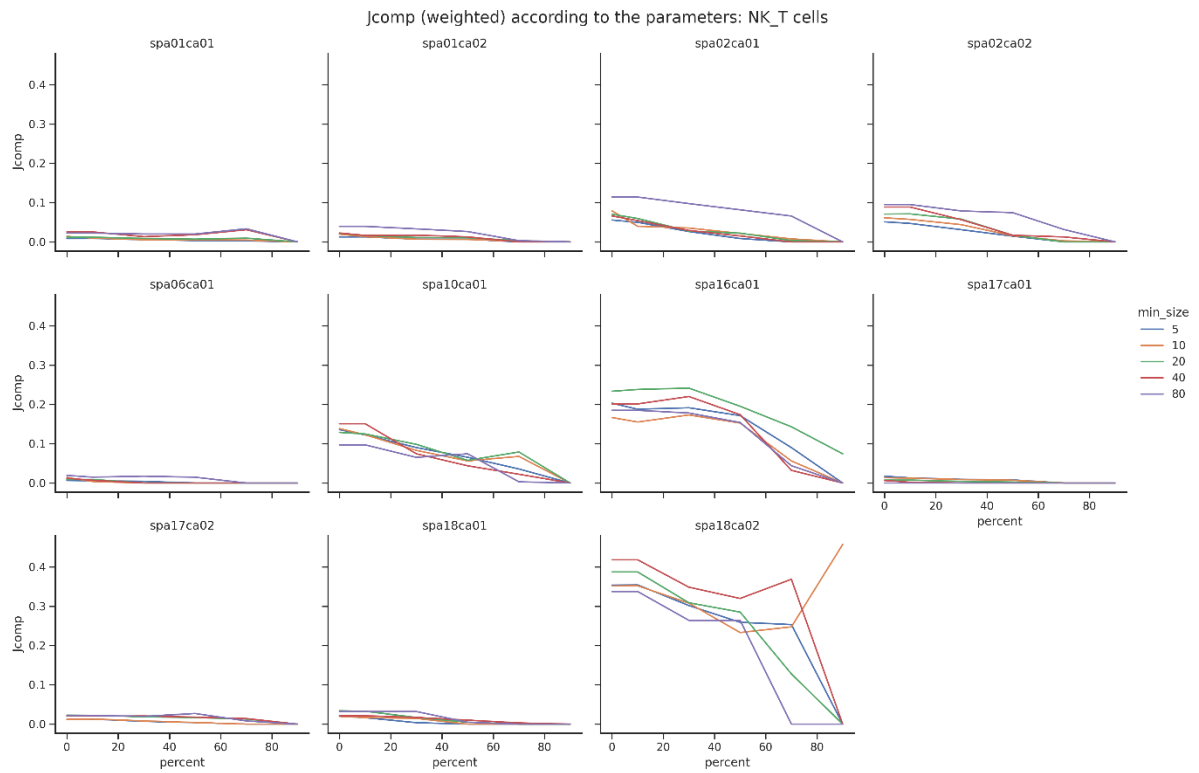
To remove the noise of the spatial map, the CCs with the feature value below the certain percentile threshold are removed, and the local and composite Jaccard indexes are calculated

between the final CCs of the feature pair (features x and y).

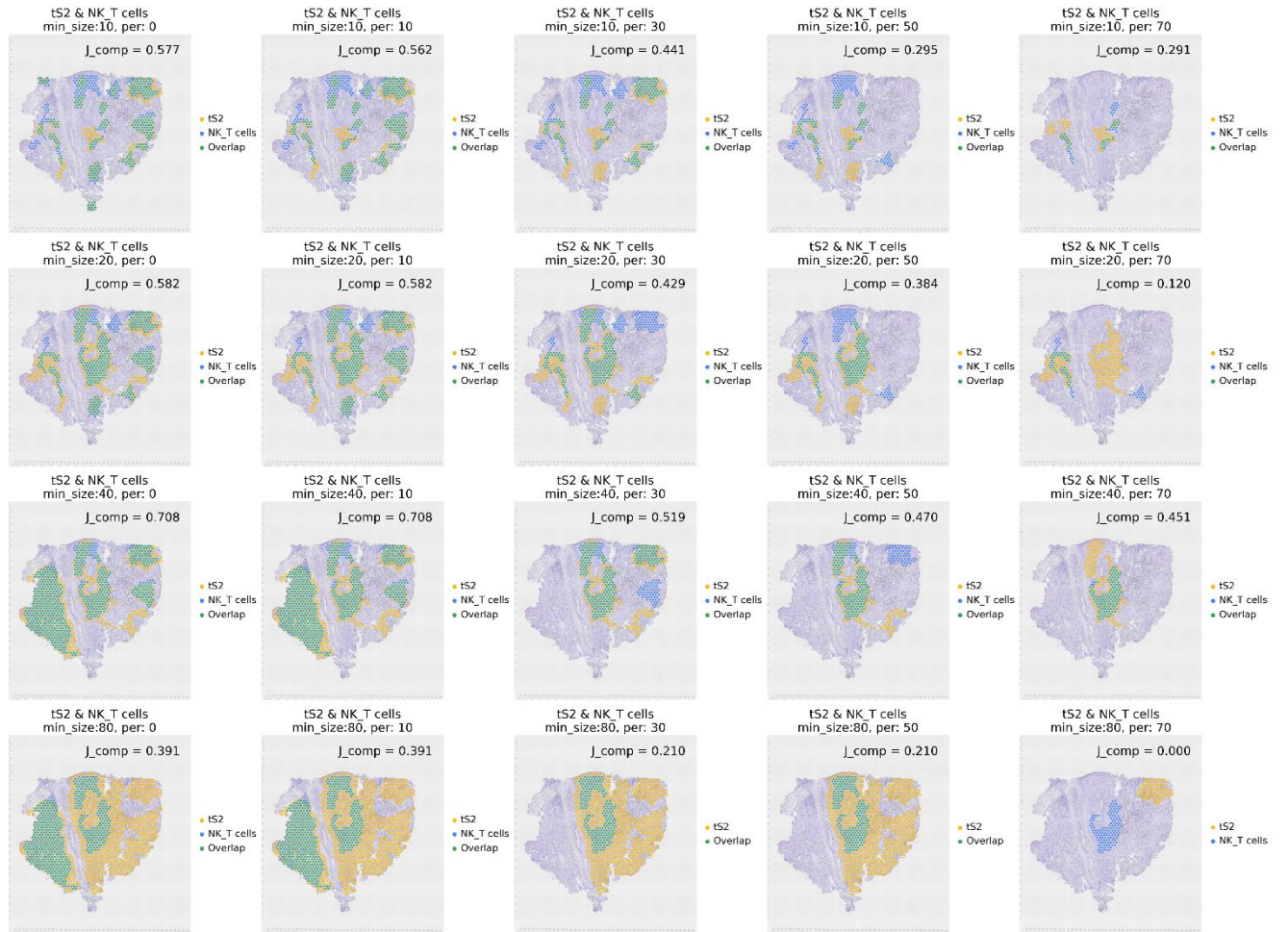
(a)



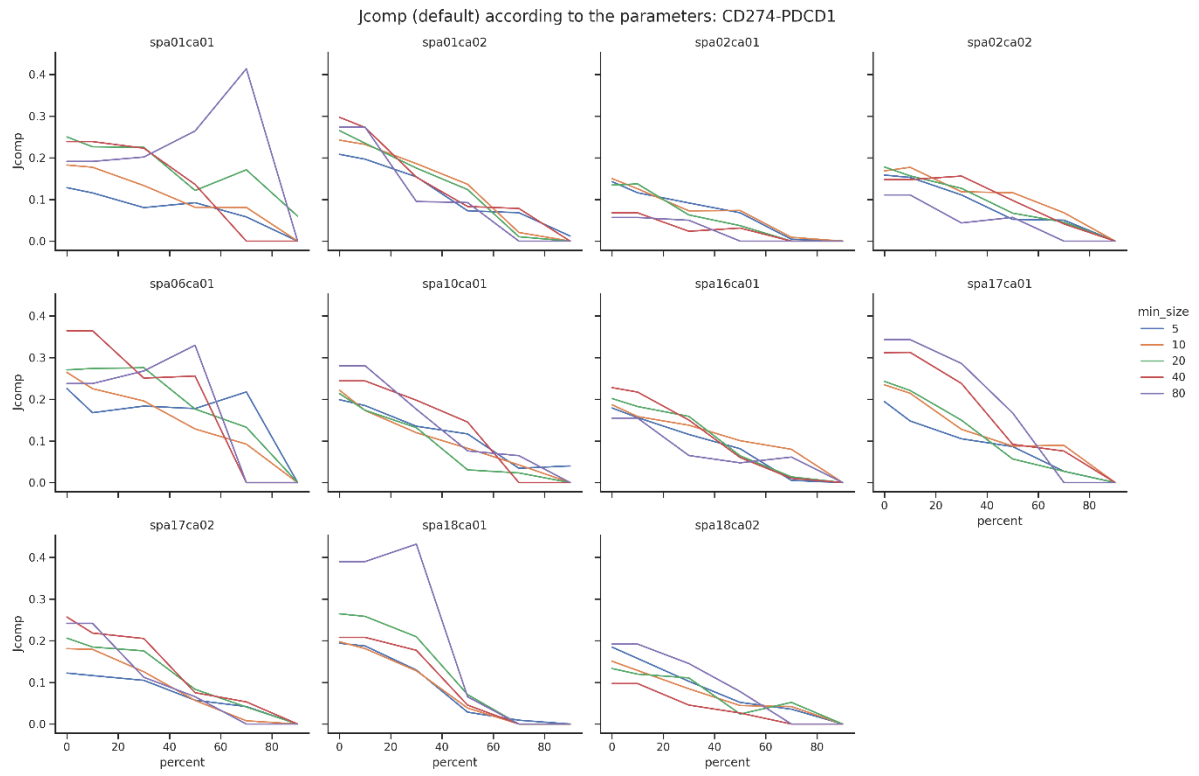
(b)



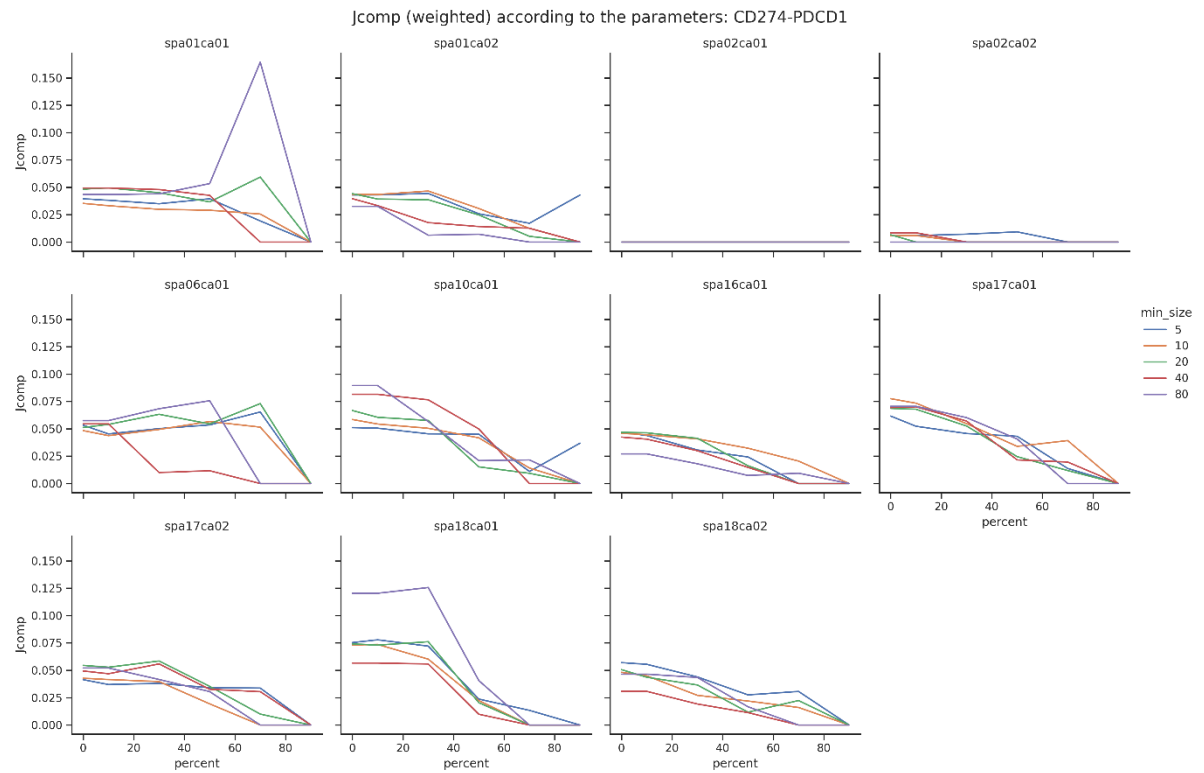
(c)



(d)



(e)



Supplementary Fig. 3. Parameter optimization for STopover

To determine the optimal parameter range for STopover, we computed set-based and weighted Jaccard indexes between tumor cells (tS2) and NK/T cells across a barcode-based dataset comprising 11 lung cancer tissues. We systematically varied two parameters: the minimum size of connected components (smin), represented by the number of spots or grids, and the percentile threshold used to eliminate connected components with low average feature values (pt). The range of minimum connected components extended from 10 to 80 (10, 20, 40, 80), while the percentile value varied from 0 to 70 (0, 10, 30, 50, 70). The line plot visualizes the changes in **(a)** set-based and **(b)** weighted Jaccard indexes as these parameters were adjusted.

(c) In one of the barcode-based SRT datasets of lung cancer (spa18ca02), we calculated the aggregated connected components between tS2 and NK/T cells while varying these two parameters. The set-based Jcomp values are displayed in the top right corner of the plot.

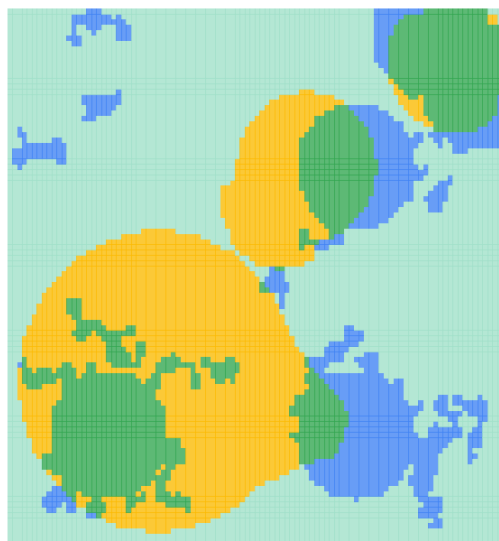
Additionally, we evaluated the optimal parameter range for STopover when applied to the ligand-receptor pair, *CD274-PDCD1*, which exhibits sparse expression patterns. The line plot depicts the changes in **(d)** set-based and **(e)** weighted Jaccard indexes as parameters were adjusted in this specific context.



Supplementary Fig. 4. Aggregated CCs obtained across various parameters in simulated dataset

The aggregated CCs were computed between the simulated tumor and immune distributions by changing two parameters: the minimum size of CCs, represented by the number of spots or grids, and the percentile threshold for removing the CCs with low average feature values. The minimum number of CCs was varied from 10 to 80 (10, 20, 40, 80), and the percentile value was varied from 0 to 70 (0, 10, 30, 50, 70). The set-based J_{comp} values are displayed in the top right corner of the plot.

a Tumor & Immune: STopover



$J_{comp} = 0.061$

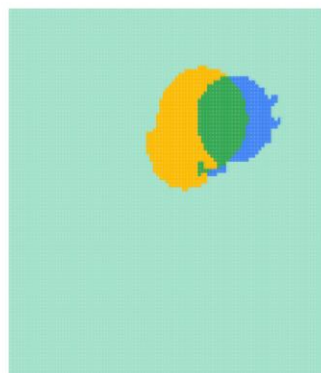
Others
Tumor
Immune
Overlap

b Tumor & Immune
top 1 CCxy



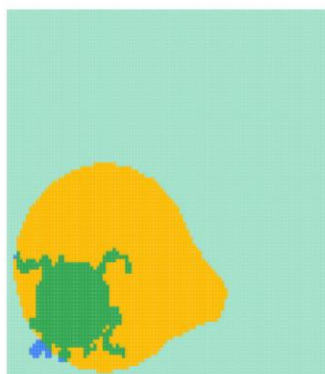
$J_{local} = 0.223$

Tumor & Immune
top 2 CCxy



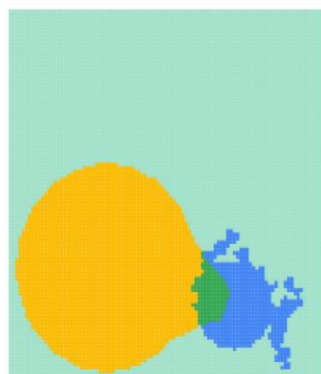
$J_{local} = 0.055$

Tumor & Immune
top 3 CCxy



$J_{local} = 0.041$

Tumor & Immune
top 4 CCxy



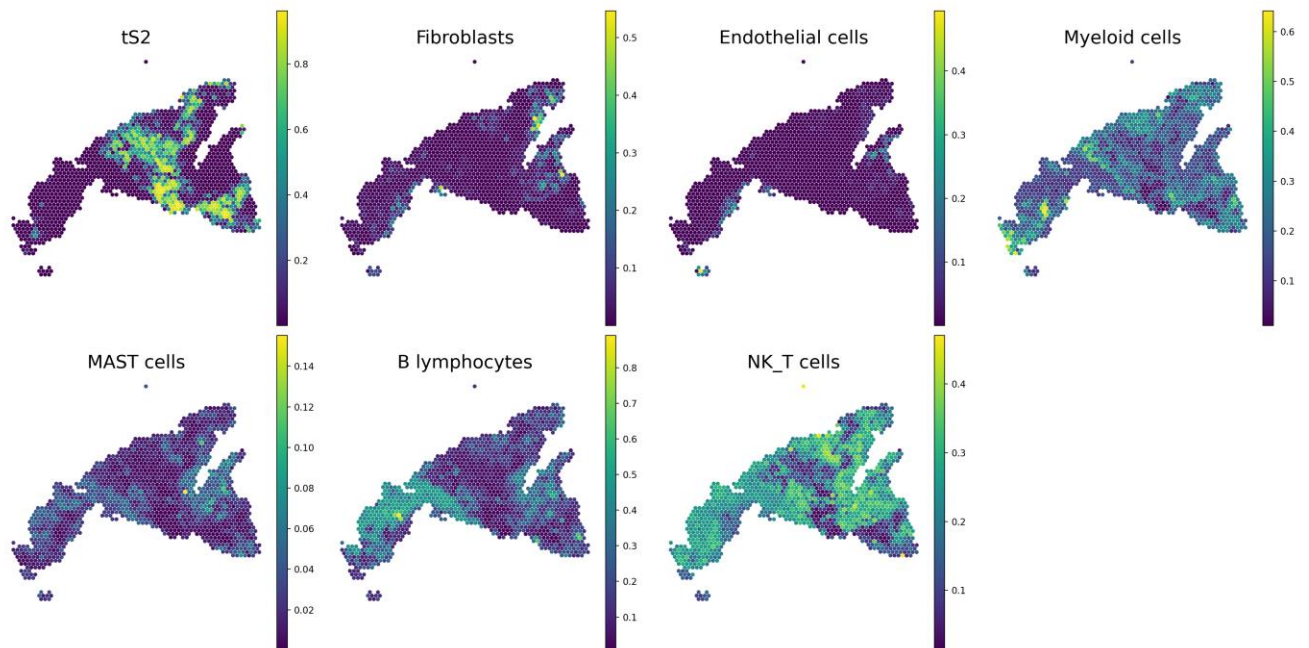
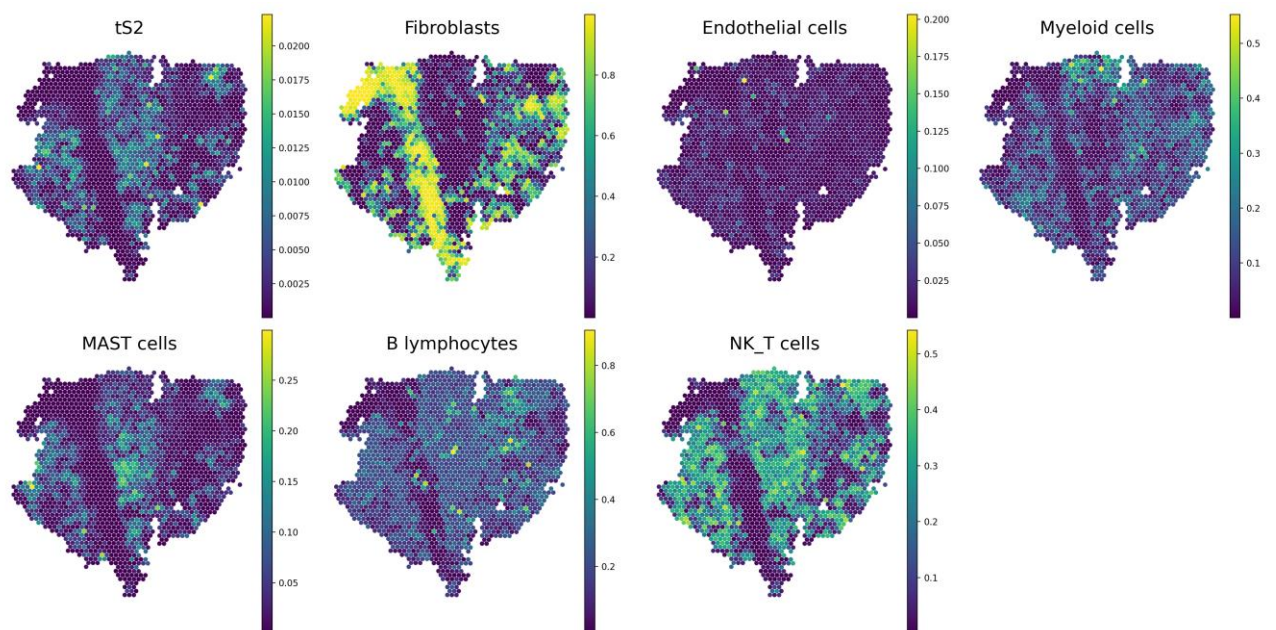
$J_{local} = 0.009$

Others
Tumor
Immune
Overlap

Supplementary Fig. 5. Calculation of weighted Jaccard index from the extracted CC pairs in the simulation dataset.

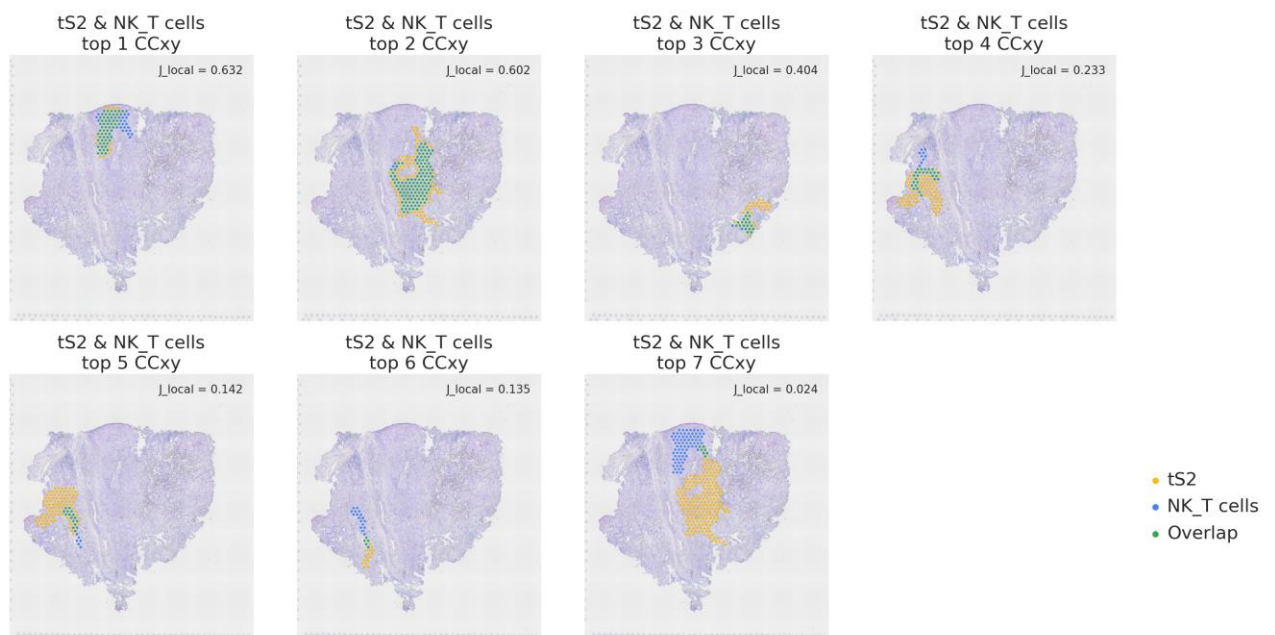
(a) Visualization of the connected components (CCs) for tumor cells (yellow) and immune cells (blue), along with the intersecting subregions (green) between the two combined CCs on the grid. The weighted Jaccard index was computed between these combined CCs (J_{comp}).

(b) Visualization of the top 4 CC pairs with the highest spatial overlap, as indicated by the J_{local} score, between tumor and immune cells. CCs from tumor cells (yellow), immune cells (blue), and intersecting subregions (green) are displayed on the grid. The weighted Jaccard indexes were computed for each CC pair.

a**PD-L1 low tissue (*spa06ca01*)****b****PD-L1 high tissue (*spa18ca02*)**

Supplementary Fig. 6. Spatial distribution of tS2 and other main cell types composing the lung cancer tissue in barcode-based SRT.

The spatial composition of tS2 and other main cell types (fibroblasts, endothelial cells, myeloid cells, MAST cells, B lymphocytes, and NK/T cells), in representative **(a)** PD-L1 low (*spa6ca01*) and **(b)** high tissues (*spa18ca02*) were estimated and visualized.

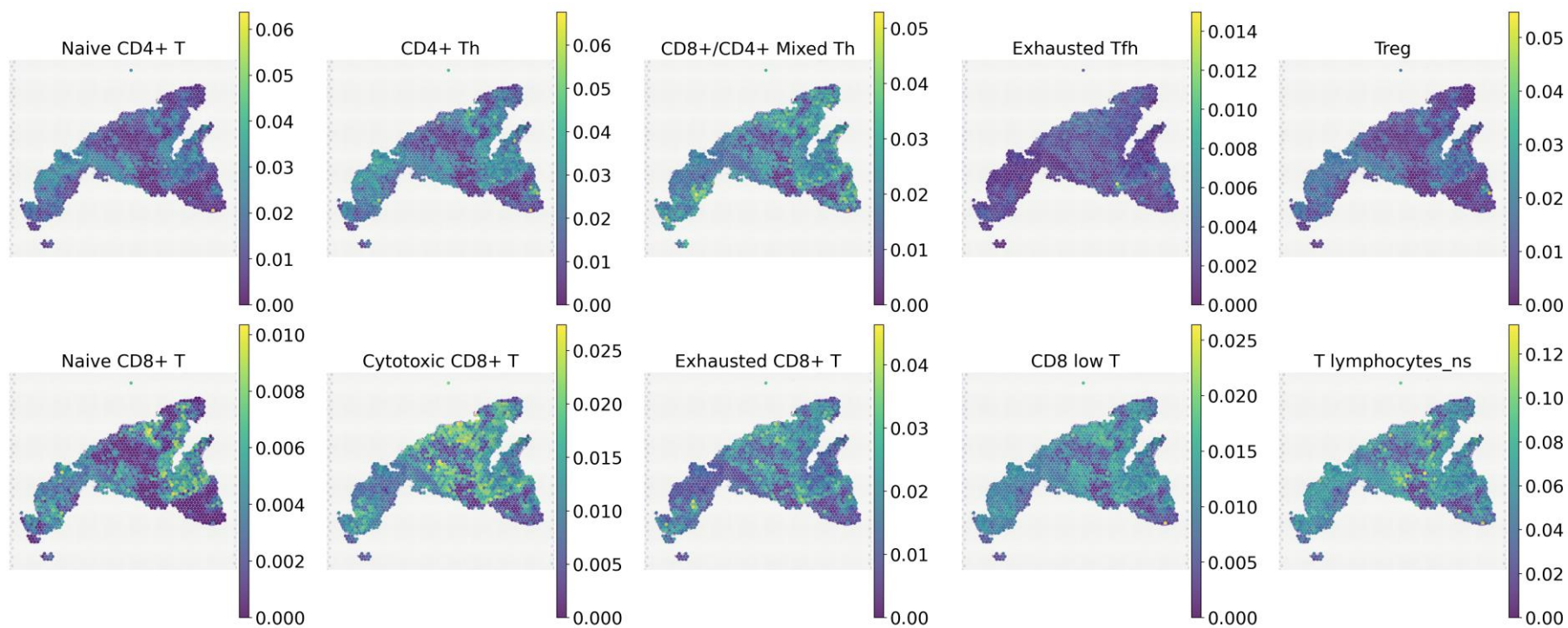
a**b**

Supplementary Fig. 7. The location of the top CC pairs between tS2 and NK/T cells in a PD-L1 high lung cancer tissue (*spa18ca02*)

The pairs of CCs between tS2 and either **(a)** MAST cells or **(b)** NK/T cells were extracted using STopover. The top pairs with the highest J_{local} were then visualized in the descending order of J_{local} values.

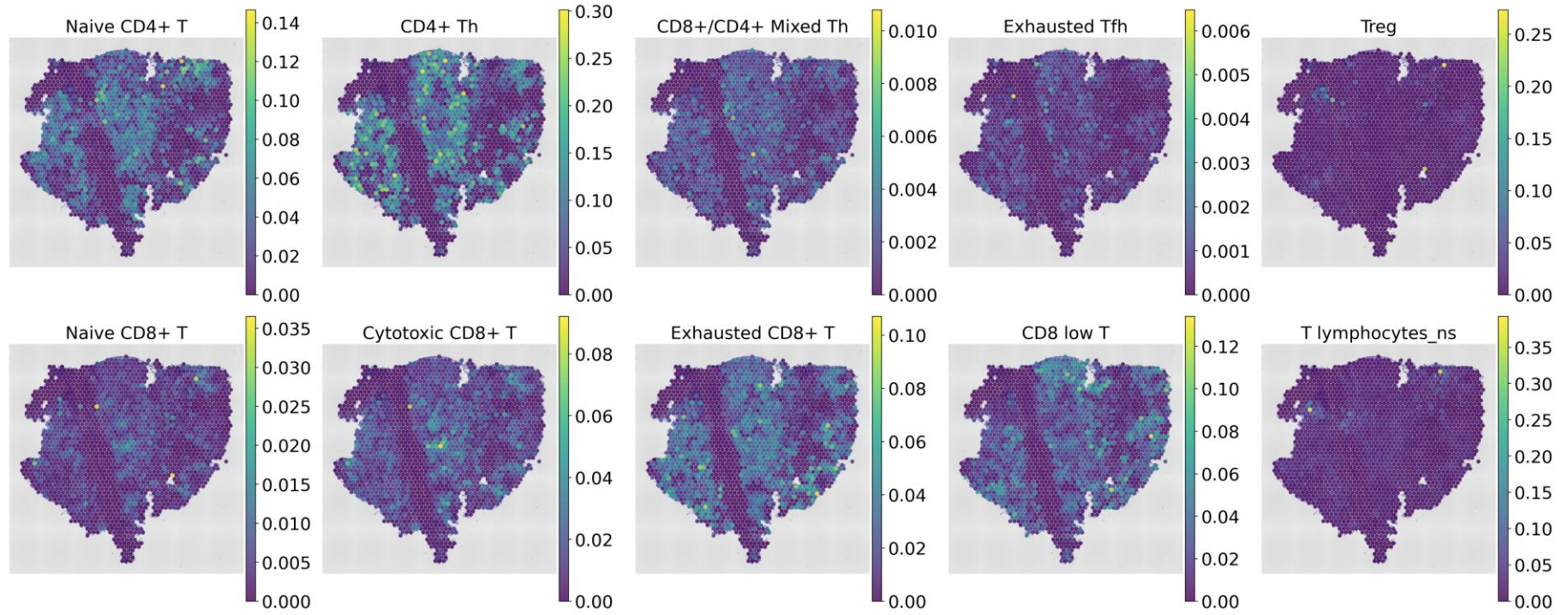
a

PD-L1 low tissue (*spa06ca01*)



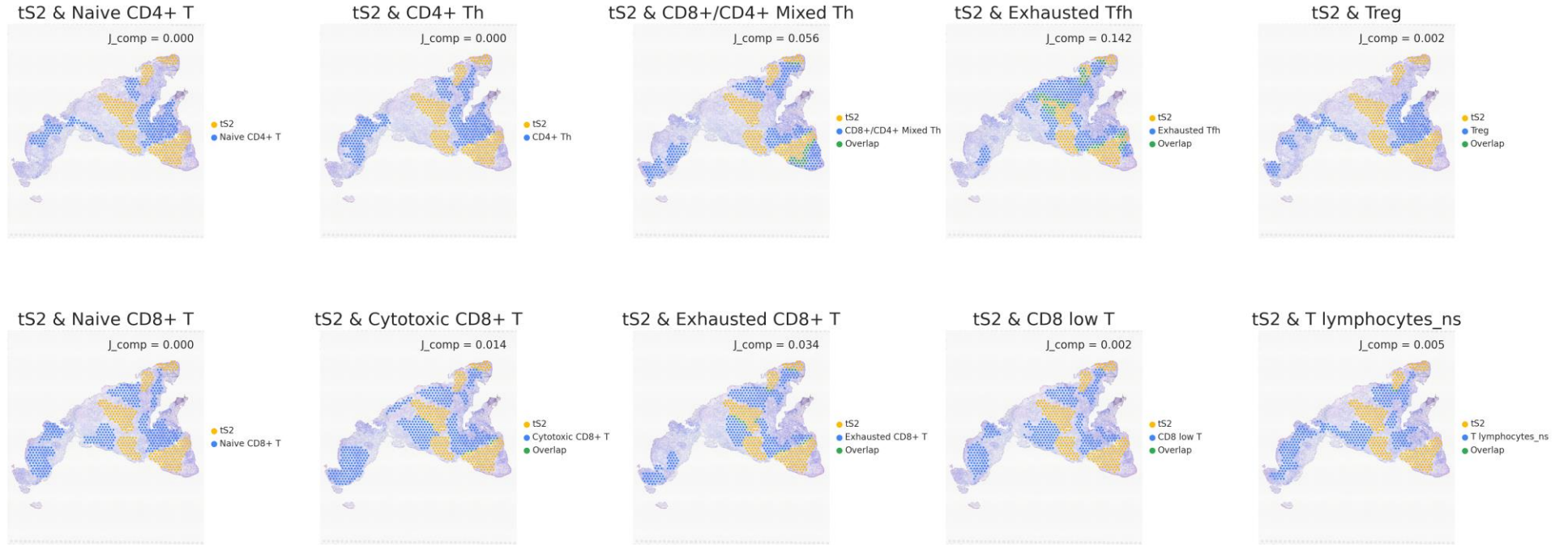
b

PD-L1 high tissue (*spa18ca02*)



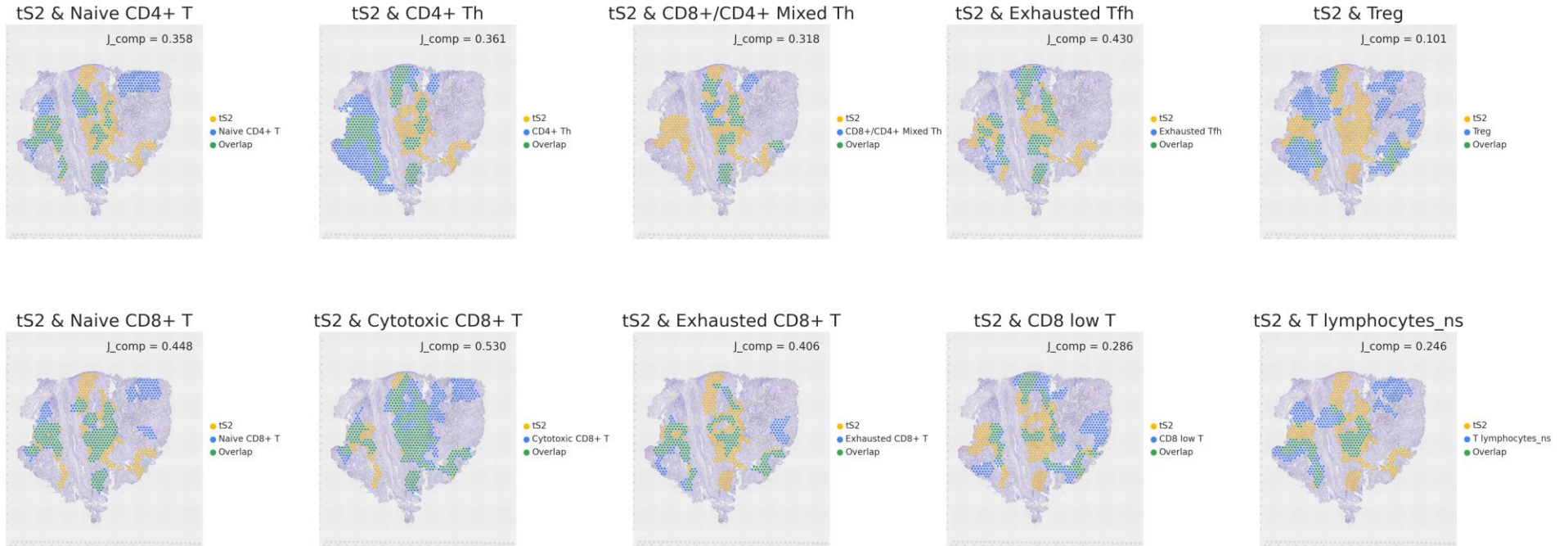
c

PD-L1 low tissue (*spa06ca01*)



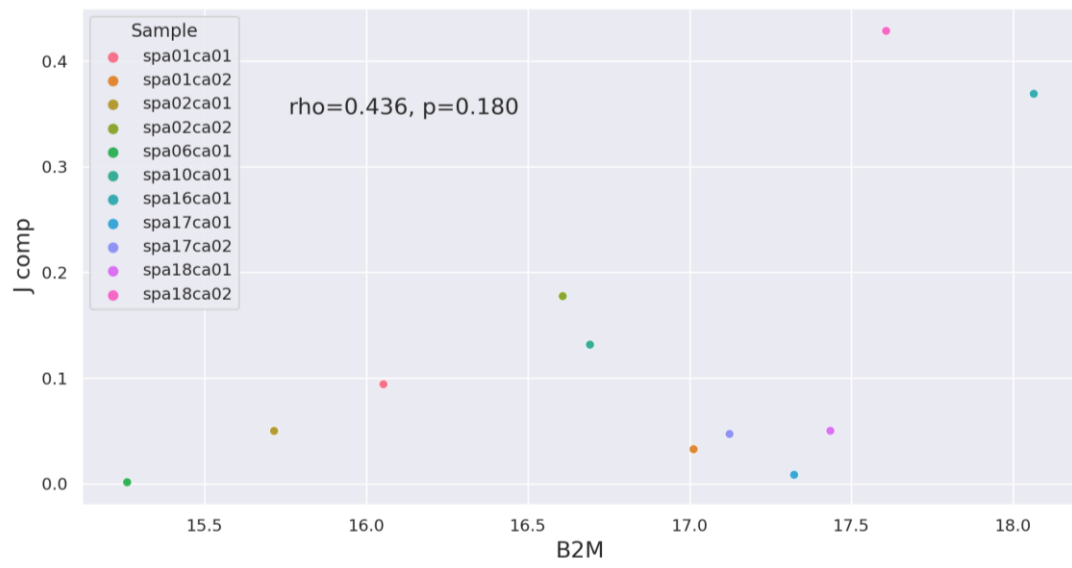
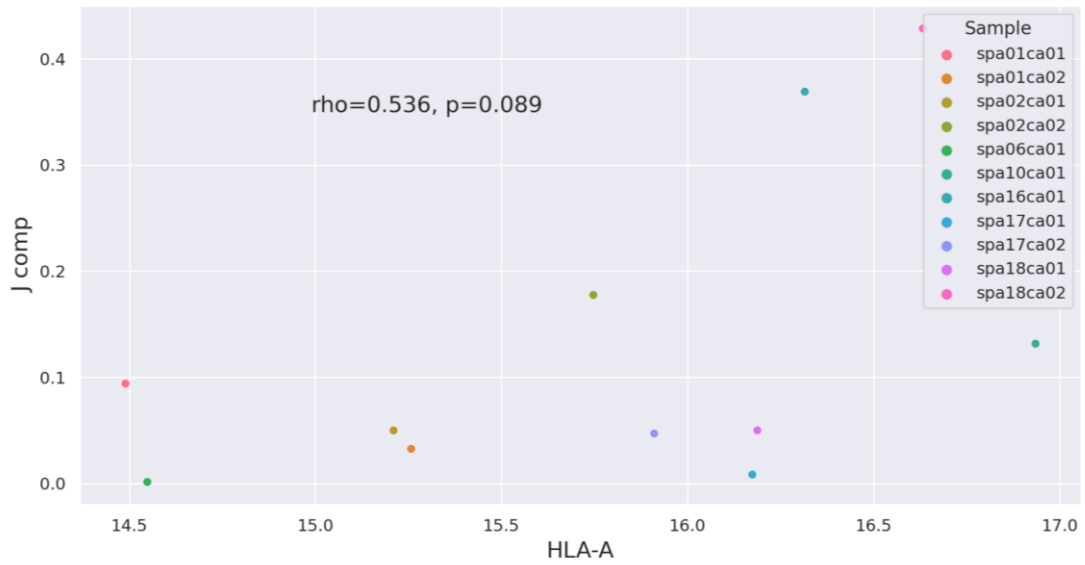
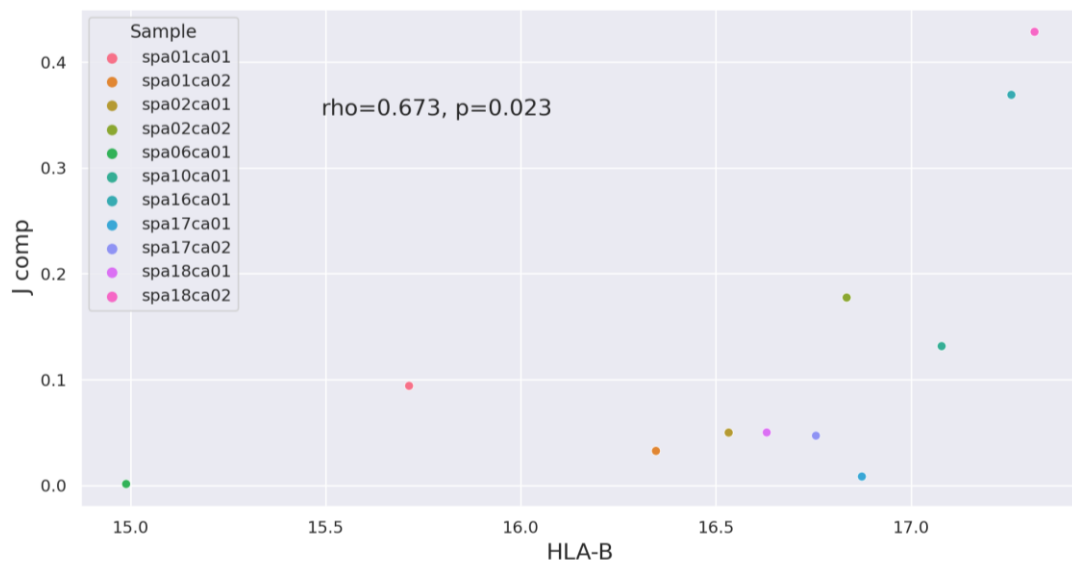
d

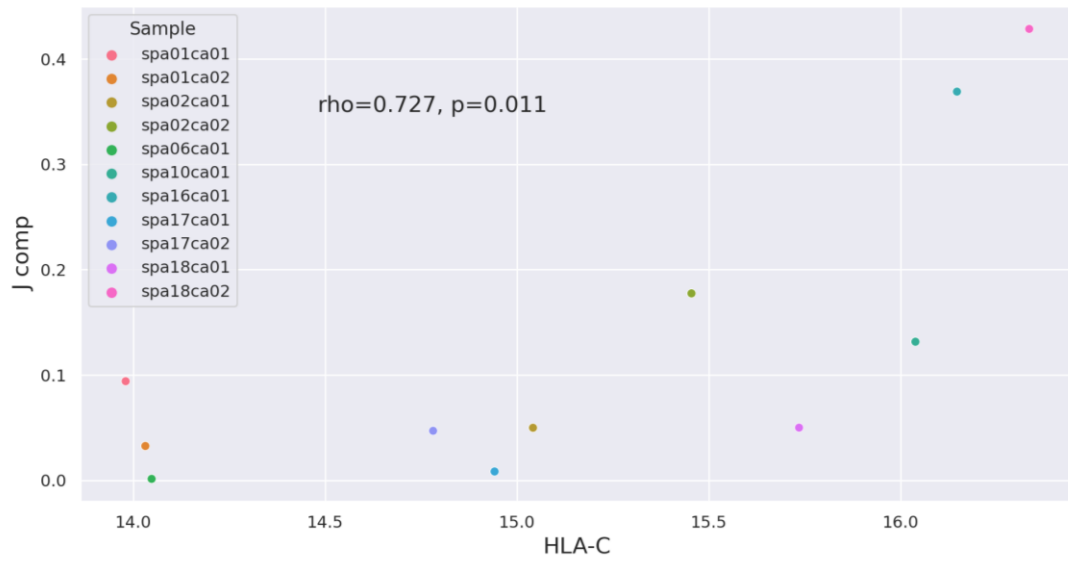
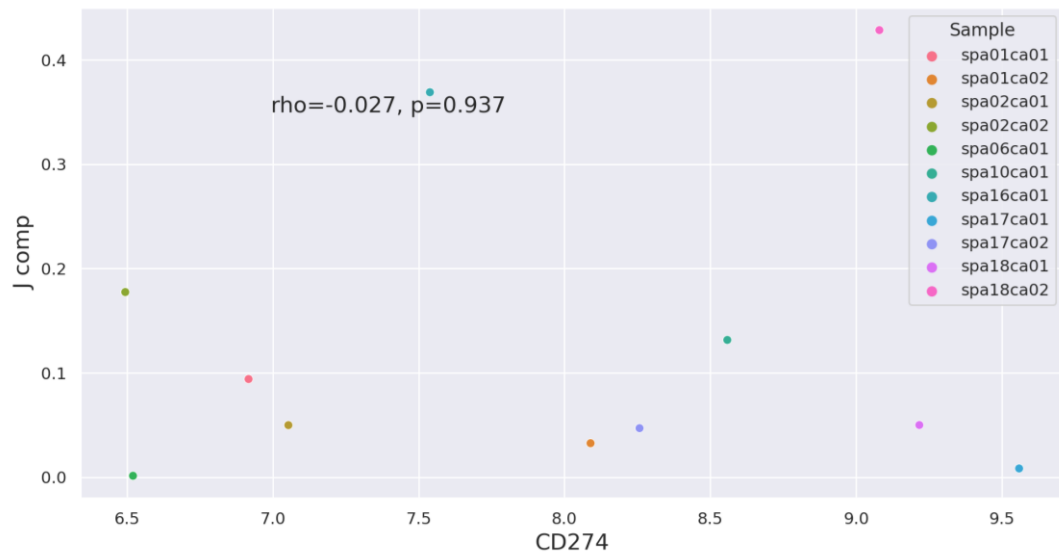
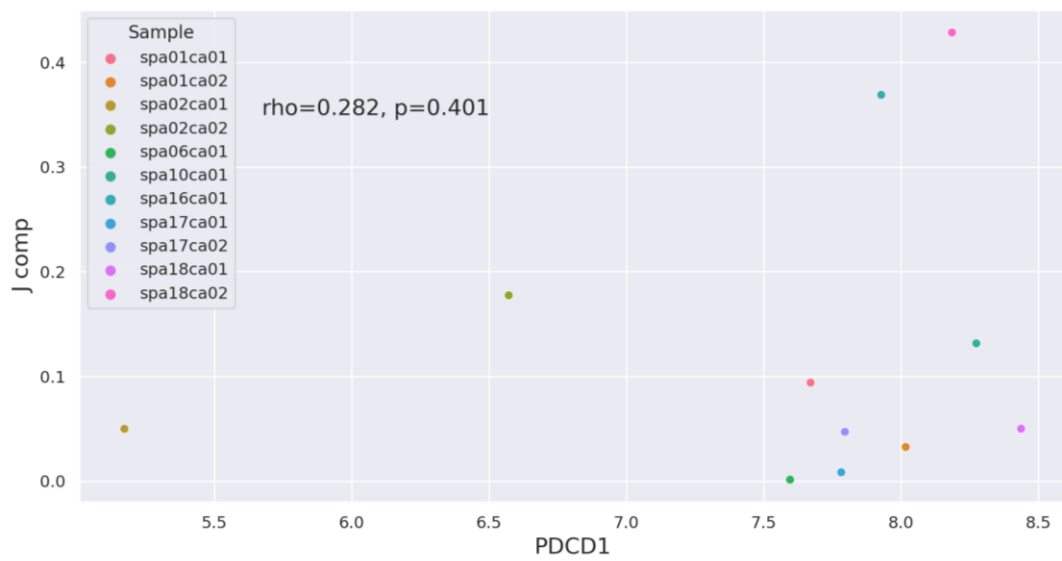
PD-L1 high tissue (*spa18ca02*)



Supplementary Fig. 8. Colocalization patterns between tS2 and multiple T cell subtypes in barcode-based SRT of lung cancer

The spatial composition of multiple T cell subtypes, in representative **(a)** PD-L1 low (*spa6ca01*) and **(b)** high tissues (*spa18ca02*) were estimated and visualized. Then, the key location of tS2 and multiple T cells subtypes were represented by CCs, and the overlapping tissue domains were highlighted as the intersecting subregions between the two aggregated CCs. The analysis was performed in the two representative **(c)** PD-L1 low (*spa6ca01*) and **(d)** high tissues (*spa18ca02*).

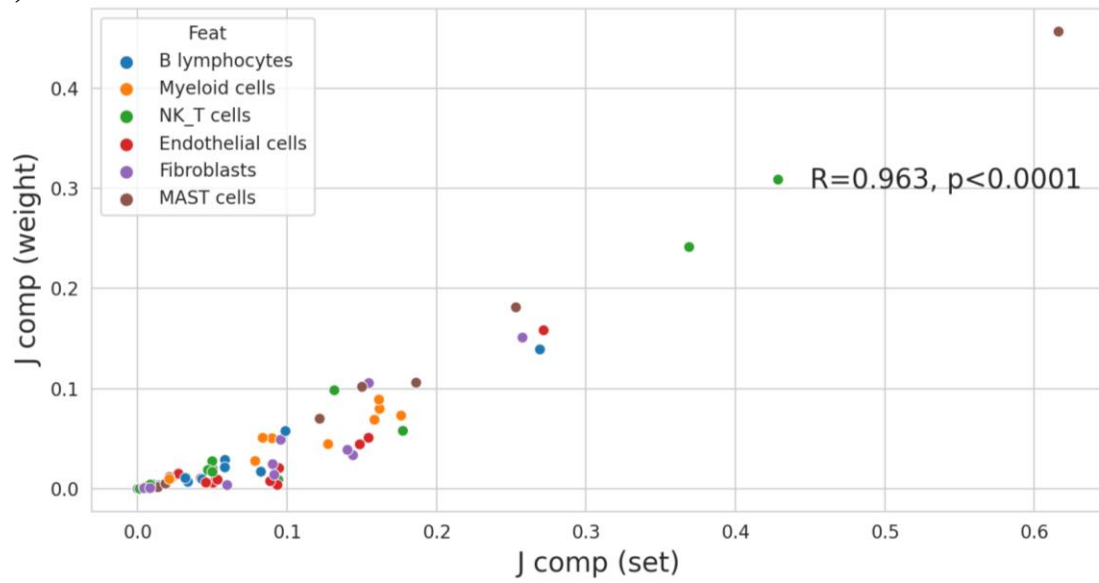
a**b****c**

d**e****f**

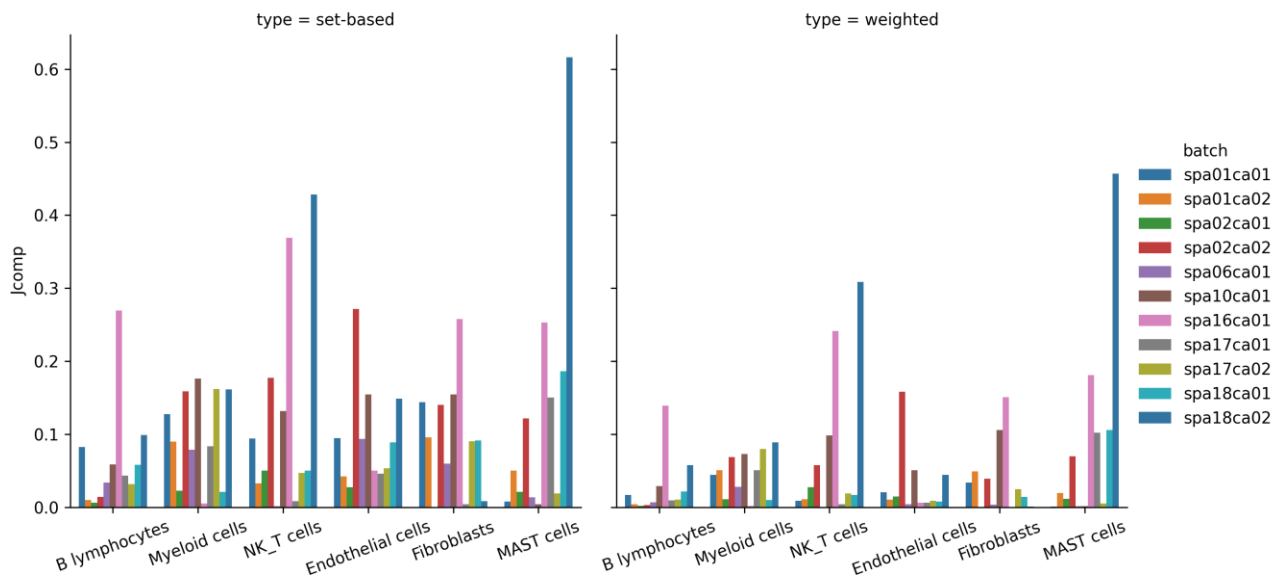
Supplementary Fig. 9. Scatter plots between pseudobulk RNA expression and J_{comp} value of tS2 and NK/T cells

The scatter plot displays the correlation between pseudobulk RNA expression of (a) B2M, (b) HLA-A, (c) HLA-B, (d) HLA-C, (e) CD274, and (f) PDCD1, which were calculated by log-transforming the total RNA counts, and the J_{comp} value, which represents the extent of spatial overlap between tS2 and NK/T cells. The plot visualizes the data points obtained from 11 lung cancer tissues. The Spearman's correlation coefficient is calculated and shown in the top right corner of each plot.

(a)



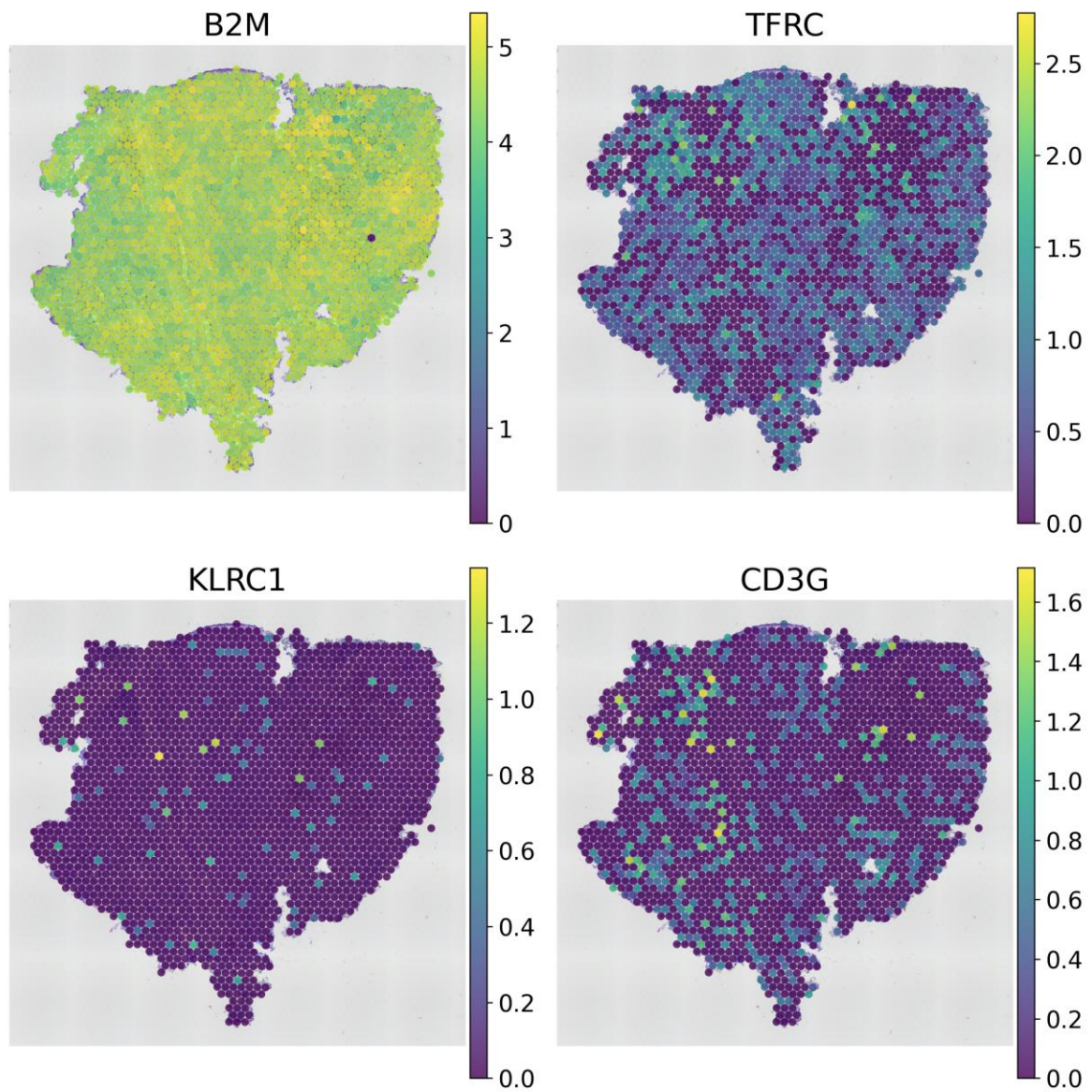
(b)



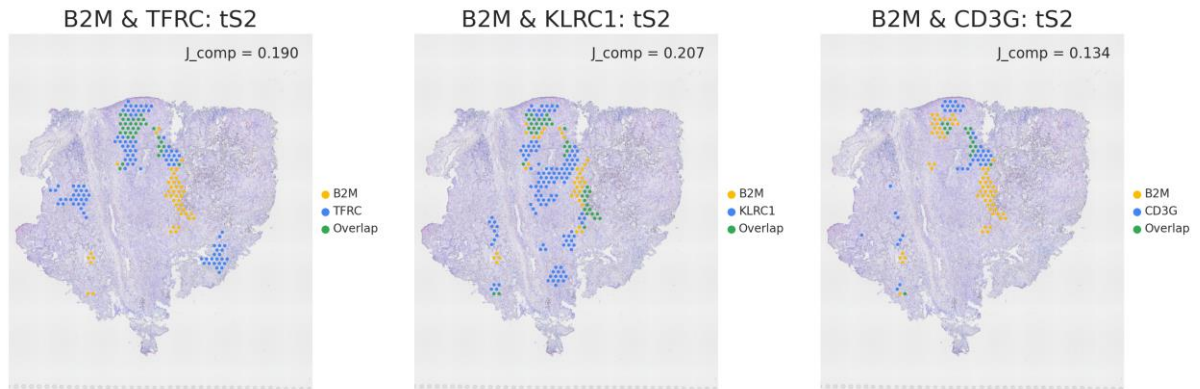
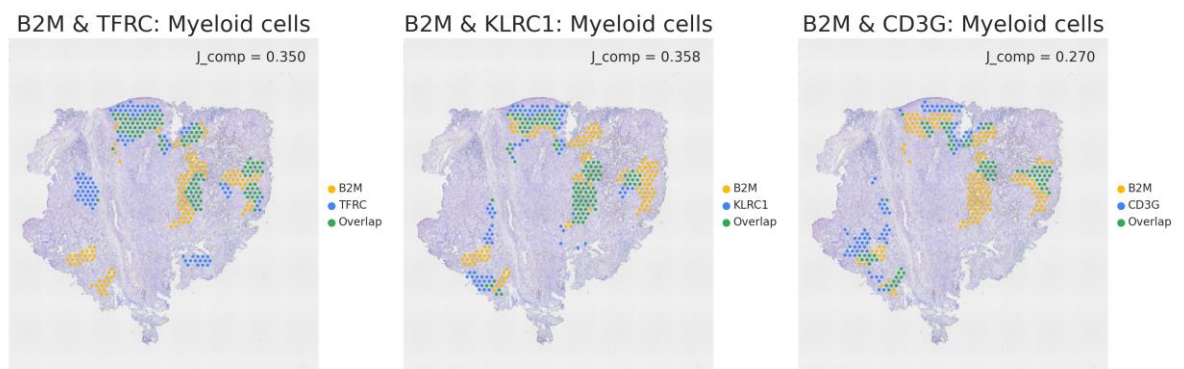
Supplementary Fig. 10. Comparison of set-based and weighted Jaccard index across 11 barcode-based SRT of lung cancer

(a) The scatter plot displays the correlation between set-based and weighted Jaccard index between tumor cells (tS2) and other cell types (B lymphocytes, myeloid cells, NK/T cells, endothelial cells, fibroblasts, and mast cells) in 11 lung cancer tissues.

(b) Comparison of set-based (left panel) and weighted (right panel) Jaccard indexes between tumor cells (tS2) and each cell type across 11 lung cancer tissues.

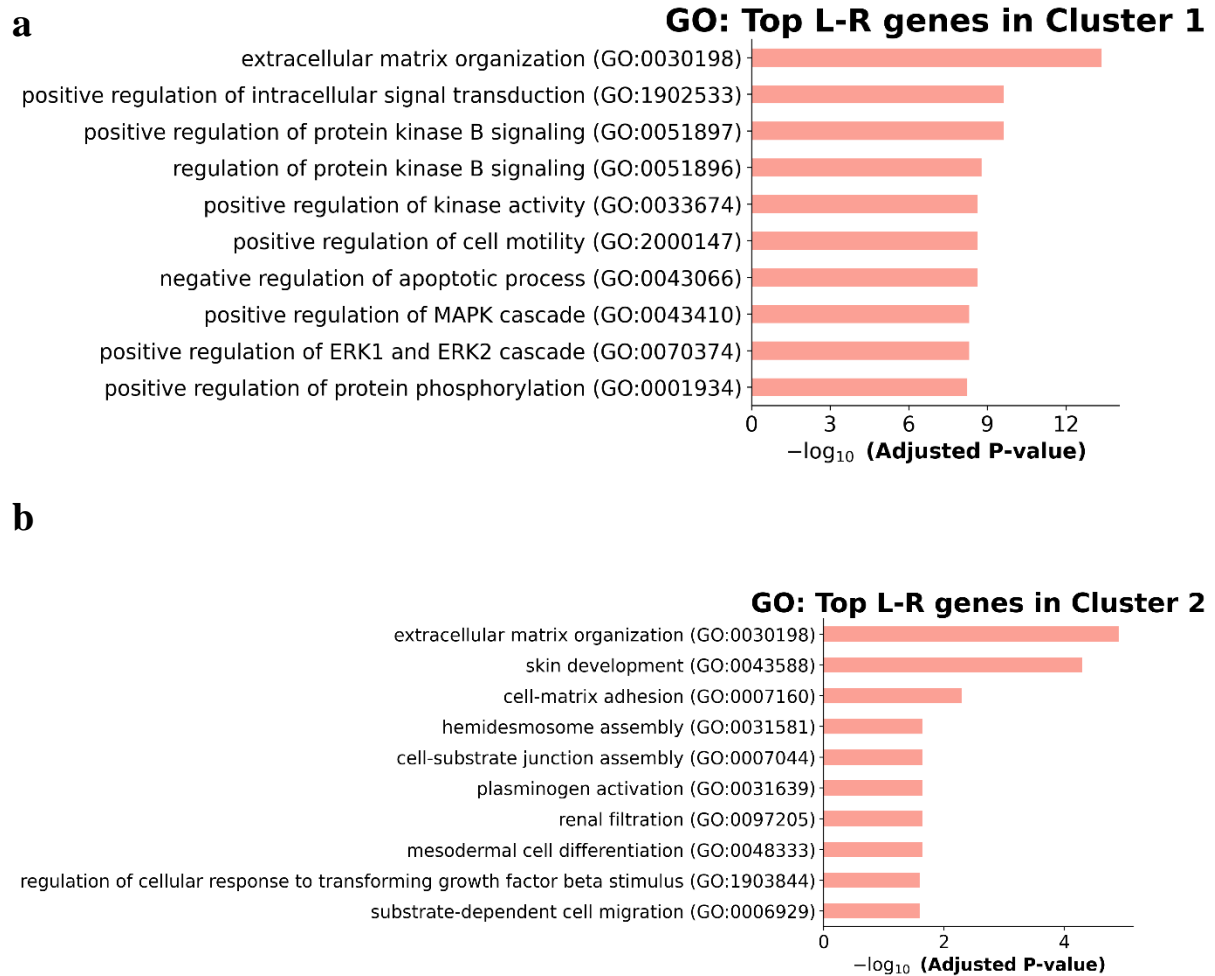


Supplementary Fig. 11. Spatial expression of the top 3 ligand-receptor pairs in PD-L1 high lung cancer tissue (*spa18ca02*)

a**b**

Supplementary Fig. S12. The spatial overlap patterns of the top ligand-receptor (LR) pairs constrained to the tS2 or myeloid cell domain in PD-L1 high lung cancer tissue (*spa18ca02*)

The aggregated CCs of the top three LR pairs ($J_{comp} > 0.2$) with high ligand gene expression and J_{comp} values, were extracted. Then, the intersecting regions between the two aggregated CCs of each LR pair and CCs calculated from either (a) tumor cells (tS2) or (b) myeloid cells were extracted. The location of modified CCs was mapped to the tissue and J_{comp} values were computed between the two modified CCs.

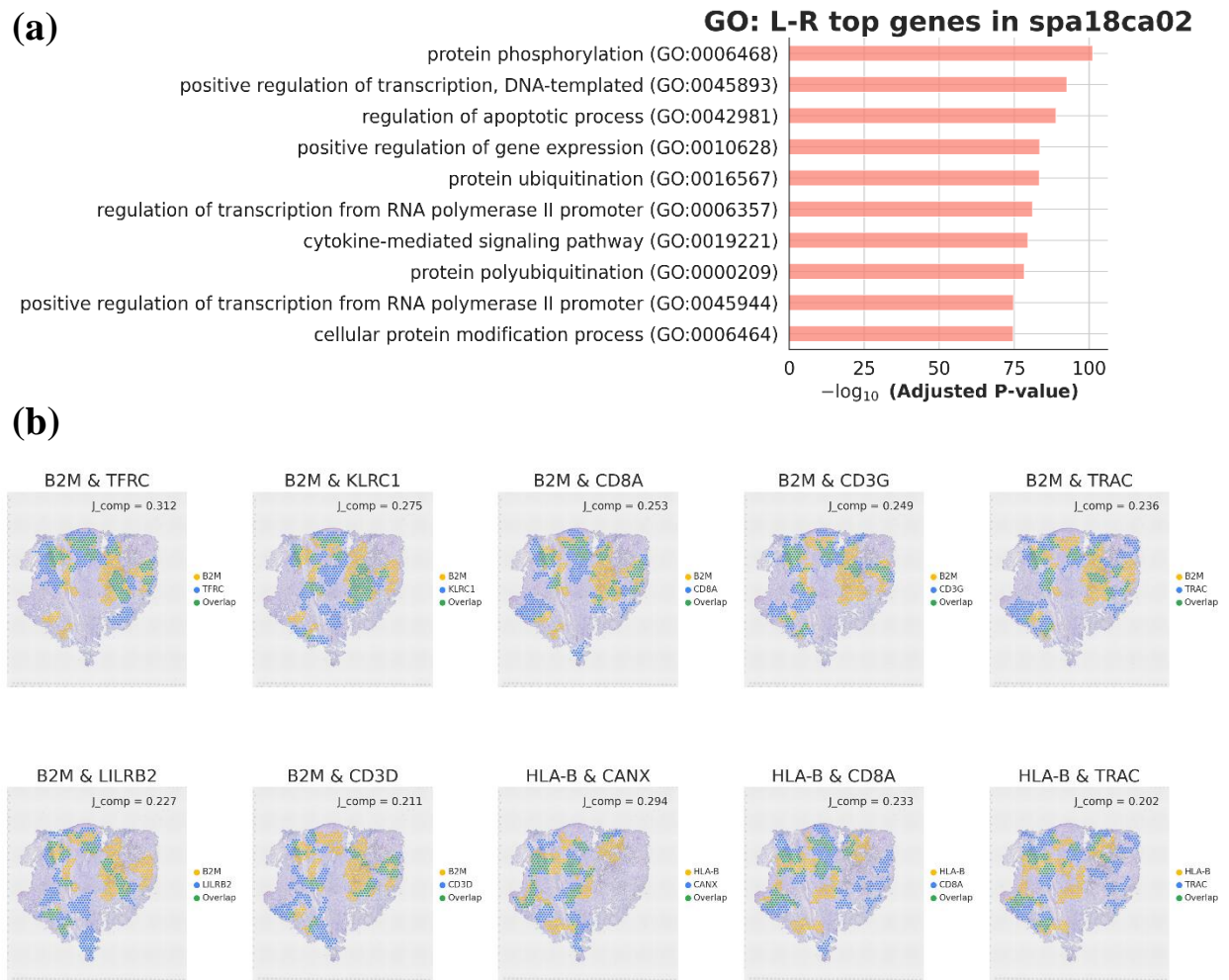


Supplementary Fig. 13. The common top ligand-receptor (LR) interactions in Clusters 1 and 2 defined by infiltration patterns of immune and stromal cells to tumor cells.

Please refer to Fig. 4a for definition of Clusters 1 and 2.

(a) Gene Ontology (GO) analysis was conducted for the top common colocalized LR pairs in Cluster 1 based on a J_{comp} threshold of 0.2. The enriched biological process terms are listed in ascending order of adjusted p-values.

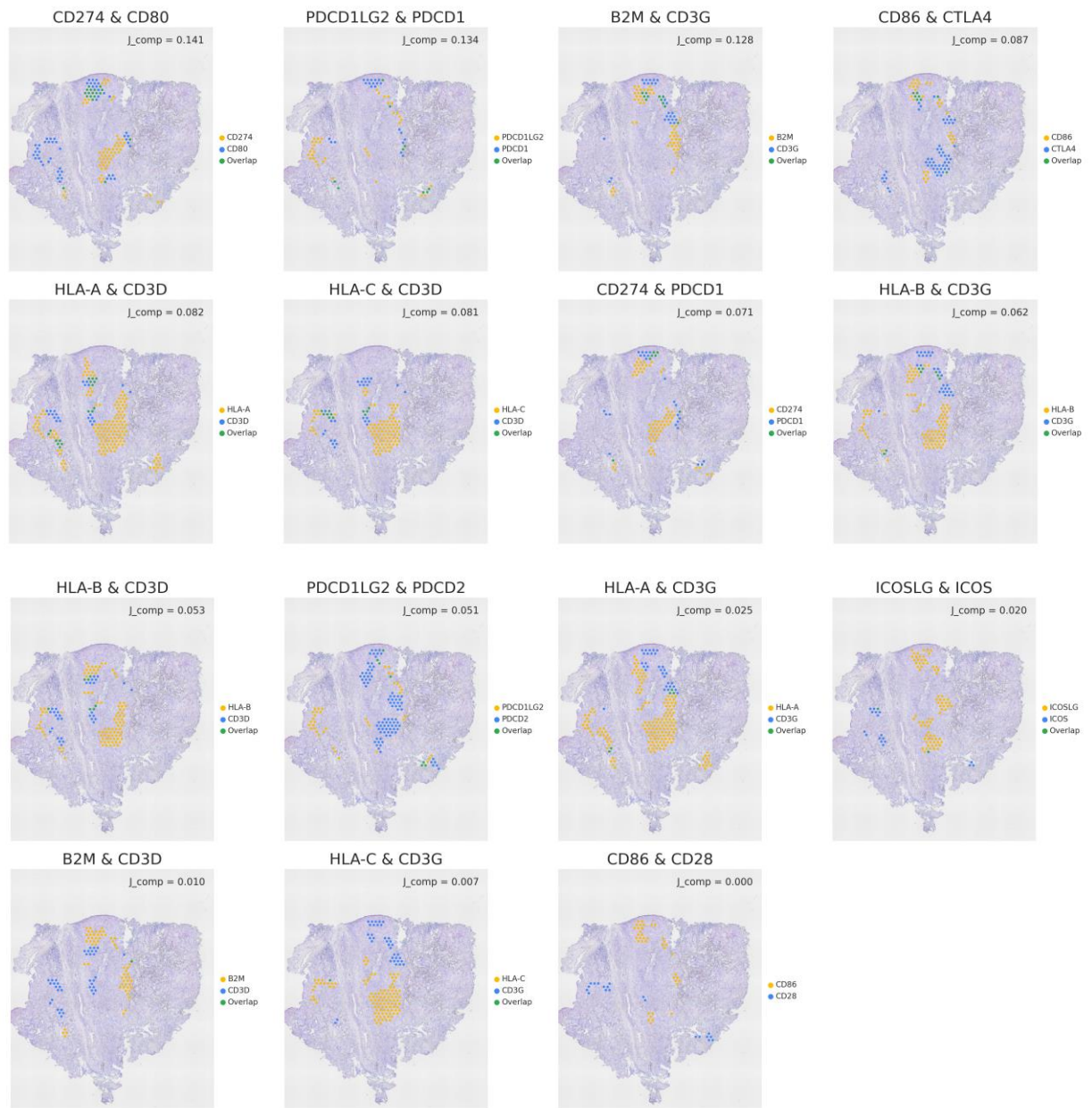
(b) Gene Ontology (GO) analysis was conducted for the top common colocalized LR pairs in Cluster 2 based on a J_{comp} threshold of 0.2. The enriched biological process terms are listed in ascending order of adjusted p-values.



Supplementary Fig. 14. The top ligand-receptor (LR) interactions estimated by STopover using the Omnipath database.

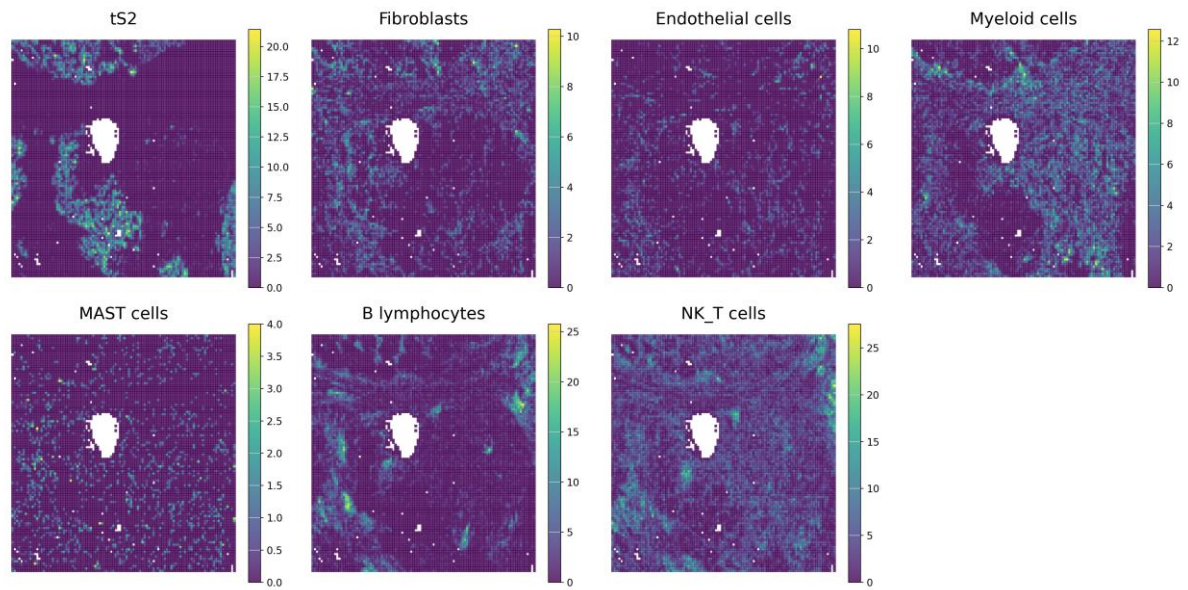
(a) Gene Ontology (GO) analysis was conducted for the top colocalized LR pairs selected based on a J_{comp} threshold of 0.2. The enriched biological process terms are listed in ascending order of adjusted p-values.

(b) The locations of connected components (CCs) for the top 10 LR pairs showing the highest average ligand gene expression in the tissue and the highest J_{comp} value were mapped onto the tissue. CC locations for features x and y are colored yellow and blue, respectively, while intersection locations are shown in green.



Supplementary Fig. 15. The spatial overlap patterns of the T cell action-related LR pairs constrained to the tS2 and NK/T cell colocalized domain in PD-L1 high lung cancer tissue (*spa18ca02*)

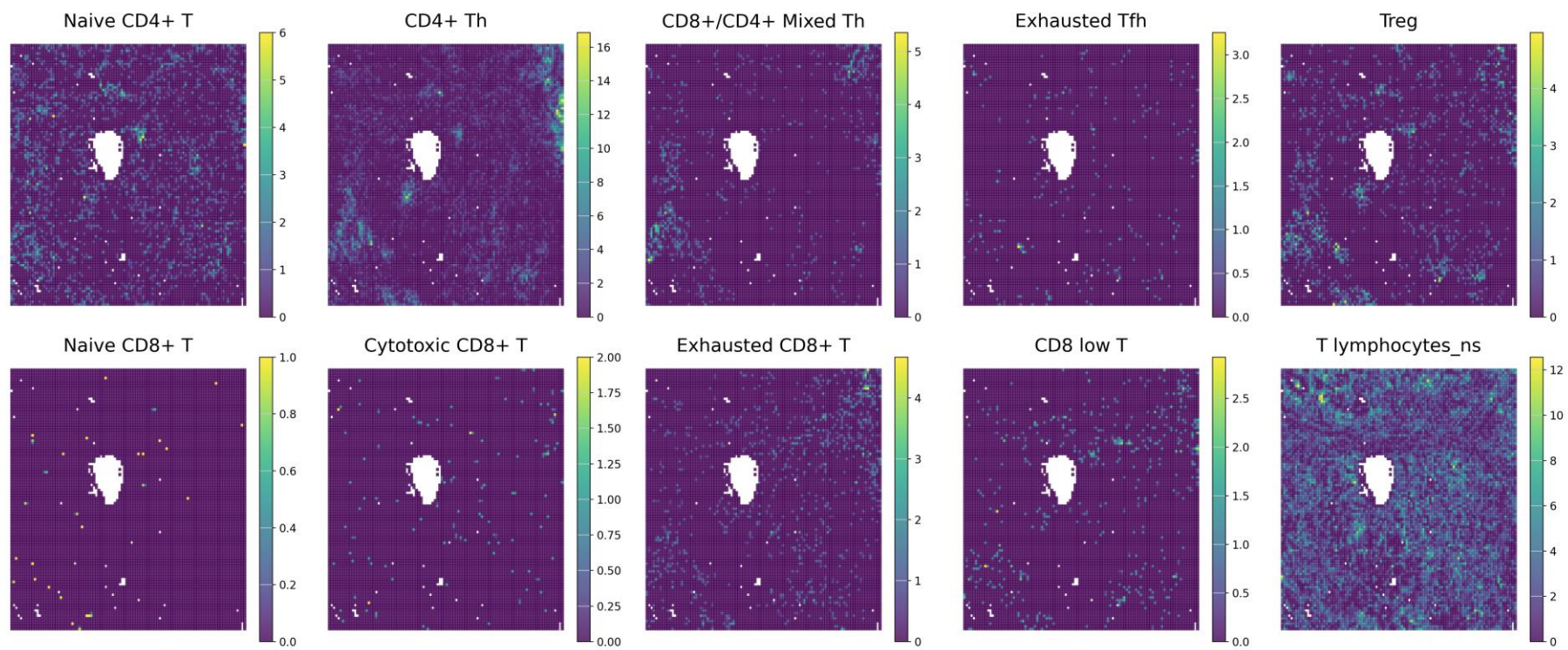
The aggregated CCs were extracted for the T cell action-related LR pairs. Then, the intersecting regions between the two aggregated CCs of each LR pair and the colocalized domain of tS2 and NK/T cells were extracted. The location of the modified CCs was mapped to the tissue, and J_{comp} values were computed between the two modified CCs.



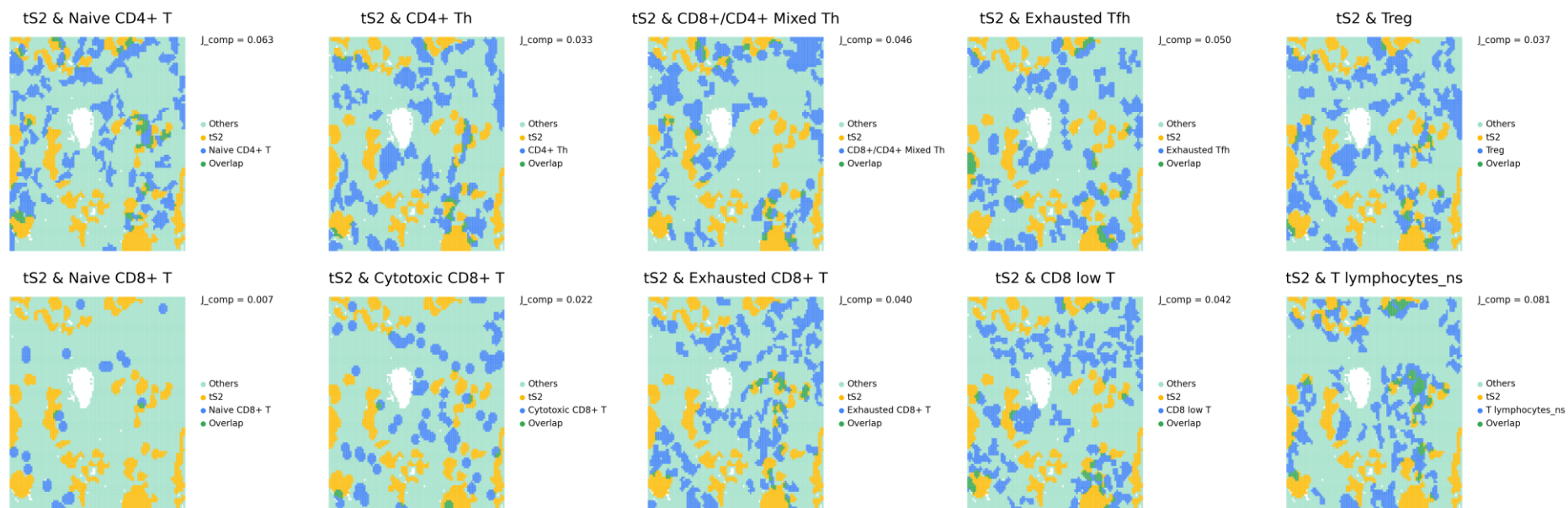
Supplementary Fig. 16. Spatial distribution of tS2 and other main cell types composing the lung cancer tissue in image-based SRT.

The spatial map showing the abundance of tumor cells (tS2) and other main cell types (fibroblasts, endothelial cells, myeloid cells, MAST cells, B lymphocytes, and NK/T cells) were visualized on the transformed grid.

(a)



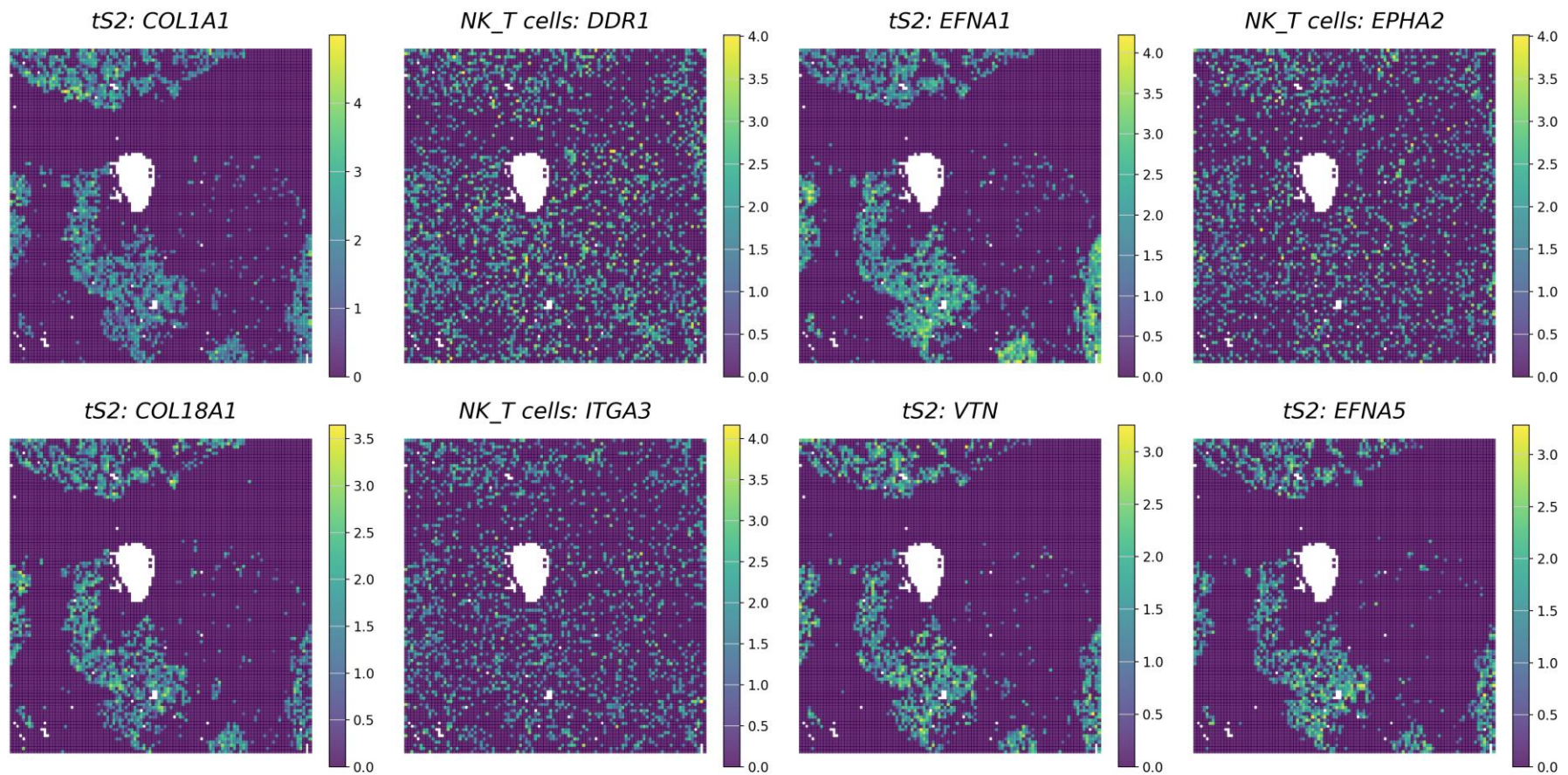
(b)



Supplementary Fig. 17. The colocalization patterns between tS2 and multiple T cell subtypes in image-based SRT of lung cancer

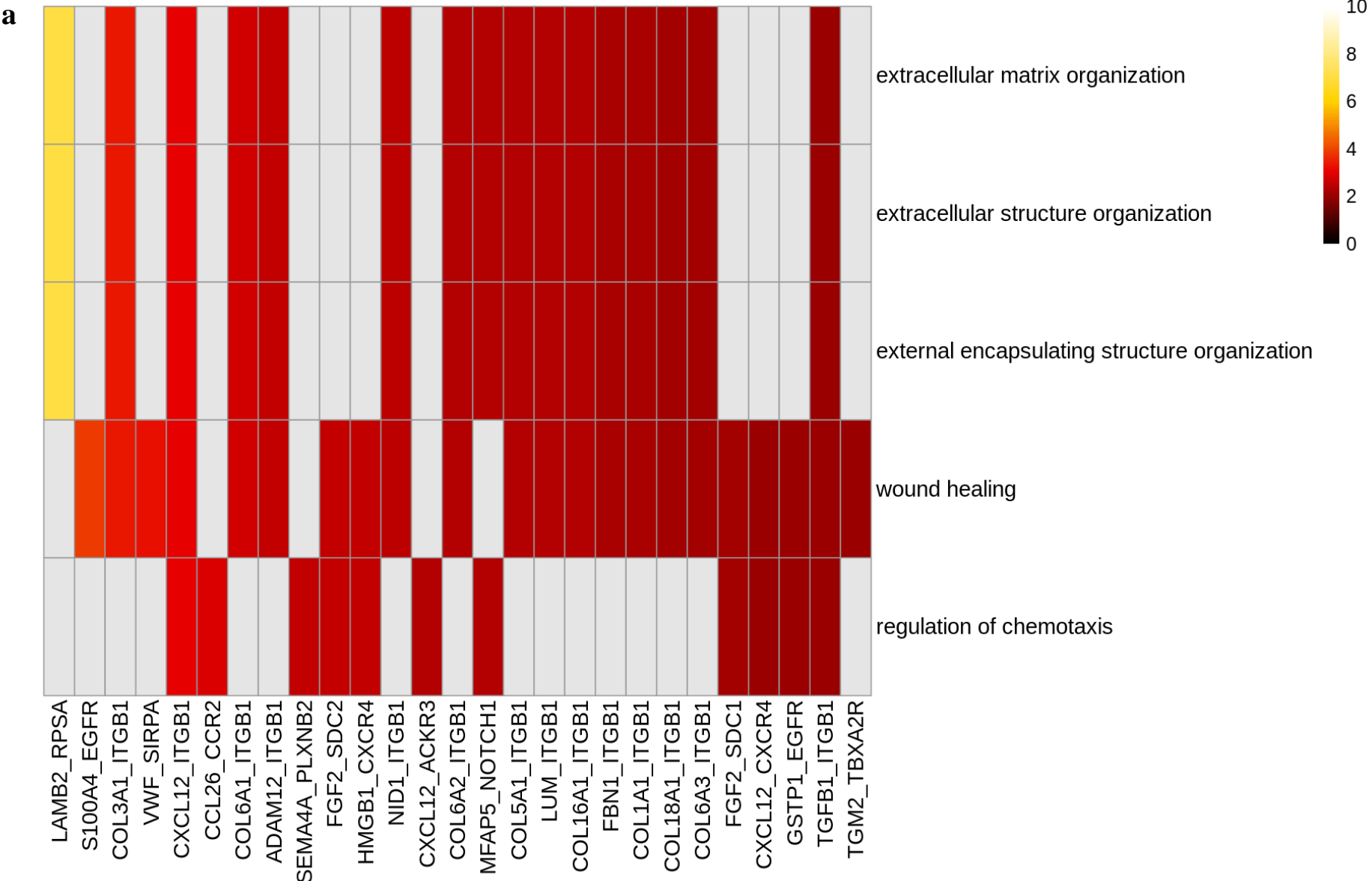
(a) The spatial map showing the abundance of tumor cells (tS2) and multiple T cell subtypes were visualized on the transformed grid.

(b) The key locations of tS2 and multiple T cells subtypes were represented by CCs, and the overlapping tissue domains were highlighted as the intersecting subregions between the two aggregated CCs.

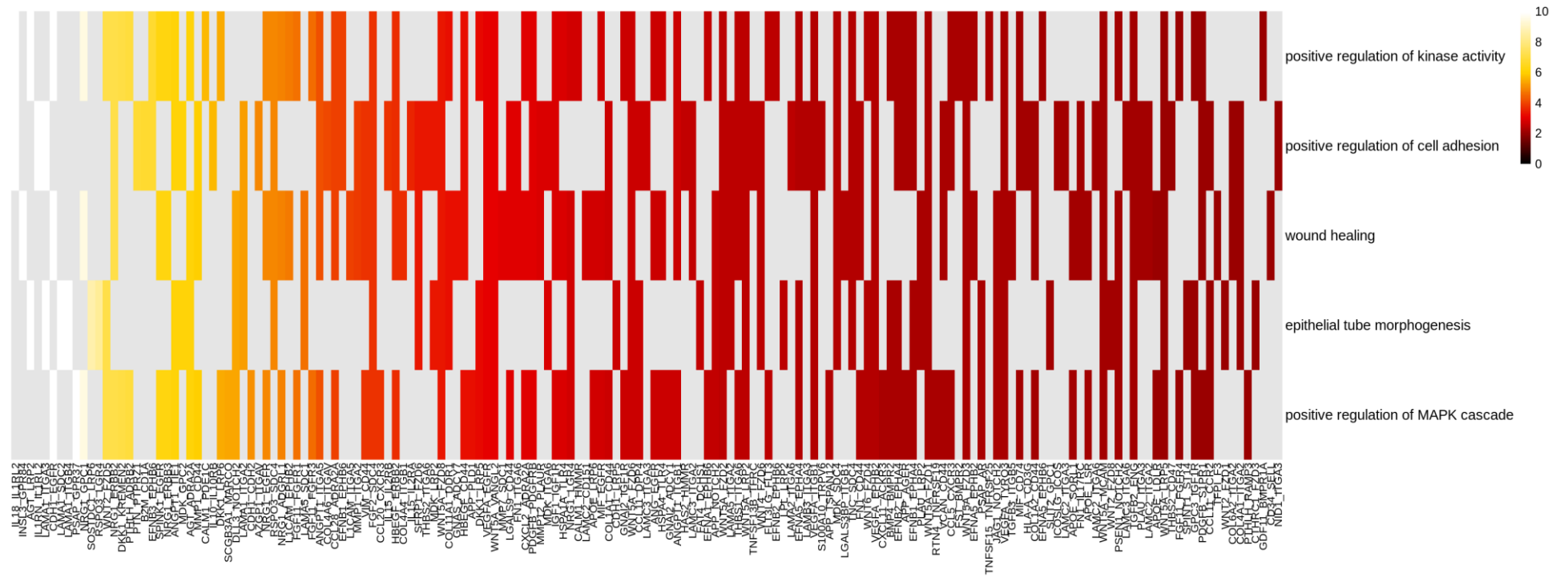


Supplementary Fig. 18. Spatial distribution of the top ligand-receptor expression specific to tS2 and NK/T cells

The spatial map displaying the log-normalized expression of the top ligand and receptor pairs specific to tumor cells (tS2) and NK/T cells, respectively, was visualized on the transformed grid.



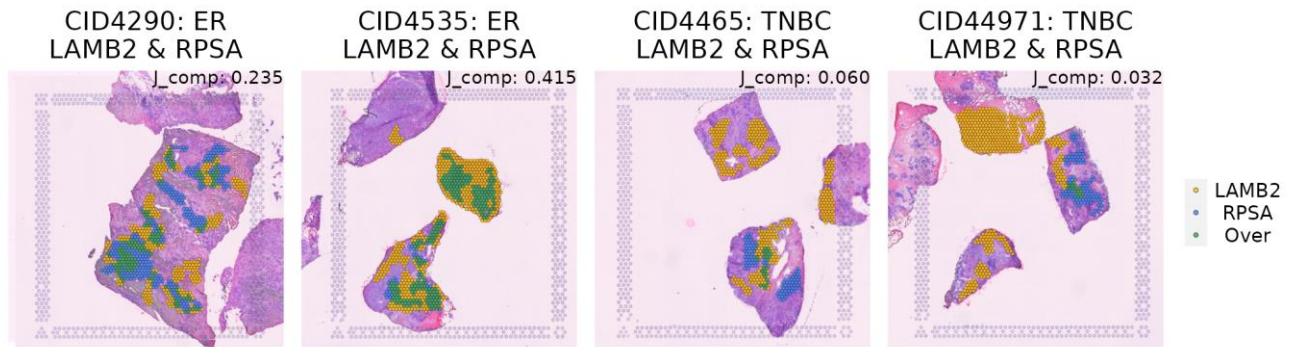
b



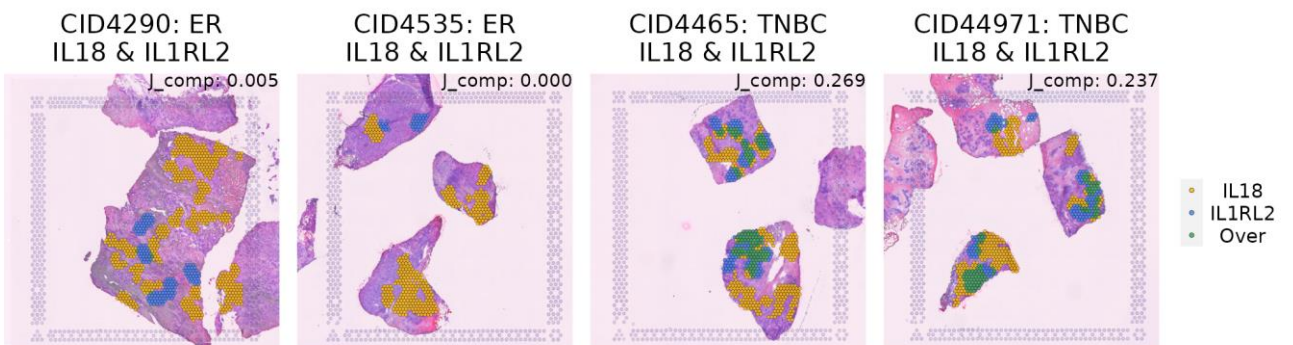
Supplementary Fig. 19. The top differentially upregulated LR pairs and related Gene Ontology (GO) terms in ER+ or TNBC tissues.

The spatial LR interaction profiles were estimated by STopover, and differentially upregulated LR interactions in ER+ or TNBC tissues were selected ($J_{comp} > 0.2$ and fold change of $J_{comp} > 2$). The enrichment analysis was performed for the genes in LR pairs and the top 5 enriched GO terms with the lowest adjusted p-values were selected. LR pairs in which either ligand or receptor gene intersected with the genes composing the top GO terms were listed. The upregulated functional terms, the intersecting LR pairs, and the fold change of J_{comp} in **(a)** ER+ and **(b)** TNBC tissues were visualized in heatmaps. The LR pairs were displayed in the descending order of fold change of J_{comp} . In summary, STopover can explain the spatial heterogeneity of TME in breast cancer tissues of different subtypes.

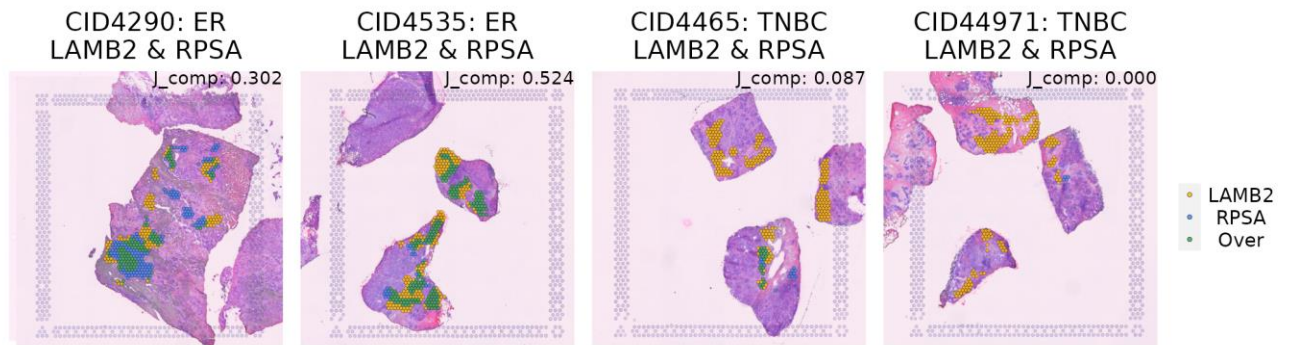
a The top upregulated LR interaction in ER+ tissues



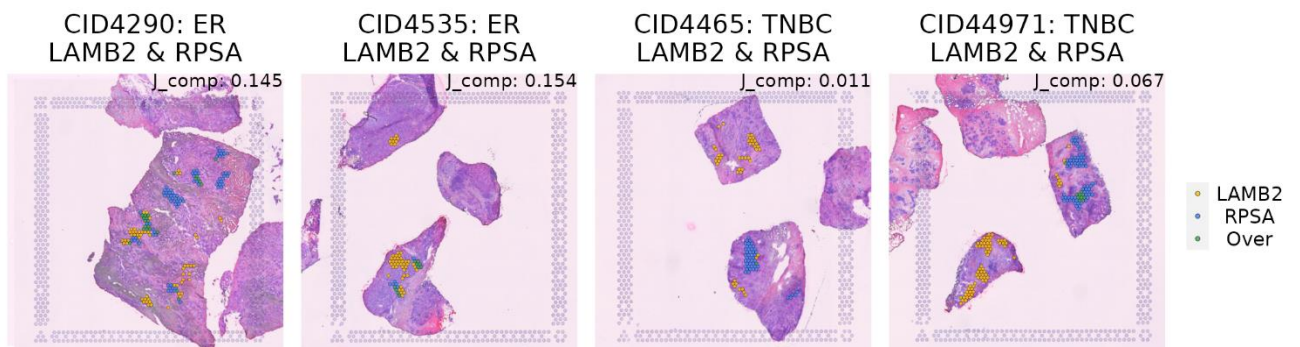
b The top upregulated LR interaction in TNBC tissues



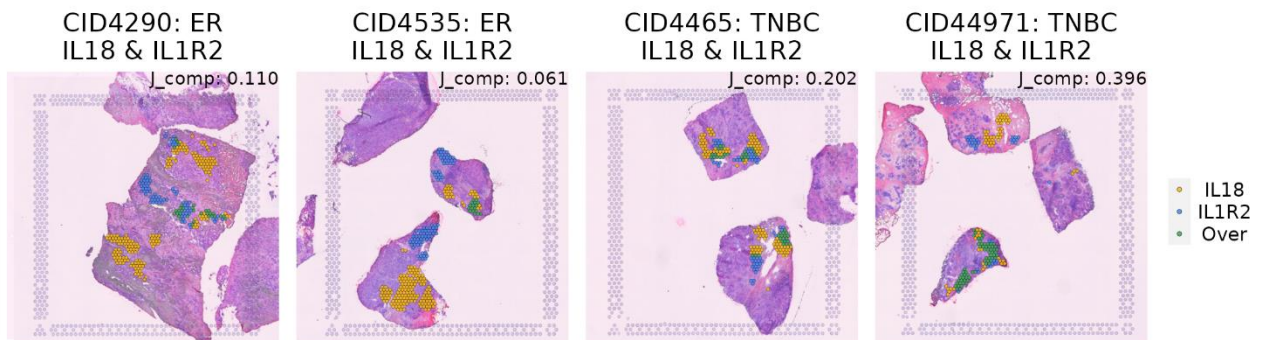
c **Constrained to cancer-associated fibroblasts (CAFs)**



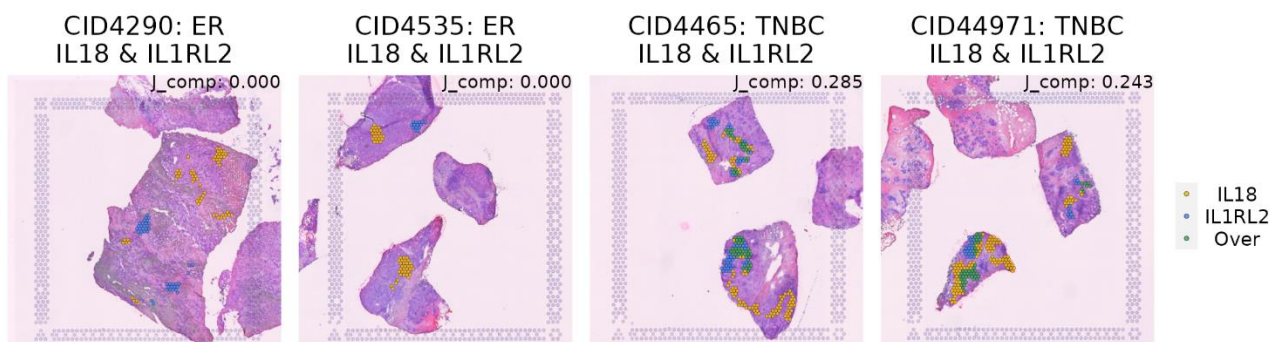
Constrained to cancer epithelial cells



d **Constrained to cancer-associated fibroblasts (CAFs)**

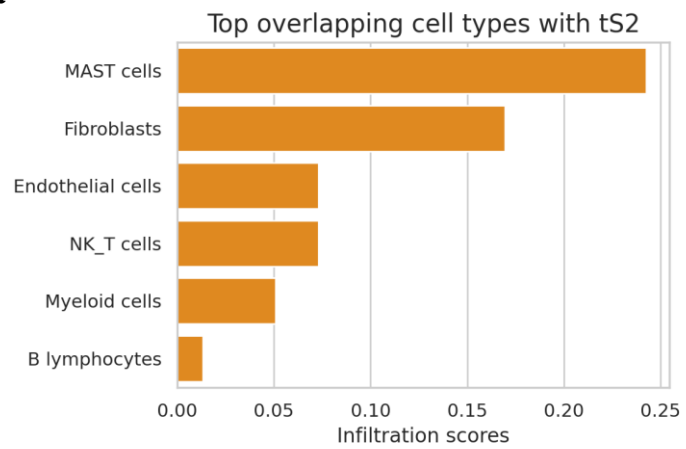
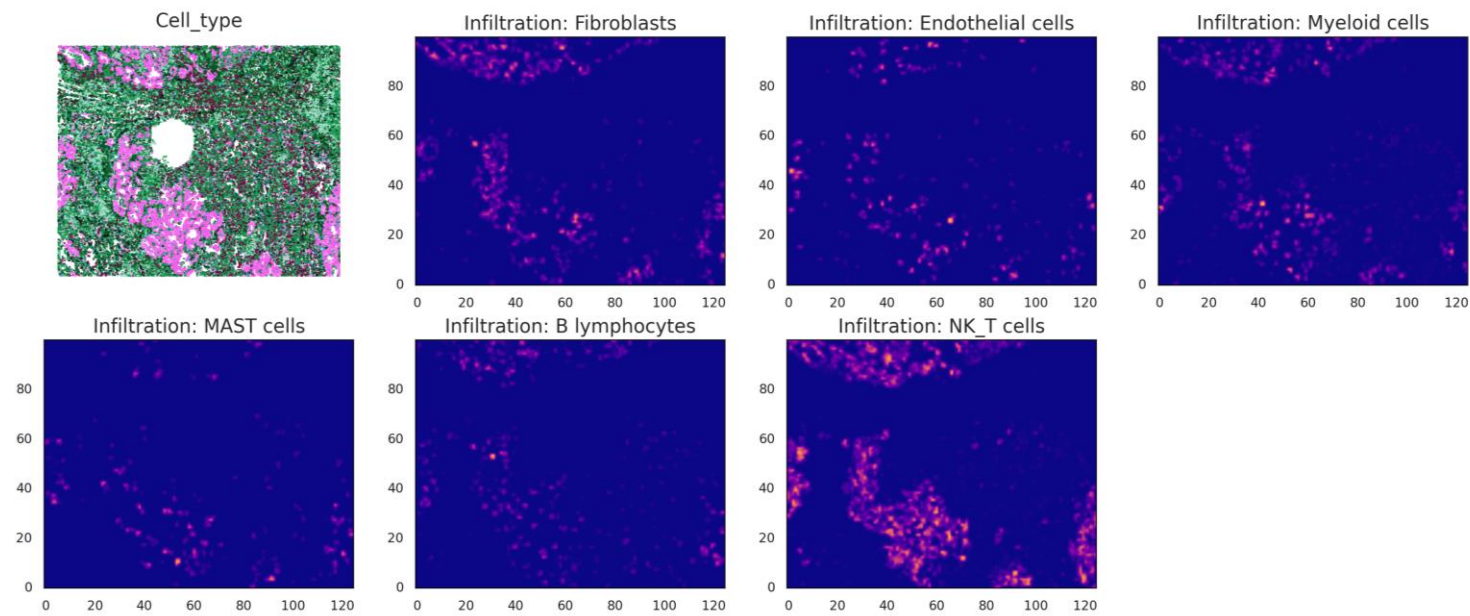


Constrained to cancer epithelial cells

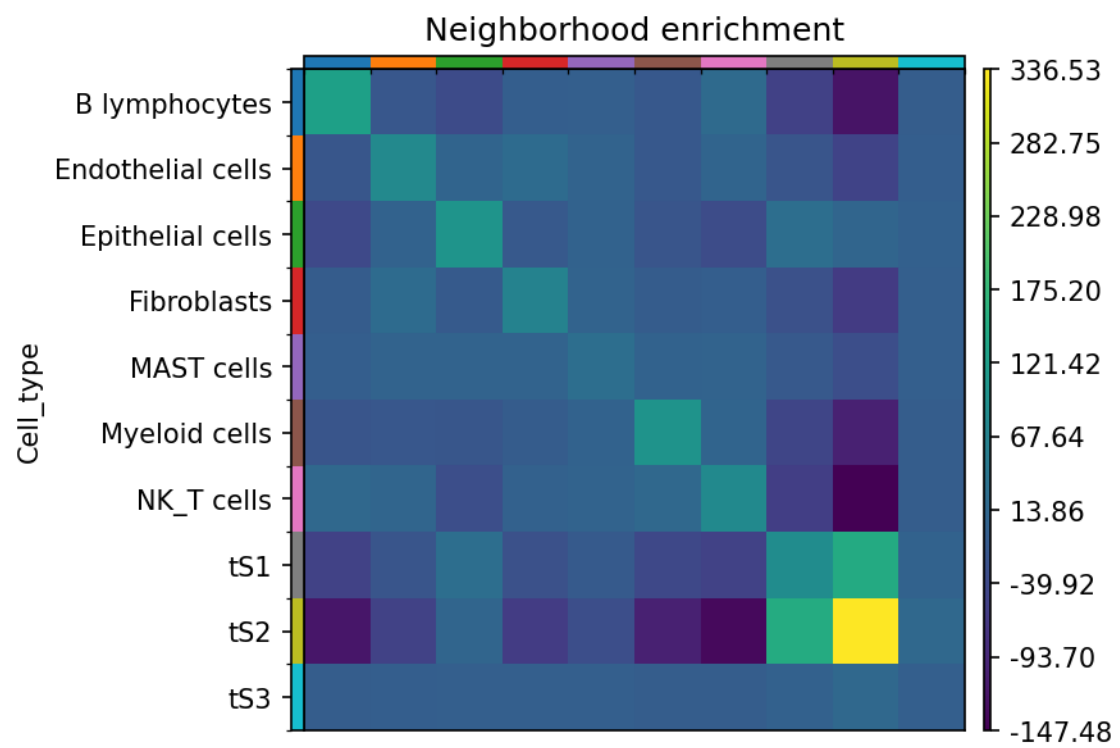


Supplementary Fig. 20. The spatial overlap patterns of the top differential upregulated LR pairs in ER+ or TNBC breast tissues.

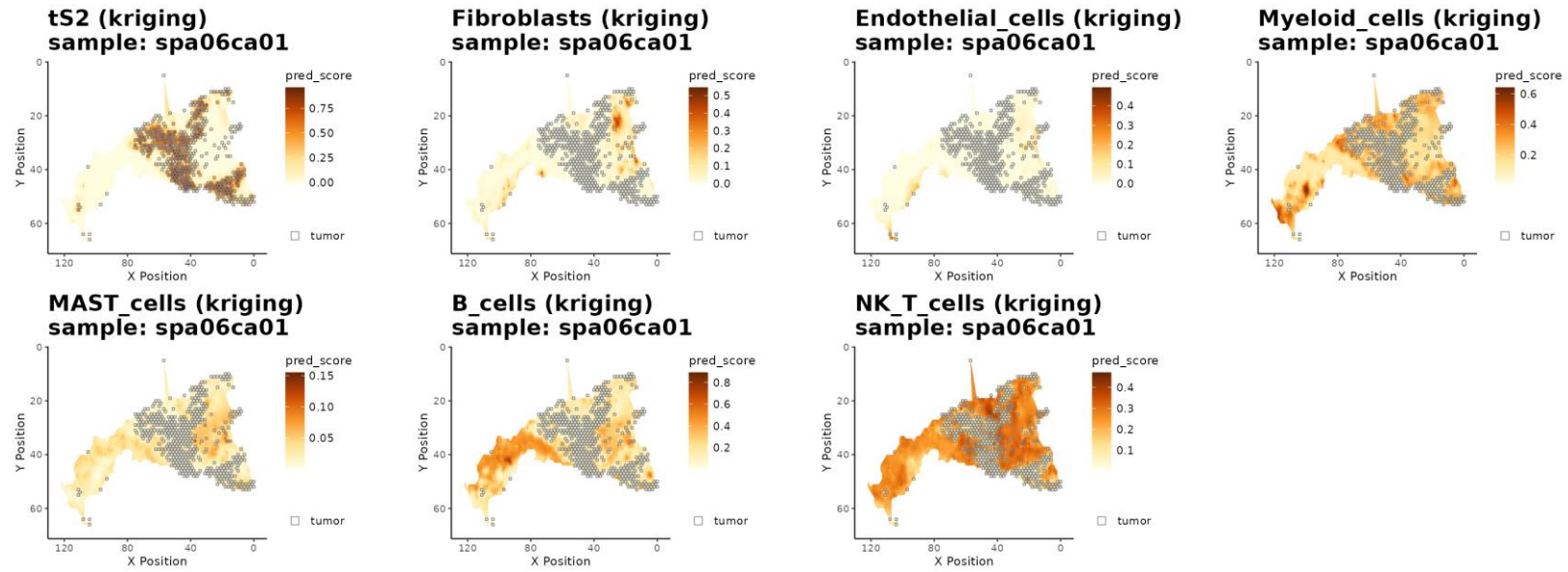
The aggregated CCs of the top differentially upregulated LR pairs ($J_{comp} > 0.2$ and average fold change > 2) in ER+ and TNBC tissues were extracted. The top LR pair was *LAMB2-RPSA* in ER+ tissues and *IL18-IL1RL2* in TNBC. The key location for (a) *LAMB2-RPSA* and (b) *IL18-IL1RL2* interactions were represented by CCs, and the overlapping tissue domains were highlighted as the intersecting subregions between the two aggregated CCs. Then, the intersecting regions between the two aggregated CCs of each LR pair and CCs calculated from either cancer-associated fibroblasts (CAFs) or cancer epithelial cells were extracted for (c) *LAMB2-RPSA* and (d) *IL18-IL1RL2* interactions. The location of modified CCs was mapped to the tissue and J_{comp} values were computed between the two modified CCs.

a**b**

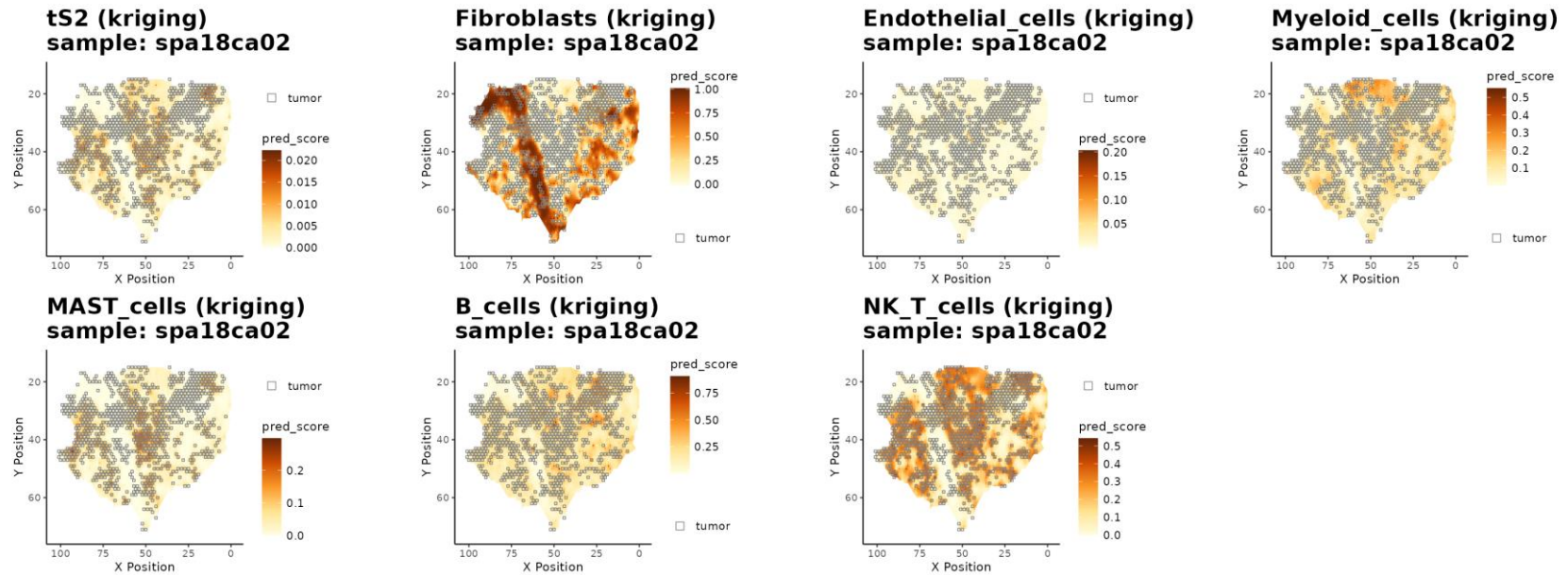
c



d



e



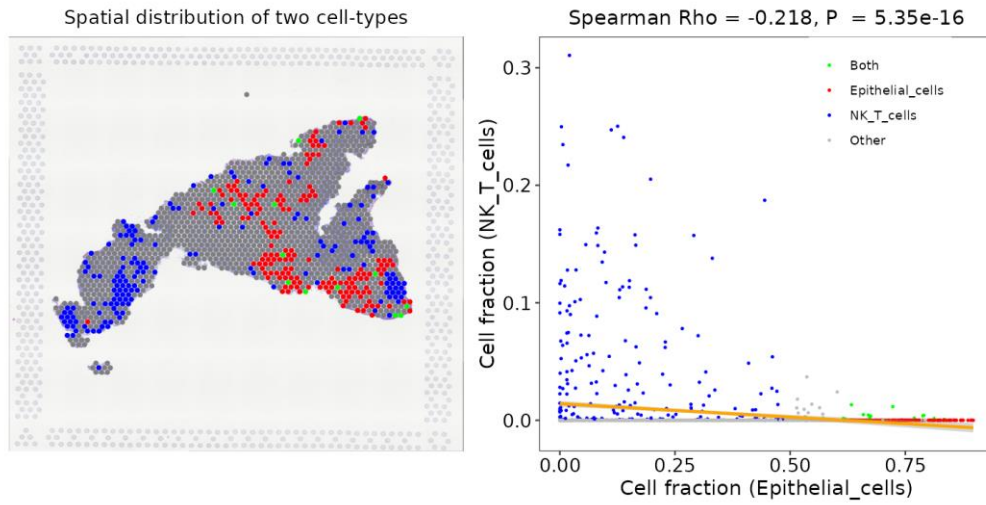
Supplementary Fig. 21. Investigation of spatial heterogeneity of the lung cancer using ATHENA and spatialGE.

First, ATHENA was applied to the image-based SRT of the lung cancer dataset and infiltration scores of six cell types (fibroblasts, endothelial cells, myeloid cells, MAST cells, B lymphocytes, and NK/T cells) to the tumor cells (tS2) were calculated. **(a)** The global infiltration score represents the overall infiltration of a certain cell type into the cancer cell in a given tissue section, and it was visualized as a barplot in the left panel. **(b)** The local infiltration score represents the local extent of infiltration of a certain cell type into the cancer cell and it was visualized on a grid with a unit size (step_size parameter) of 220.

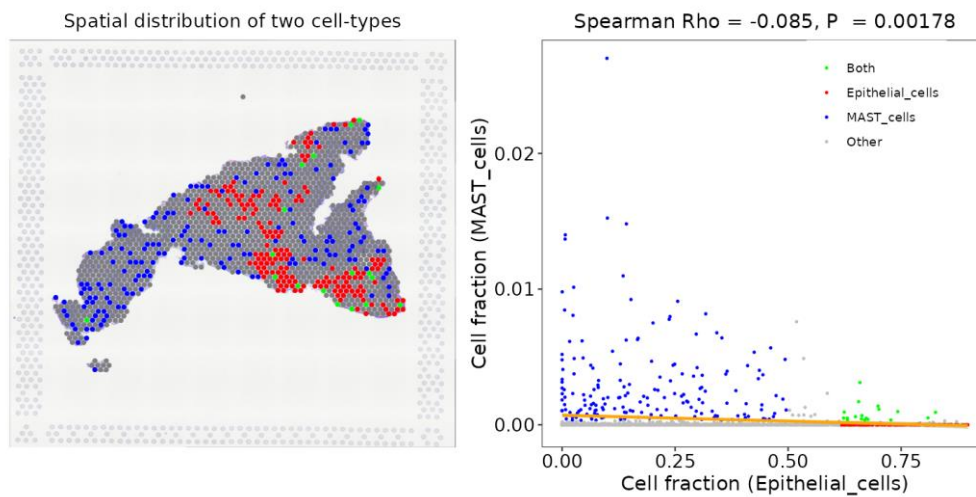
Second, Squidpy was applied to the image-based SRT of lung cancer dataset and the infiltration score of six cell types to the tumor cells was calculated. **(c)** The heatmap shows the neighborhood enrichment (Z-score) of colocalization between all pairs of cell types present in the lung cancer tissue.

Third, spatialGE was applied to barcode-based SRT of lung cancer dataset and the spots were classified into either tumor or stromal spots. The spatial cell fraction predicted by CellDART was adopted, and high-resolution spatial maps of all cell types were generated. Based on the tumor classification results and high-resolution spatial map, the immune phenotypes of the **(d)** PD-L1 low (*spa06ca01*) and **(e)** PD-L1 high (*spa18ca02*) cancer tissues can be qualitatively assessed.

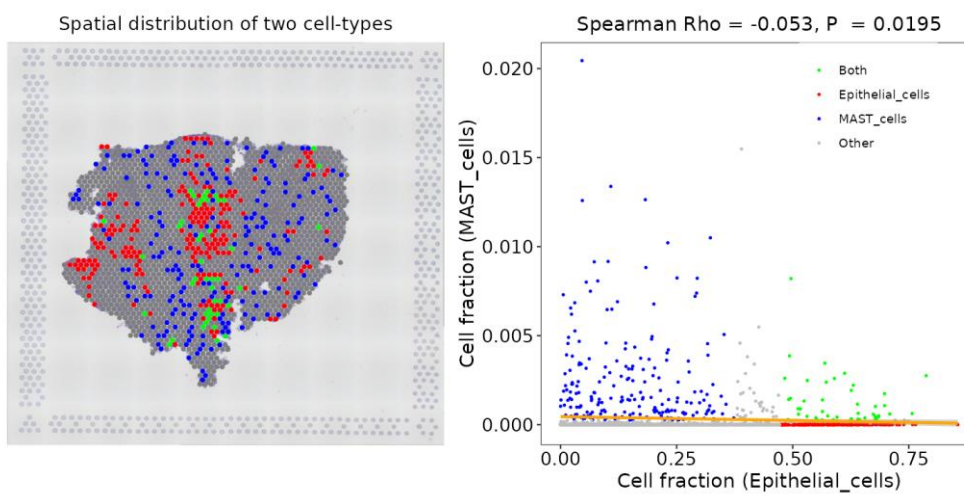
(a) Epithelial cells vs. NK/T cells in PD-L1 low tissue (*spa06ca01*)

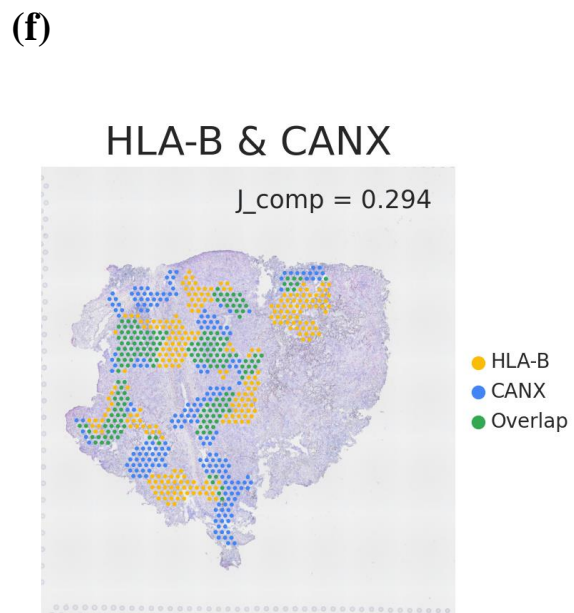
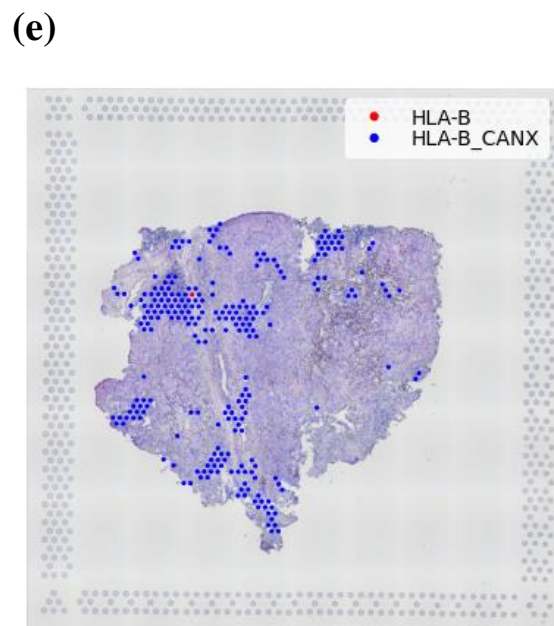
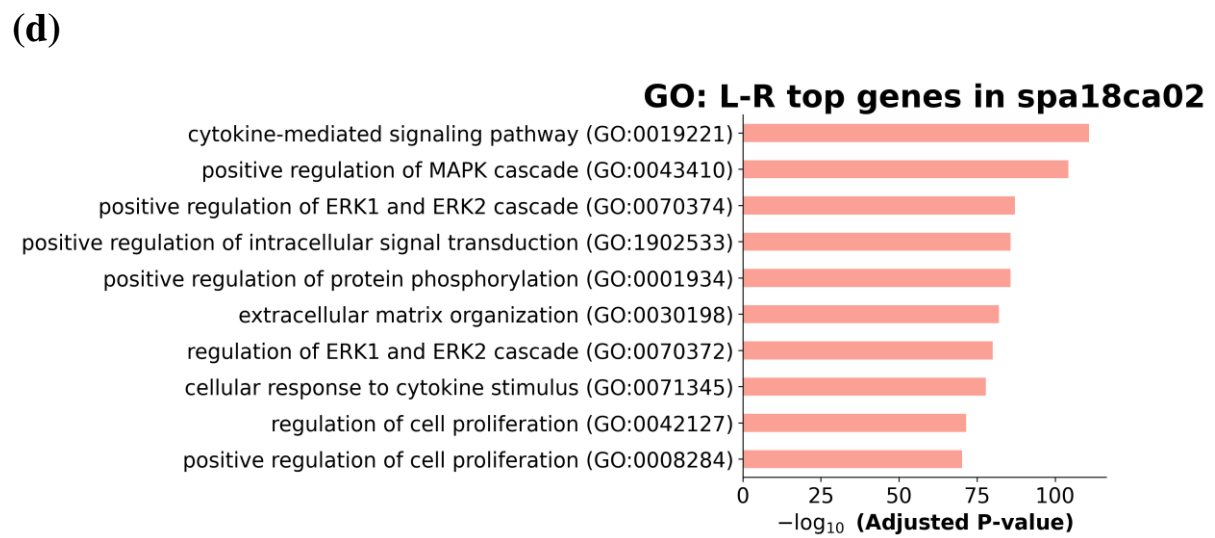
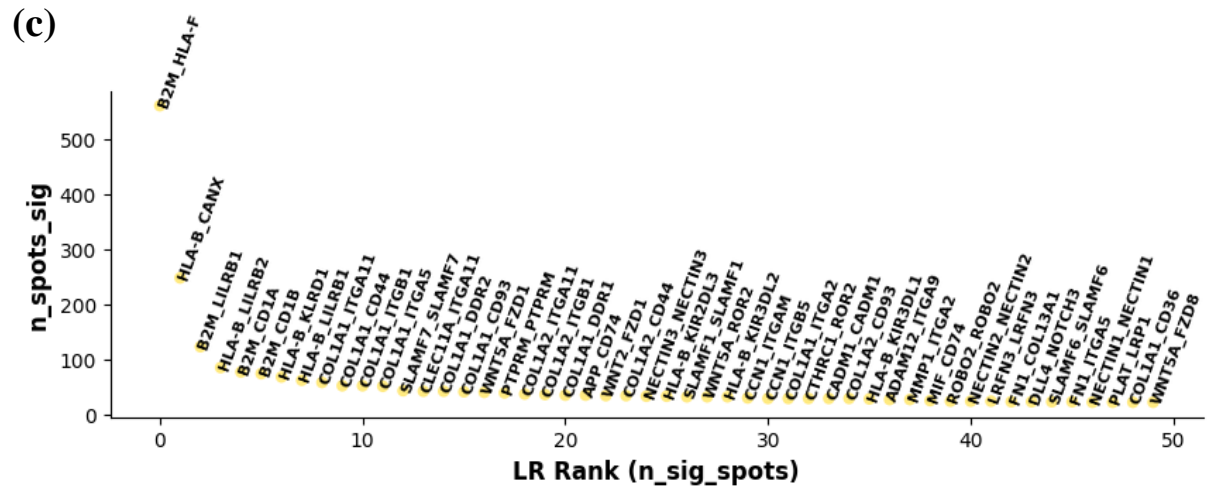


Epithelial cells vs. mast cells in PD-L1 low tissue (*spa06ca01*)



(b) Epithelial cells vs. mast cells in PD-L1 high tissue (*spa18ca02*)





Supplementary Fig. 22. Investigation of spatial heterogeneity in lung cancer using SpaCET and stLearn.

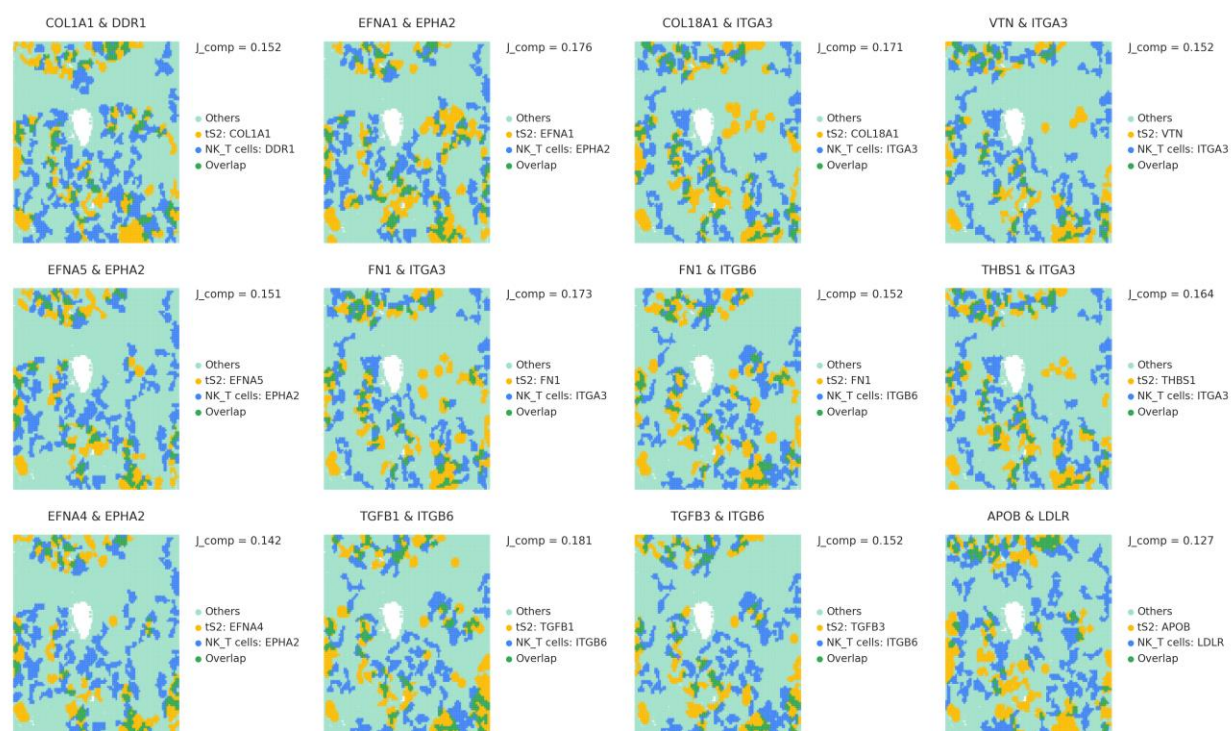
First, we applied SpaCET to the barcode-based SRT datasets of lung cancer. We used spatial cell fraction predictions provided by CellDART. Next, we evaluated the cell-cell colocalization patterns of six cell types (fibroblasts, endothelial cells, myeloid cells, MAST cells, B lymphocytes, and NK/T cells) with epithelial cells in both PD-L1 low (spa06ca01) and PD-L1 high (spa18ca02) tissues. **(a)** In the case of PD-L1 low tissue, only NK/T cells and mast cells showed significant interactions, while in **(b)** PD-L1 high tissue, mast cells showed significant interactions. Only the significant cell types are displayed. In the left panel, spatial patterns of epithelial cells (red), cell types of interest (blue), and colocalized regions (green) were visualized on the tissue. In the right panel, scatter plots and Spearman's correlation coefficients between epithelial cells and cell types of interest are displayed.

Second, we applied stLearn to the barcode-based SRT datasets of lung cancer to estimate dominant ligand-receptor (LR) interactions. **(c)** The summary plot illustrates the ranking of LR pairs based on the number of significant spots (x-axis) and the number of significant spots (y-axis). **(d)** Gene Ontology (GO) analysis was conducted for all significant colocalized LR pairs. The enriched biological process terms are listed in ascending order of adjusted p-values. One of the top LR interaction pairs that overlapped with the LR interaction results from STopover (based on Omnipath) was selected: *HLA-B* and *CANX*. Spatial patterns of the ligand, *HLA-B*, and receptor, *CANX*, as well as colocalized regions, were visualized on the tissue using **(e)** stLearn (*HLA-B*: red, *CANX*: green, colocalized: blue) and **(f)** STopover (*HLA-B*: yellow, *CANX*: blue, colocalized: green).

a



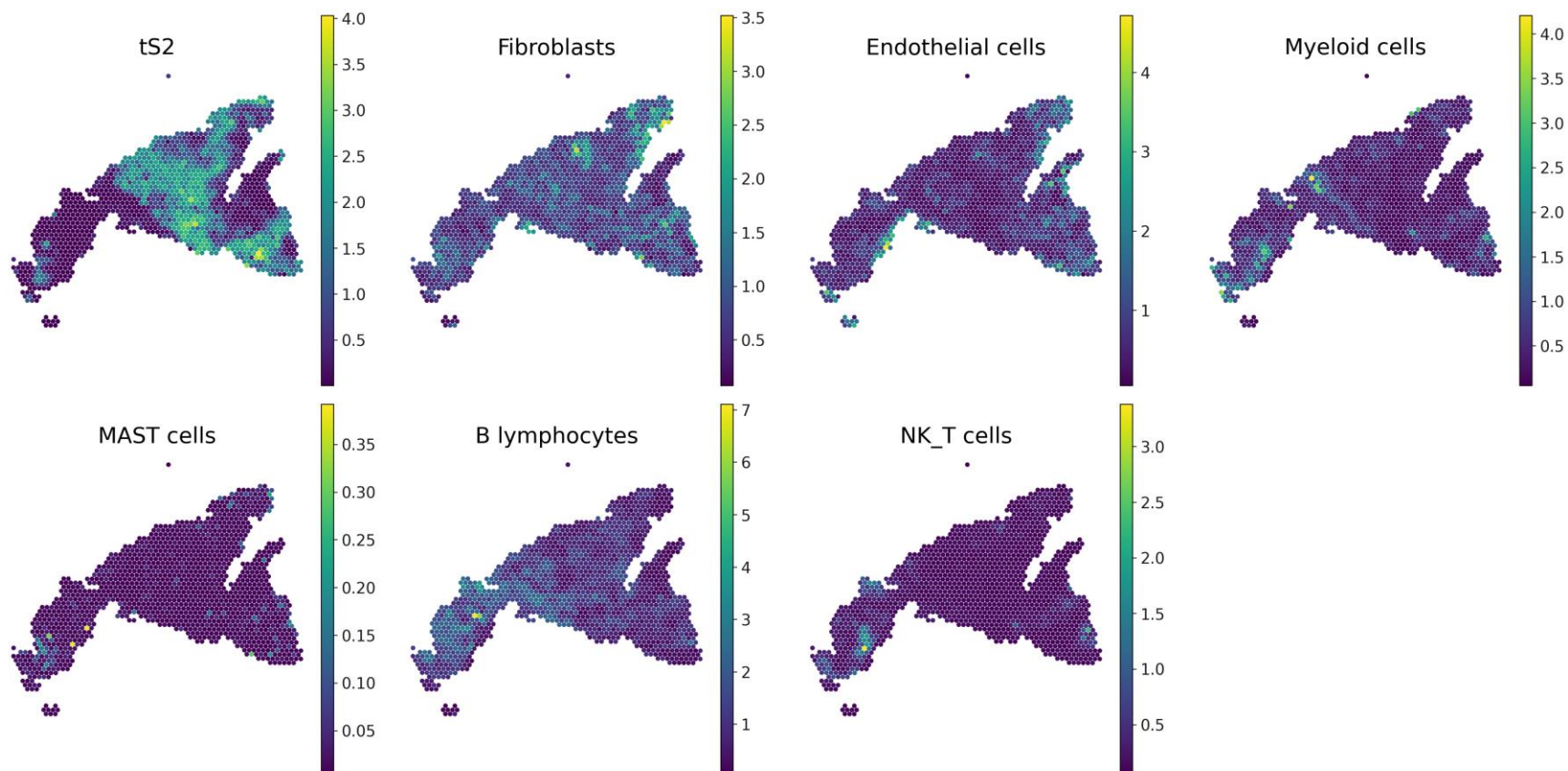
b



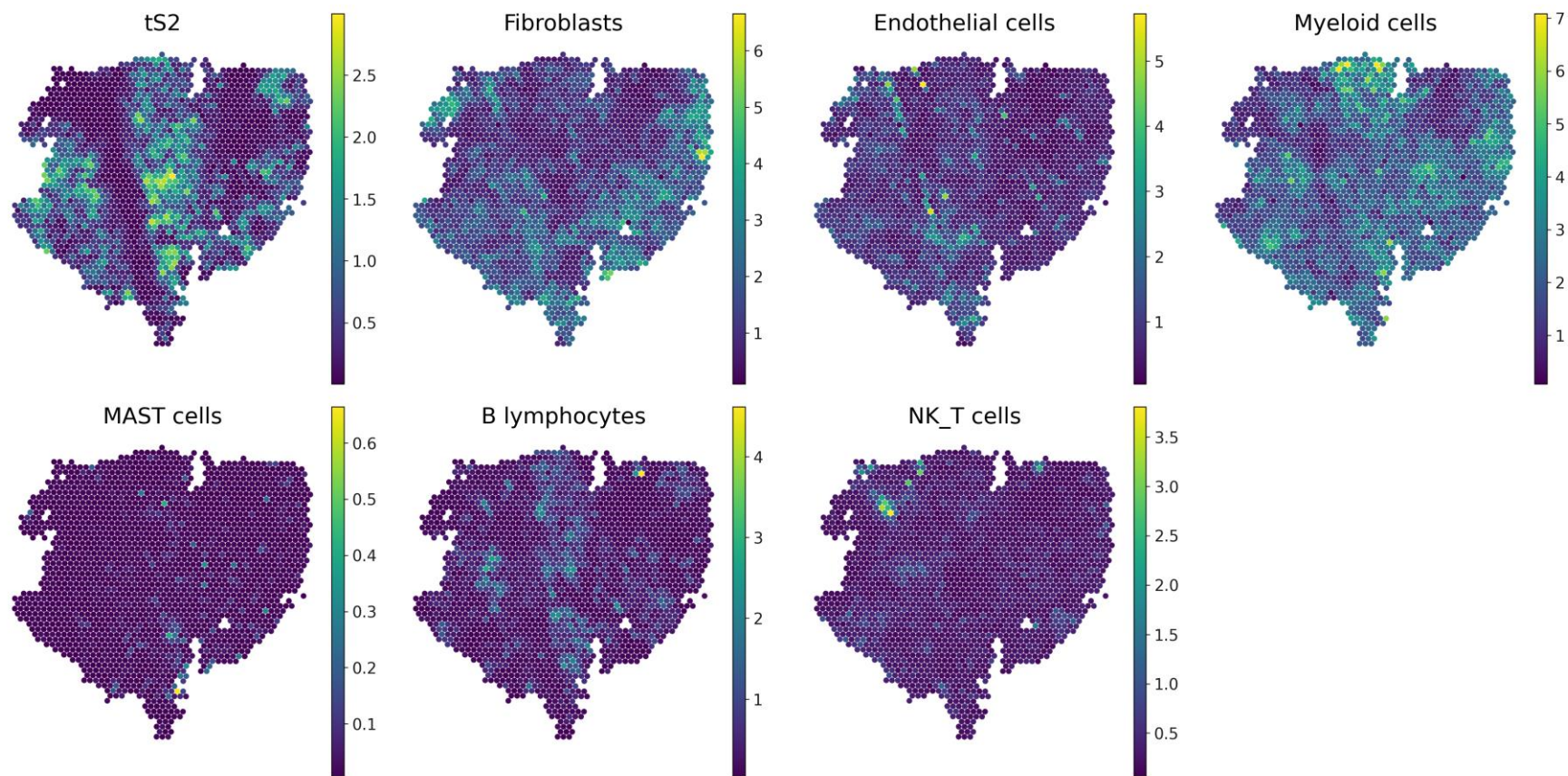
Supplementary Fig. 23. Evaluation of a method for estimating cell type-specific LR interaction in barcode-based SRT.

To assess the feasibility of an alternative approach for estimating cell type-specific LR interaction in barcode-based SRT, an image-based SRT dataset was utilized, as it provides real cell type-specific expression profiles. **(a)** The alternative approach suggested for barcode-based SRT was applied, and the tS2 and NK/T cell-specific LR interaction was predicted. It was predicted by intersecting the regions between the two aggregated CCs of the given LR pairs and colocalized domain of tS2 and NK/T cells. The modified CCs were mapped to the tissue, and the overlapping tissue domain was considered the key niche for tS2 and NK/T cell-specific LR interactions. **(b)** Then, the ligand expression in tS2 and the receptor expression in NK/T cells were used to identify the key niches of LR interactions. The results were considered the reference standard for the tS2 and NK/T cell-specific interaction.

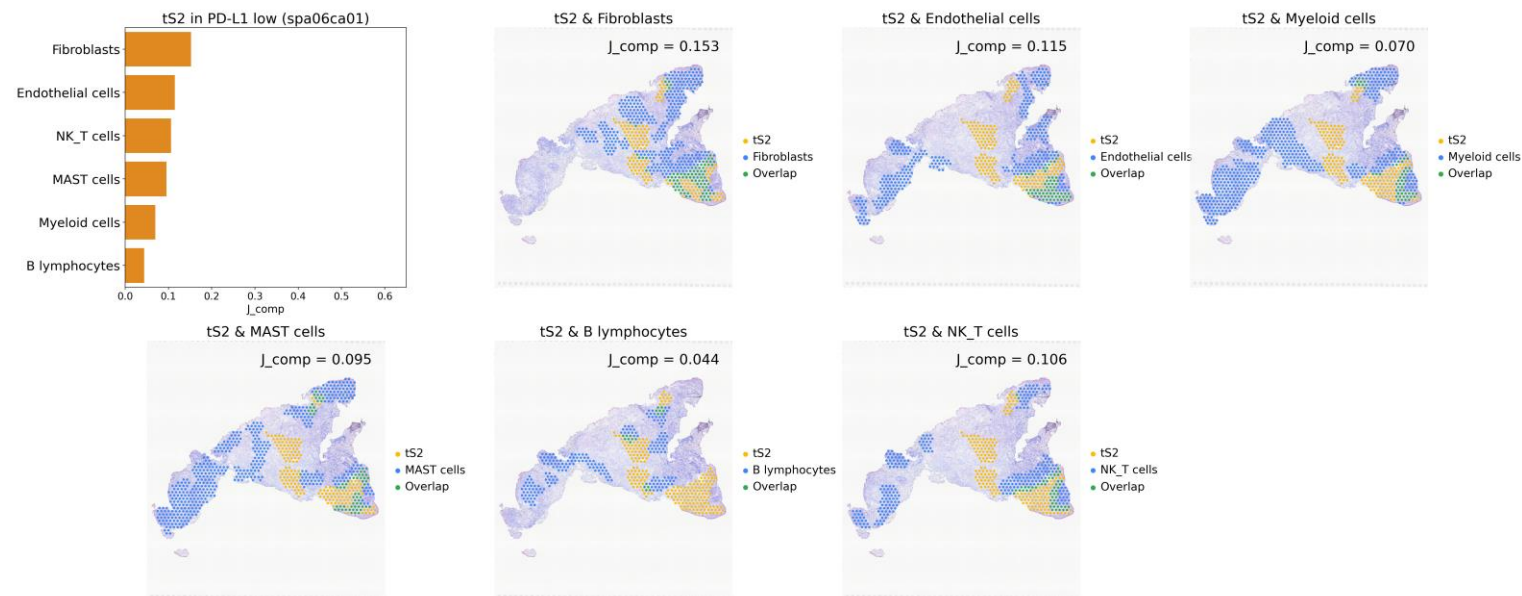
(a)



(b)



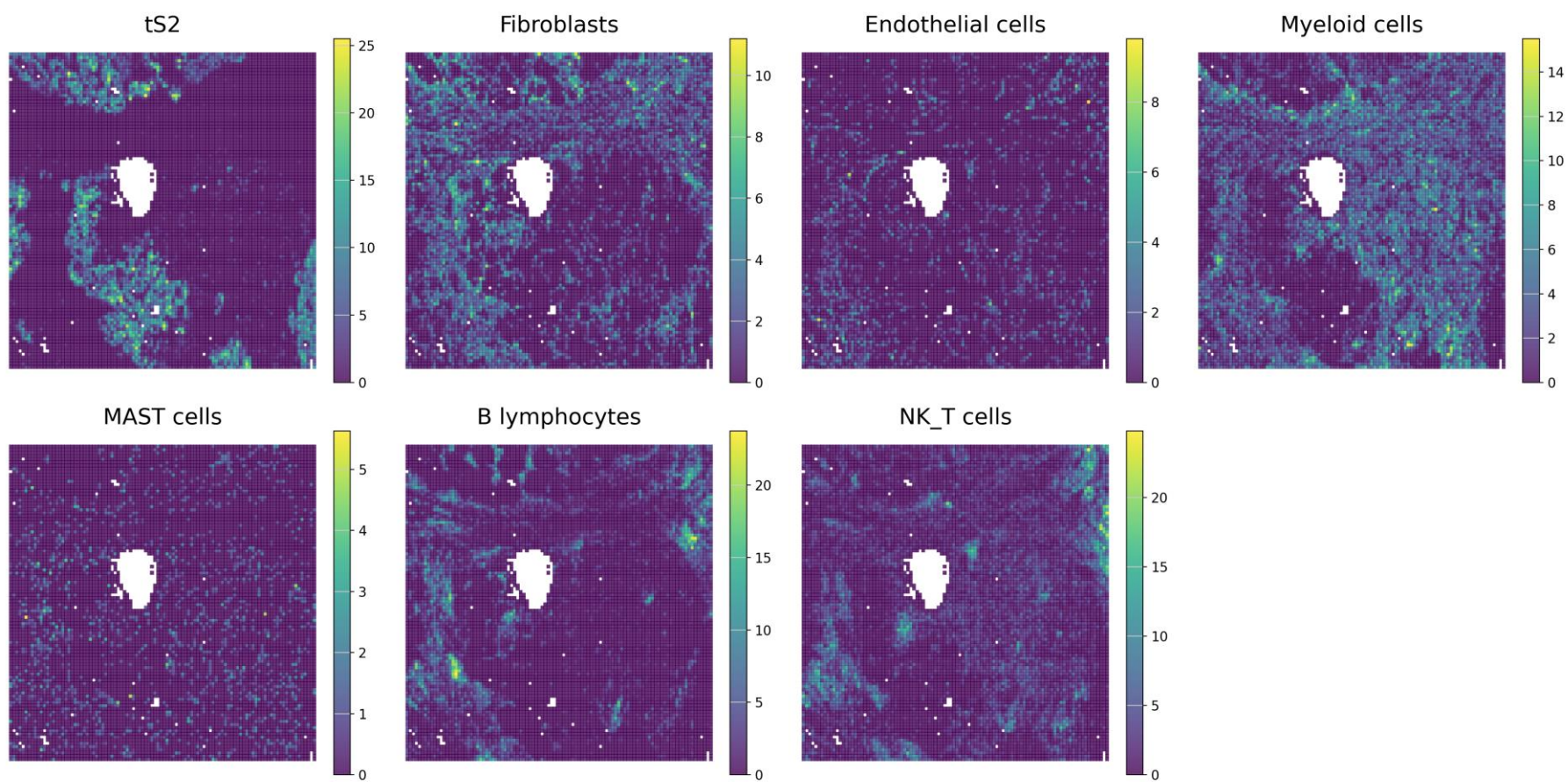
(c)



(d)

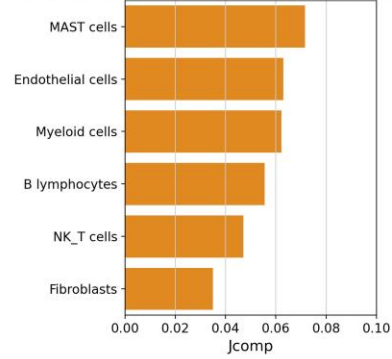


(e)

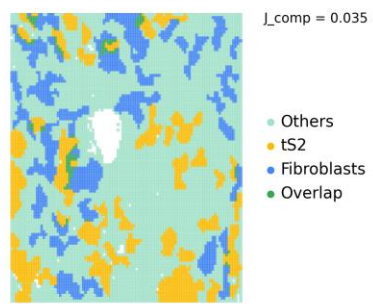


(f)

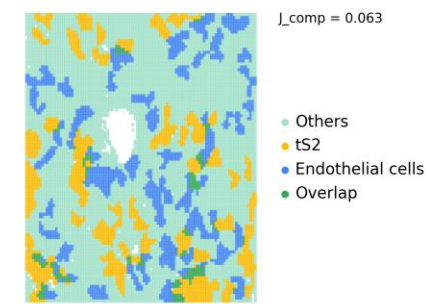
Top overlapping cell types with tS2: default



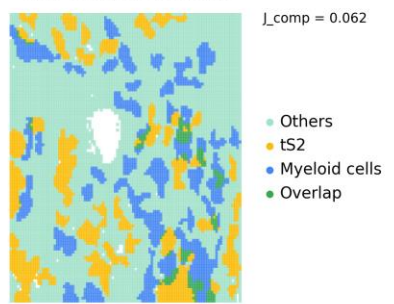
tS2 & Fibroblasts



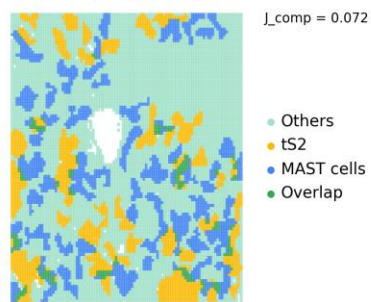
tS2 & Endothelial cells



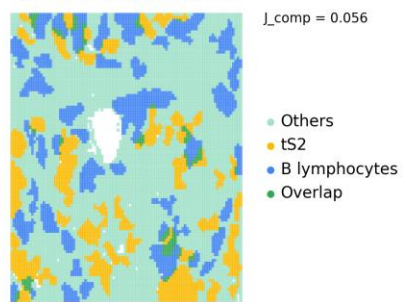
tS2 & Myeloid cells



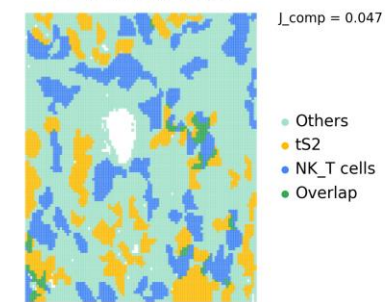
tS2 & MAST cells



tS2 & B lymphocytes



tS2 & NK_T cells

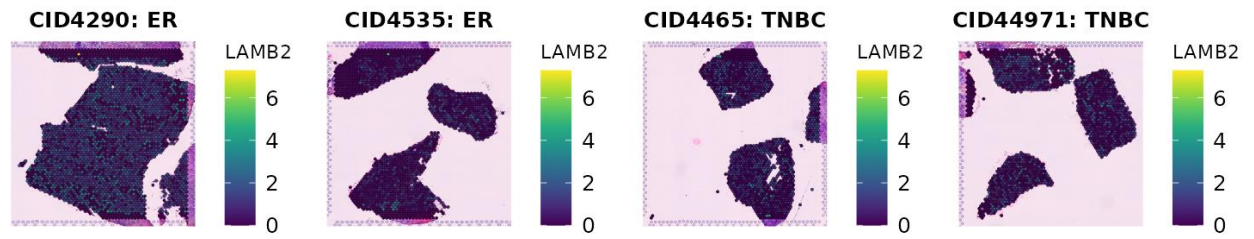


Supplementary Fig. 24. Colocalization patterns predicted by STopover using different cell type deconvolution and annotation methods

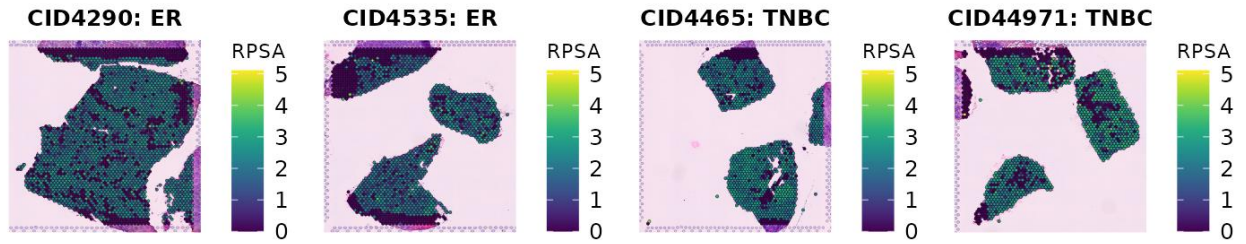
First, the spatial distribution of cell types in barcode-based SRT of lung cancer tissues was predicted using Cell2location, a cell type deconvolution tool. The spatial composition of tumor cell type (tS2) and other main cell types (fibroblasts, endothelial cells, myeloid cells, MAST cells, B lymphocytes, and NK/T cells) in **(a)** PD-L1 low (*spa6ca01*) and **(b)** PD-L1 high tissues (*spa18ca02*) was visualized. Subsequently, STopover was applied to investigate the spatial colocalization patterns between tumor cells (tS2) and other main cell types in both tissues. **(c)** The set-based J_{comp} values between the tumor cell type (tS2) and the other cell types in the *spa06ca01* tissue were visualized as a bar plot in the top left corner of the plot. Additionally, the aggregated connected components (CCs) for tS2 (yellow) and other main cell types (blue) were mapped onto the tissue, with the intersecting tissue domain highlighted in green. **(d)** Similarly, the set-based J_{comp} values for tS2 and other cell types in *spa18ca02* tissue were visualized with a barplot, and the CC locations were mapped onto the tissue.

Second, cells in the image-based SRT of lung cancer were annotated based on TACCO, a cell type annotation tool. **(e)** The spatial map showing the abundance of tS2 and other main cell types (fibroblasts, endothelial cells, myeloid cells, MAST cells, B lymphocytes, and NK/T cells) was visualized on the transformed grid. Subsequently, STopover was applied to estimate spatial colocalization between tumor cells and other main cell types. **(f)** The set-based J_{comp} scores were calculated between the tumor cell type (tS2) and other main cell types and were visualized with a bar plot in the top left corner. The locations of CCs for tS2 (yellow) and other cell types (blue) were mapped onto the tissue, with the overlapping domain highlighted in green.

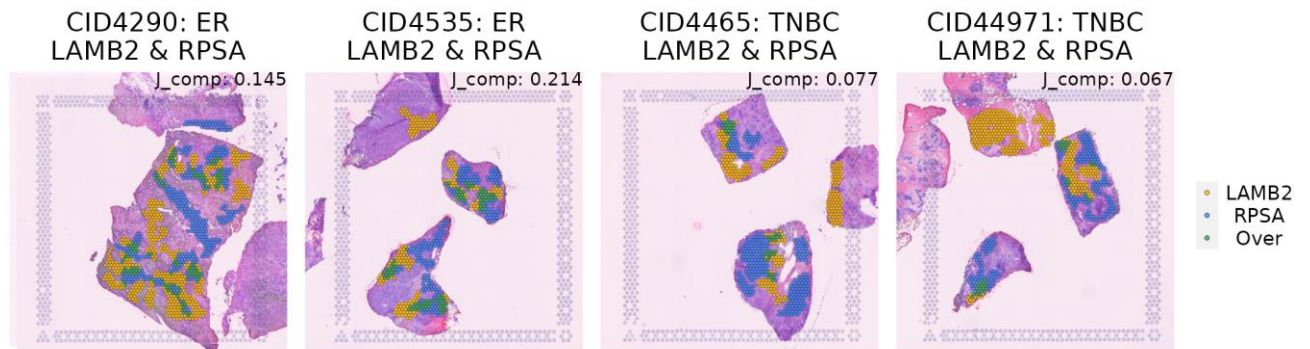
(a)



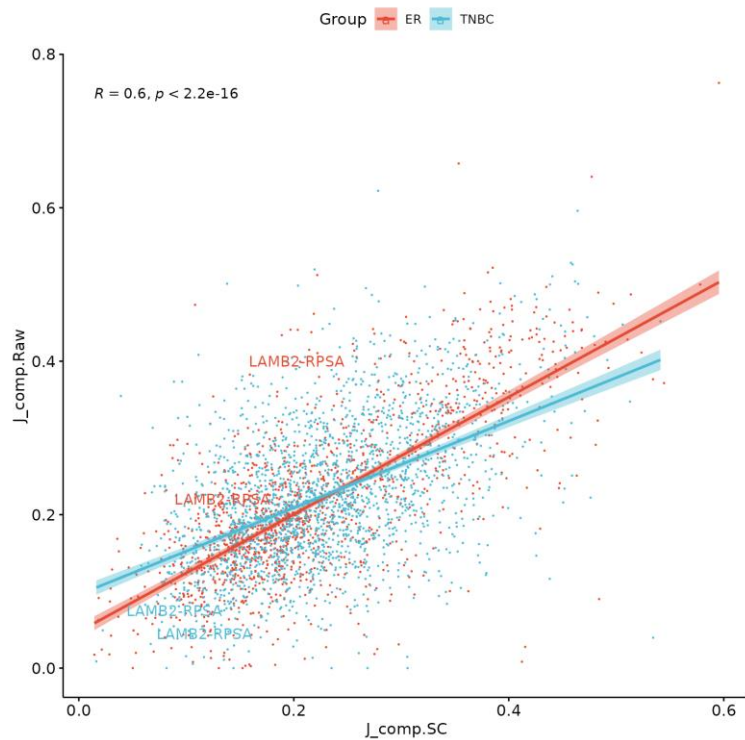
(b)



(c)



(d)



Supplementary Fig. 25. STopover analysis before and after correction for RNA diffusion

The tool to correct the lateral diffusion of RNA molecules in barcode-based SRT, called SpotClean, was applied to breast cancer datasets. This correction process was applied to genes with an average expression over 0.1. The spatial expression patterns of the corrected RNA for a ligand, **(a)** *LAMB2*, and receptor, **(b)** *RPSA*, were visualized on the tissue. **(c)** The connected components (CCs) of the *LAMB2* (yellow) and *RPSA* (blue), along with the intersecting subregions (green) between the two aggregated CCs, were visualized on the tissue. The set-based J_{comp} values between cancer epithelial cells and other main cell types in four breast cancer tissues were displayed in the top right corner of the plot. **(d)** The scatter plot illustrates the correlation between J_{comp} values for ligand and receptor pairs in CellTalkDB from four breast cancer tissues before (J_comp.Raw) and after correction (J_comp.SC) for RNA diffusion. The red line and blue line represent linear regression lines for estrogen receptor-positive (ER+) and triple-negative (TNBC) breast cancer, respectively. The annotated text indicates the location of the data points for *LAMB2-RPSA* in the four cancer tissues (ER+: red, TNBC: blue). The Spearman's correlation coefficient is calculated and displayed in the top left corner of the plot.