Systematic benchmarking of imaging spatial transcriptomics platforms in FFPE tissues

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Abstract

Emerging imaging spatial transcriptomics (iST) platforms and coupled analytical methods can recover cell-to-cell interactions, groups of spatially covarying genes, and gene signatures associated with pathological features, and are thus particularly well-suited for applications in formalin fixed paraffin embedded (FFPE) tissues. Here, we benchmarked the performance of three commercial iST platforms on serial sections from tissue microarrays (TMAs) containing 23 tumor and normal tissue types for both relative technical and biological performance. On matched genes, we found that 10X Xenium shows higher transcript counts per gene without sacrificing specificity, but that all three platforms concord to orthogonal RNA-seq datasets and can perform spatially resolved cell typing, albeit with different false discovery rates, cell segmentation error frequencies, and with varying degrees of sub-clustering for downstream biological analyses. Taken together, our analyses provide a comprehensive benchmark to guide the choice of iST method as researchers design studies with precious samples in this rapidly evolving field.

38 **MAIN**

39 Spatial transcriptomics (ST) tools measure the gene expression profiles of tissues or cells
40 *in situ*. These approaches overcome the limitations of single-cell RNA-sequencing (scRNA-seq)
41 methods by negating the need for cellularization and maintaining both local and global spatial
42 relationships between cells within a tissue. ST can thus recover cell-cell interactions with high
43 confidence, groups of spatially covarying genes, groups of cells predictive of cancer survival, and
44 gene signatures associated with pathological features [1, 2]. These advantages, coupled with rapidly
45 emerging computational and analytical methods, have led to substantial excitement about
46 deploying these platforms in fundamental biology studies, and in the clinic for research and
47 diagnostic purposes [3, 4, 5].

48 ST tools can be split into two broad categories: sequencing (sST) and imaging (iST) based
49 modalities. sST methods tag transcripts with an oligonucleotide address indicating spatial location,
50 most commonly by placing tissue slices on a barcoded substrate; isolating tagged mRNA for next-
51 generation sequencing; and computationally mapping transcript identities to locations [6]. In
52 contrast, iST methods most commonly use variations of fluorescence *in situ* hybridization (FISH)
53 where mRNA molecules are tagged with hybridization probes which are detected in a
54 combinatorial manner over multiple rounds of staining with fluorescent reporters, imaging, and
55 de-staining **(Fig. 1a)** [7]**.** Computational reconstruction then yields maps of transcript identity with
56 single-molecule resolution. Compared to sST methods, iST methods are targeted to subsets of the
57 transcriptome due to their reliance on pre-defined gene panels and they adopt the higher spatial
58 resolution and sensitivity of FISH, yielding single-cell resolution data [8].

59 While the iST methods share some similarities, significant differences arise in primary
60 signal detection and amplification, sample processing, and the subsequent fluorescent cycling

61 chemistry (**Fig. 1b**) [9,10,11]. The need for amplification of signal is coupled to the sample processing,
62 namely whether the sample is cleared, gel-embedded, or photobleached to quench
63 autofluorescence. There are tradeoffs due to differences in sample processing for each iST method.
64 For example, clearing of the sample increases signal quality but can prevent follow-up H&E
65 staining and complicate immunostaining, which, in turn, can make cell segmentation more
66 challenging. Finally, there are tradeoffs between imaging time, molecular plex, and imaging area
67 covered, which result from the particular combination of the molecular protocol and the imaging
68 hardware implementation [12].

69 A key historic limitation in the widespread use of iST methods with human clinical samples
70 was the incompatibility of most methods with formalin-fixed, paraffin-embedded (FFPE) tissue
71 samples [13, 14]. FFPE is the standard format for clinical sample preservation for pathology due to
72 its ability to maintain tissue morphology and sample stability at room temperature for decades [15].
73 The ability to process FFPE samples with iST would enable the use of archival tissue banks for
74 studies and obviate the need for specialized sample harvesting workflows. However, FFPE
75 samples tend to suffer from decreased RNA integrity, particularly after having been stored in
76 archives for extended periods of time [16].

77 Three companies recently released the first FFPE compatible commercial iST platforms:
78 10X's Xenium, Nanostring's CosMx, and Vizgen's MERSCOPE [9,10,11,17]. These three platforms
79 each use different protocols, probe designs, signal amplification strategies, and computational
80 processing methods, and therefore may potentially yield different sensitivities and downstream
81 results. The main chemistry difference lies in transcript amplification: 10X Xenium uses a small
82 number of padlock probes with rolling circle amplification; CosMx uses a low number of probes
83 amplified with branch chain hybridization; and MERSCOPE uses direct probe hybridization but

84 amplifies by tiling the transcript with many probes (**Fig. 1b**). However, no head-to-head
85 performance comparisons on matched samples have been published. Understanding the key
86 differences across platforms will allow users to make better-informed decisions regarding panel
87 design, method choice, and sample selection as they design costly experiments, often on precious
88 samples that have been bio-banked for years [18].

89 In this study, we compared currently available FFPE-compatible iST platforms on matched
90 tissue samples. We prepared a set of samples representative of typical archival FFPE tissues,
91 comprised of 23 different tissue types, and acquired matched data from sequential sections
92 according to the manufacturer's best practices at the time of writing, generating a dataset of >3.3M
93 cells. We analyzed the relative sensitivity and specificity of each method on shared transcripts,
94 and further quantified the concordance of the iST data across each platform with orthogonal data
95 sets from The Cancer Genome Atlas (TCGA) program and Genotype-Tissue Expression (GTEx)
96 databases [19,20]. Then we focused on cell-level comparisons, evaluating the out-of-the-box
97 segmentation for each platform based on detected genes and transcripts and coexpression patterns
98 of known disjoint markers. Finally, we cross-compared the ability of each platform to identify cell
99 type clusters with breast and breast cancer tissues as an example use case. Taken together, our
100 work provides the first head-to-head comparison of these platforms across multiple archival
101 healthy and cancerous FFPE tissue types.

102 **RESULTS**

103 **Collection of matched iST data across 23 FFPE tissue types reveals high transcript counts**
104 **obtained by Xenium and CosMx.**

105 To test the performance of the latest generation of FFPE-compatible iST tools, we
106 measured the spatial expression of the same genes on the same samples as much as possible given
107 current panel configurations. To accomplish this, we used two previously generated multi-tissue
108 tissue microarrays (TMAs) from clinical discarded tissue (**see Methods**). We focused on FFPE
109 tissues as the standard method for sample processing and archival in pathology. One TMA
110 consisted of one hundred and seventy-three 0.6 mm diameter cores (i.e. sampled regions) from
111 seven different cancer types, with 3-6 patients per cancer type, and 3-6 cores per patient (**Fig. 1c,d,**
112 **Supplementary Table 1**). A separate TMA consisted of forty-eight 1.2 mm diameter cores
113 spanning sixteen normal tissue types isolated with each tissue type coming from one patient and
114 represented in 2-3 cores (**Fig. 1c,d, Supplementary Table 2**). CosMx and Xenium suggest pre-
115 screening samples based on H&E, while MERSCOPE recommends a $DV_{200} > 60\%$. Since our goal
116 was to determine the compatibility of iST platforms under typical workflows for biobanked FFPE
117 tissues, and since TMAs are challenging to assay by DV_{200}, samples were not prescreened based
118 on RNA integrity. Samples were screened by H&E in the process of TMA assembly. Both TMAs
119 were sliced into serial sections for processing by 10X Xenium, Vizgen MERSCOPE, and
120 Nanostring CosMx, following manufacturer instructions (**see Methods**).

121 The three different iST platforms offer different degrees of customizability and panel
122 compositions. In terms of panel design, MERSCOPE and Xenium offer either fully customizable
123 panels or standard panels with optional add-on genes, while CosMx offers a standard 1K
124 (substantially larger plex) panel with optional add-on genes. We opted to run the CosMx 1K panel

125 as available commercially, as well as the Xenium human breast, lung, and multi-tissue off-the-
126 shelf panels. We then designed two MERSCOPE panels to match the pre-made Xenium breast and
127 lung panels, by filtering out any genes which could potentially lead to high expression flags in any
128 tissue in the Vizgen online portal. This resulted in a total of six panels, with each panel overlapping
129 the others on >94 genes (**Fig. 1e, Supplementary Table 3**). Samples were run following
130 manufacturer instructions over the course of 74 days after slicing (**Fig. 1f, Supplementary Table**
131 **4**), with efforts made to ensure that head-to-head comparisons were available at similar time points
132 for each pair of platforms. In data review, we noticed that MERSCOPE breast and lung panel were
133 originally acquired with a 5 µm imaging depth, which was unintentionally thinner than the
134 manufacturer recommendation of 10 µm, and could thus lead to aberrantly low counts. Thus, a
135 second round of breast panel acquisition was performed with a 10 µm imaging depth
136 (**Supplementary Table 1a**), resulting in a median 3.0-fold increase in expression across all
137 transcripts. We excluded the 5 µm MERSCOPE breast panel data from all further comparisons but
138 left the lung panel data in as an illustrative example of an unsuccessful run. However, we
139 emphasize that MERSCOPE performance should be judged based on the rerun breast panel.

140 Each data set was processed according to the standard base-calling and segmentation
141 pipeline provided by each manufacturer. The resulting count matrices and detected transcripts were
142 then subsampled and aggregated to individual cores of the TMA (**Methods**). Across all datasets
143 we generated >190 million transcripts, >3.3 million cells, across 7 tumor types, and 16 normal
144 tissue types. Overall, we found that the cores from each TMA were generally well adhered to the
145 tissue and detected transcripts, and we were able to collect data from all three modalities for 217
146 cores (**Supplementary Table 4**). The total number of transcripts recovered for each run was
147 highest for Xenium, followed closely by CosMx, and then MERSCOPE (**Supplementary Table**

148 **4**). The total number of cells initially reported was highest for Xenium followed by MERSCOPE
149 and CosMx (**Supplementary Table 4**). Based on the initially reported number of transcripts, the
150 tumor TMA appeared to provide more counts than the normal tissue TMA, which we ascribed to
151 a higher tissue quality in the tumor samples (**Supplementary Table 4**). We note that the total
152 number of transcripts from the MERSCOPE normal TMA run was below what would be typically
153 thought of as a successful run, even when rerunning with the breast panel at 10 µm imaging depth.
154 Such a sample would normally be excluded from analysis, but we continued the data through to
155 illustrate how low transcript capture affects downstream results.

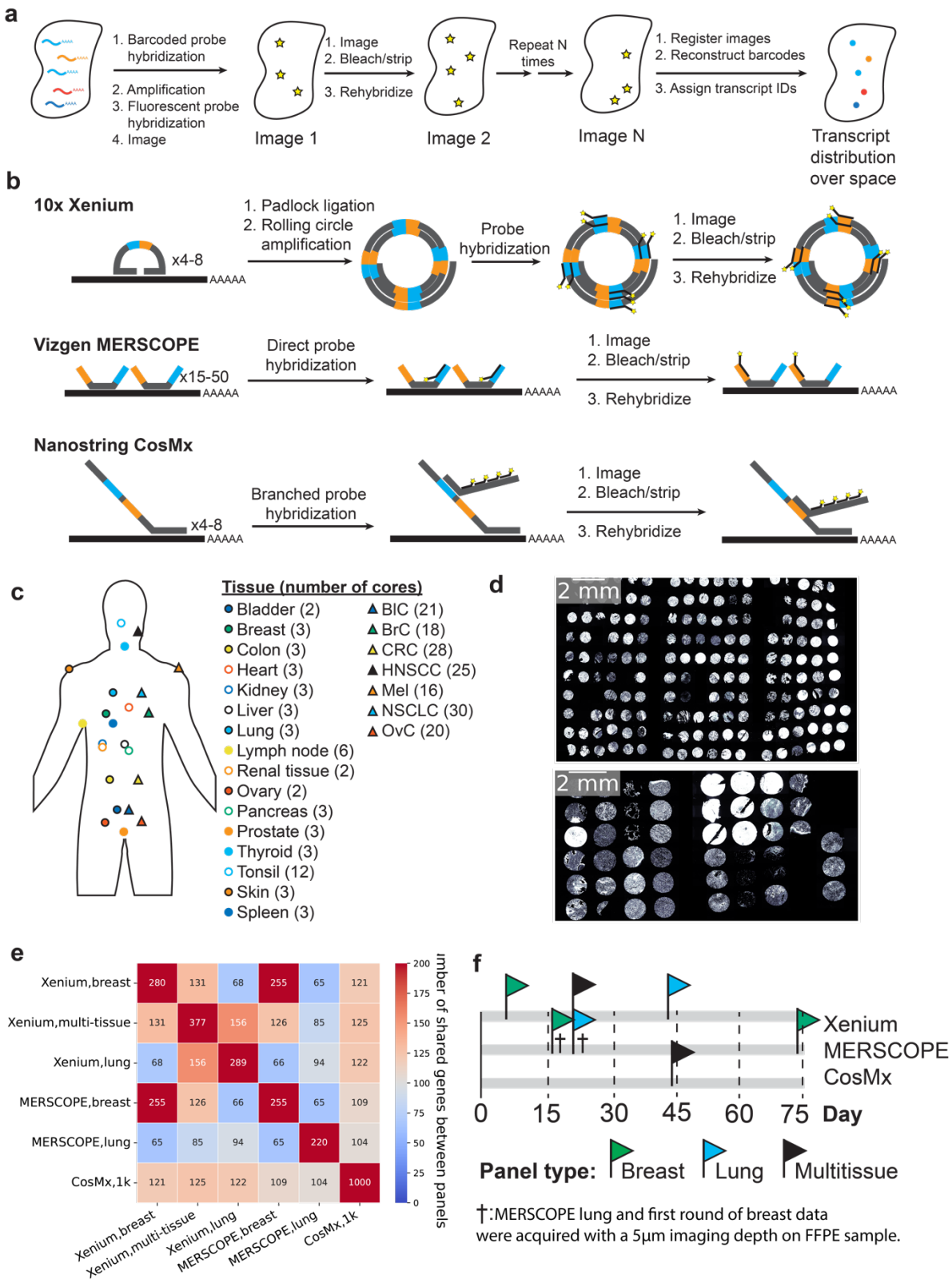

Figure 1: Experimental design and iST platforms. (a) Overall approach for generating iST data. (b) Different amplification approaches for Xenium, MERSCOPE, and CosMx. (c) Overview of

159 the tissue types and numbers of cores used in this study. BlC = bladder cancer, BrC = breast cancer,
160 CRC = colorectal cancer, HNSCC = head and neck squamous cell carcinoma, Mel = Melanoma,
161 NSCLC = non-small cell lung cancer, OvC = ovarian cancer. (d) DAPI images from the Xenium
162 run of each TMA, including tumors (top) and normal tissues (bottom) (e) The number of common
163 target genes in each panel used in this study. (f) Overall timeline of the imaging days for each
164 study. Day = 0 corresponds to the day of slicing. † denotes the MERSCOPE breast and lung panels
165 acquired with a 5 µm imaging thickness, thinner than manufacturer instructions.
166

167 **10X Xenium shows higher transcript counts per gene without sacrificing specificity**

168 We next sought to directly compare the performance of each iST platform on matched
169 genes. We began with a pseudo-bulk-based approach at the core level since this would not depend
170 on differences in cell segmentation performance (see **Methods**) [21].

171 First, we examined the run-to-run reproducibility within a single platform for Xenium and
172 MERSCOPE, finding that the total transcript count of all shared genes was highly correlated across
173 data sets acquired with different panels, regardless of the tissue of origin (**Supplementary Fig.**
174 **1a**). We also examined the pseudo-bulk gene expression correlation for cores from the same patient
175 in the same dataset and found that correlation was high (Pearson's r => 0.7) in almost all cases
176 (**Supplementary Fig. 1b-c**), indicating good sample-to-sample reproducibility within a given
177 platform.

178 To evaluate the relative sensitivity of each platform, we plotted the total transcript counts
179 of every shared gene between all combinations of platform and panel, summed across all matched
180 cores. We found generally linear relationships between all pairs of platforms (**Fig. 2a-c,**
181 **Supplementary Fig. 2**). Xenium consistently showed higher expression levels on the same genes
182 than CosMx in the tumor TMA, with the Xenium breast having 14.6-fold more counts than the
183 CosMx multi-tissue data sets (**Fig. 2a**). The Xenium multi-tissue panel data showed a slightly
184 smaller difference, with 12.3-fold higher expression on the same genes (**Fig. 2a**), while the lung

185 panel, which was acquired closest in time following slicing, also displayed a median of 14.0-fold
186 higher expression **(Fig. 2a)**. MERSCOPE showed higher expression levels than CosMx when
187 using the breast (10 µm) panel (median of 5.4-fold higher), and comparable expression levels even
188 when using the lung (5 µm) panel (median of 1.1-fold) (**Fig. 2b**). Finally, Xenium showed 2.6-
189 fold higher median expression with the breast panels (10 µm) than MERSCOPE, and 13.6-fold
190 higher median expression with the lung panels (5 µm) **(Fig. 2c)**. In the normal tissue TMA, we
191 found that results were generally consistent, except that the MERSCOPE breast panel showed
192 decreased transcript counts relative to the same panel in the tumor TMA (**Supplementary Fig. 2b-**
193 **c**), which is consistent with this TMA being unsuccessful for MERSCOPE. Considering the overall
194 higher transcripts per cell across platforms for the tumor TMA **(Supplementary Table 4)**, this
195 suggests that the ability to detect transcripts falls off more strongly with sample quality with
196 MERSCOPE, altering the performance relative to CosMx but not Xenium. Examining the CosMx
197 as compared to Xenium data also revealed an upward curve in the lower expression regime
198 indicative of higher-than-expected calls associated with the low expression regime by CosMx
199 (**Supplementary Fig. 2a**).

200 We next wanted to assess the specificity of each platform. Each of the three platforms
201 includes negative controls which are used to evaluate sample quality [22, 23]. Xenium and CosMx
202 include both negative probes (e.g. real probes targeting nucleic acids that are not present in human
203 tissue) and negative barcodes (e.g. algorithmically allowable barcodes that are not associated with
204 any probe in the experimental panel). MERSCOPE includes only negative barcodes by default. To
205 determine specificity, we first calculated the fraction of negative barcodes and probes relative to
206 the number of transcripts for each tissue type **(Fig. 2e).** We found that MERSCOPE and Xenium
207 consistently showed the highest on-target fraction, while CosMx was lower across each tissue type

208 (**Fig. 2e**). However, this measurement is biased because of the relative numbers of controls and
209 target barcodes. We therefore also adopted a false discovery rate (FDR) calculation which
210 normalizes for these differences and is calculated against both the negative probes and negative
211 barcodes (see **Methods, Fig. 2f-g**). We found that Xenium consistently showed the lowest FDR
212 while CosMx showed the highest FDR regardless of whether we standardized to negative control
213 barcodes or probes. This finding is consistent with the upswing in the gene-gene expression plots
214 in **Fig 2a** and **Supplementary Fig. 2a**—as both indicate a higher FDR at the low end of the gene
215 expression range. These results are consistent when visualized across panel **(Fig. 2e-g)**.
216 Finally, we used the negative control barcodes to evaluate the number of genes reliably
217 detected by each platform in each tissue type. For each core, we calculated the number of genes
218 that were detected two standard deviations above the average expression of the negative control
219 probes. These numbers were then averaged for cores of the same tissue type. Because the CosMx
220 panel was almost three times larger, it yielded a larger absolute number of detected genes in 14
221 out of 20 tissue types while the Xenium breast panel was higher in the remaining 6 tissue types
222 (**Fig. 2h**, **Supplementary Table 5**). However, Xenium consistently detected the highest fraction

of genes in a panel, followed by MERSCOPE and CosMx (**Fig. 2i**).

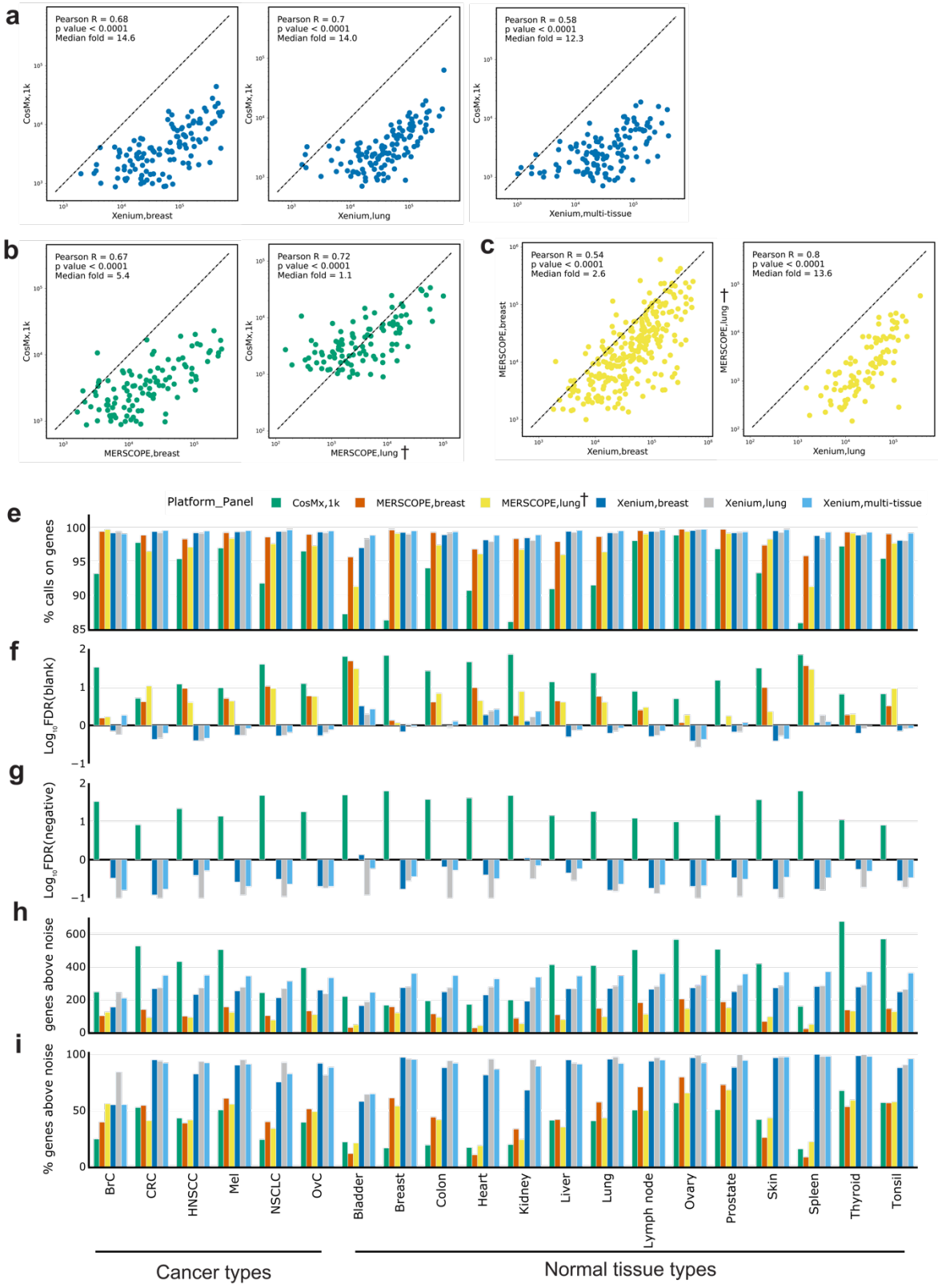

Figure 2: Technical performance comparison of iST platforms grouped by tissue types. (a) Scatter plots of summed gene expression levels (natural log transformed) of every shared gene between Xenium (breast/lung) and CosMx (1k) data, captured from matched tumor TMA cores. Each data point corresponds to a gene. **(b)** Same as (a) but between MERSCOPE (breast/lung) and CosMx(1k). **(c)** Same as (a) but between Xenium(breast/lung) and MERSCOPE(breast/lung). **(d)** Same as (a) but between Xenium(multi-tissue) and CosMx(1k). **(e)** Bar plot of percentage of all transcripts corresponding to genes relative to the total number of calls (including negative control probes and unused barcodes) averaged across cores of the same tissue type. Results are presented by panel including breast, lung, and multi-tissue panels from Xenium; breast and lung panels from MERSCOPE; and multi-tissue 1k panel from CosMx. **(f)** Bar plot of false discovery rate (FDR) where FDR(%) = (blank barcode calls / total transcript calls) x (Number of panel genes /Number of blank barcode) x 100. FDR values were $\log_{10}$ transformed to better show the differences between panels. **(g)** Same as (f) but using negative control probes to replace blank barcodes. MERSCOPE is missing in this bar plot as it does not have negative control probe by design. **(h)** Bar plot of number of genes detected above noise, estimated as two standard deviations above average of the negative control probes. **(i)** Same as (h) but normalized to the number of genes in a panel. † denotes the MERSCOPE lung panel acquired with a 5 µm imaging thickness.

iST platforms are all concordant with orthogonal RNA-seq data sets

In the absence of ground truth, it is difficult to evaluate whether a higher number of expressed genes is representative of increased sensitivity to real biology or increased false positive rates. We thus evaluated the correlation of iST data to reference RNA-seq data. We first aggregated pseudo-bulk normal tissue TMA results from all panels of the three platforms and compared them to data from the TCGA program **(see Methods)** [11]**.** We observed similar correlation coefficients across all gene panels relative to pseudo-bulk RNA-seq expression data (**Fig. 3a-b, Supplementary Table 8**). However, notably, the CosMx data showed a characteristic upswing in the low expression regime, similar to that observed when plotting gene-by-gene expression against MERSCOPE and Xenium (**Fig. 2, Supplementary Fig. 2**).

We also compared the pseudo-bulk results from the normal tissue TMA with bulk RNA-seq data obtained from GTEx[12] The Xenium breast, Xenium multi-tissue, and CosMx data sets showed similar correlations to breast data obtained from GTEx, while the MERSCOPE had

256 significantly lower correlation, consistent with a run which doesn't pass QC (Pearson's r of 0.36
257 vs 0.71, 0.68, and 0.69, respectively, **Fig. 3c**). Similar trends were observed in the lung data, with
258 MERSCOPE lung (5 µm) showing the lowest correlation while the other three data sets showed
259 higher correlations to GTEx data (**Fig. 3d**). These relative trends remained true across most normal
260 tissue types, though we found that thyroid, pancreas, and lymph nodes showed the lowest
261 correlations across all panels while prostate, tonsil, and liver showed the highest correlations
262 (**Supplementary Table 9)**. Overall, our comparison to TCGA and GTEx data suggests that while
263 some platforms may be more highly correlated to reference datasets in some cases, all are within
264 a similar correlation regime regardless of tissue type.

265 We next wanted to determine how the expression of tissue-specific transcript markers
266 varied across each platform. To accomplish this, we curated tissue markers that are unique to each
267 tissue type by selecting genes whose expression in a single tissue exceeds 20 times the sum of
268 other tissues from the GTEx database (see **Methods**). We found tissue-specific expression patterns
269 of several of these markers across all selected panels when visualized across each healthy tissue
270 type (**Fig. 3e**). MERSCOPE consistently showed expression of tissue-specific markers in multiple
271 tissue types, consistent with unsuccessful normal TMA data acquisition. However, some canonical
272 markers were not enriched in certain tissues. For example, we found that ABCC11 was highly
273 expressed in the breast tissue in the Xenium and MERSCOPE datasets, but not in CosMx. In fact,
274 although CosMx showed satisfying expression patterns for some tissue markers, many canonical
275 markers are not enriched in the expected tissues, possibly due to the high false discovery rate **(Fig.
276 3f-g)**. Across marker genes, Xenium data had a distinct expression pattern in all tissues, whereas
277 CosMx and MERSCOPE showed a less distinct pattern in many tissue types.

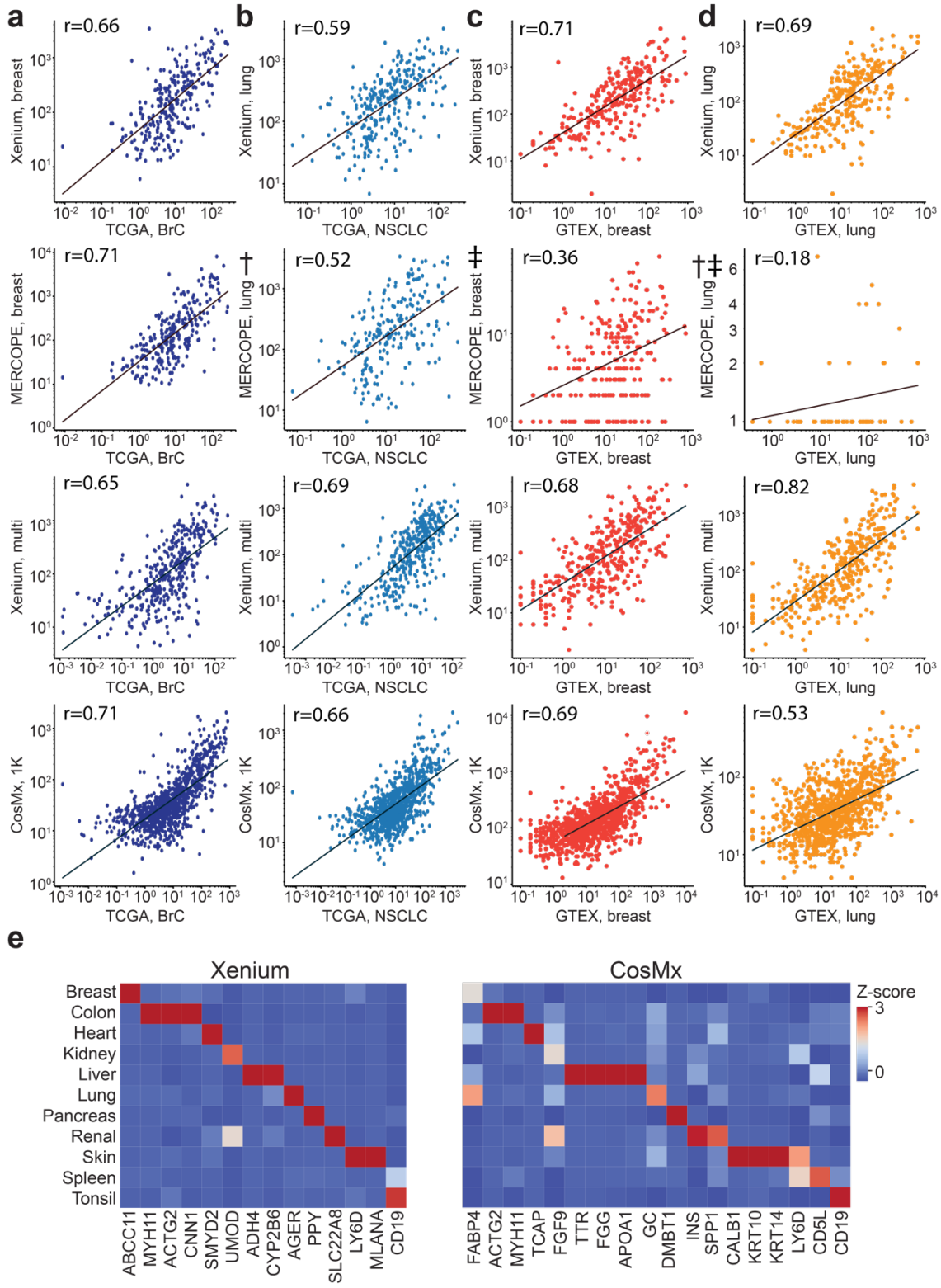

Figure 3: Concordance of iST data with reference RNA-seq datasets. (a) Scatter plots of overlapping genes, showing the averaged expression of a gene across breast cancer cores profiled by the indicated panel, normalized to 100,000 vs the average FPKM from TCGA for all samples

of a matched tissue type (BRCA). **(b)** Same as (a) but for lung cancer cores plotted vs averaged LUAD and LUSC samples from TCGA. **(c)** Same as (a) but showing breast cores vs averaged nTPM values from GTEx breast samples. **(d)** Same as (a) but for lung cores and samples. † denotes the MERSCOPE lung data acquired with a 5-µm imaging depth on FFPE sample. ‡ denotes the normal tissue TMA data of MERSCOPE which failed initial QC. **(e)** Heatmap of Z-scored average gene expression for several canonical marker genes in the indicated tissue cores for the Xenium multi-tissue panel (left) and CosMx 1K panel (right).

Out of the box segmentation and filtration can yield cells with comparable numbers of detected transcripts and genes from each platform.

Next, we compared the performance of each iST method on a single-cell level. The three platforms generate cell boundaries based on a DAPI image alone (Xenium) or a DAPI image combined with a membrane marker (CosMx and MERSCOPE). When we visually examined the segmentation outputs, Xenium data showed cell boundaries that appeared to include large regions of non-cellular space, in contrast to MERSCOPE and CosMx which tightly followed the visualized cell nucleus (**Fig. 4a**). When transcripts were overlaid with these segmentation boundaries, Xenium cell boundaries fell between regions of transcripts and thus most transcripts were assigned to cells. MERSCOPE and CosMx's tighter nuclei removed more transcripts, though those that remain appeared more confidently assigned to cells. Overall, when normalized to the imaged tissue area, Xenium and CosMx identified the most putative cells, followed by MERSCOPE (**Fig. 4b, Supplementary Table 6**). In line with the visual inspection, Xenium cells were consistently larger, regardless of data set or panel, followed by CosMx and finally MERSCOPE (**Fig. 4c, Supplementary Table 7**).

We filtered out empty regions of space and cells without any transcripts for downstream examination and quantified the fraction of cells containing differing numbers of transcripts per cell **(Fig. 4d).** We chose a permissive threshold of removing cells with fewer than 10 transcripts for Xenium and MERSCOPE, and 20 transcripts for CosMx from downstream analysis. [11, 24, 25]. The

309 tumor TMA consistently had a greater fraction of cells passing filtration, with Xenium retaining
310 the most cells (97.43% breast, 97.10% multi-tissue, 95.08% lung) followed by CosMx (83.41%)
311 and MERSCOPE (68.46% breast (10 μm), 25.77% lung (5 μm) (**Supplementary Table 3**). The
312 normal tissue TMA had overall lower cell retention performance, but the relative performance of
313 the platforms based on the fractions of cells remained the same. Notably, while CosMx and
314 Xenium still retained > 77% of the cells, MERSCOPE data of the normal tissue TMA had <3% of
315 cells retained and was thus not used in downstream analysis. Unsurprisingly, filtration decreased
316 the number of retained cells per unit area for all platforms, with the smallest decrease coming for
317 CosMx. The cells retained from CosMx had similar areas, while filtration of the Xenium and
318 MERSCOPE data sets resulted in a higher average cell area (**Fig. 4c**).

319 After filtration, we compared the number of transcripts and the number of unique genes
320 per retained cell across all tissues and all panels, focusing only on cores that were sampled by all
321 three platforms **(Fig. 4e-f**). Xenium breast panel gave the highest numbers of transcripts per cell
322 in most tissue types, 17 out of 22. The CosMx data showed the highest numbers of transcripts in
323 heart, lymph node, spleen, thyroid, and tonsil; and comparable transcript counts in breast cancer,
324 ovary, and ovarian cancer to the Xenium breast panel. The MERSCOPE data generally had the
325 lowest number of transcripts per cell, though bladder cancer and breast cancer measured with the
326 MERSCOPE breast panels approached the results from Xenium, and the bladder cancer and skin
327 data sets had higher transcripts per cell than CosMx. As expected given its larger panel size,
328 CosMx found many unique genes per cell, showing the largest numbers in 9 tissue types: breast
329 cancer, colon, heart, lymph node, ovary, ovarian cancer, spleen, thyroid, and tonsil; while Xenium
330 breast panel found the most unique genes per cell in 12 tissue types: bladder cancer, bladder, breast,
331 CRC, HNSCC, kidney, lung, melanoma, NSCLC, pancreas, prostate, and skin (**Fig. 4f**). If these

332 analyses were restricted to only the shared genes across all panels, numbers were much lower, but
333 Xenium showed higher expression levels and unique numbers of genes than either CosMx or
334 MERSCOPE (**Supplementary Fig 3c-d**).

335 We then wanted to determine how effectively different iST platforms' segmentation
336 algorithms perform. We examined the co-expression of *CD19*, a canonical B-cell marker, and
337 *CD3e*, a canonical T-cell marker across all filtered cells; the co-expression of *CD8* and *CD4*,
338 markers of T-cell subsets; and the co-expression of *CD3e* and *EPCAM*, a marker for epithelial
339 cancer cells [26, 27]. All these marker gene pairs are disjointly expressed, and a well-performing
340 segmentation algorithm should yield few cells expressing both markers. We pooled all the filtered
341 cells from matched cores and all available panels of each platform and plotted the expression of
342 one gene against the other and converted the scatter plot to a heatmap to show cell fractions. We
343 found that Xenium—despite its less visually accurate cell boundaries—and MERSCOPE, showed
344 clear patterns of disjoint expression, separating cells from different lineages, while CosMx showed
345 such a pattern for *EPCAM* vs *CD3e* but not for the other two pairs (**Fig. 4g**). Given the low counts
346 of the immune genes, it was difficult to determine if these were false positive calls or segmentation
347 errors. Nevertheless, since the CosMx panel is much higher plex, and retained similar numbers of
348 transcripts and genes to Xenium, we wondered how these two methods performed in terms of cell
349 type recovery.

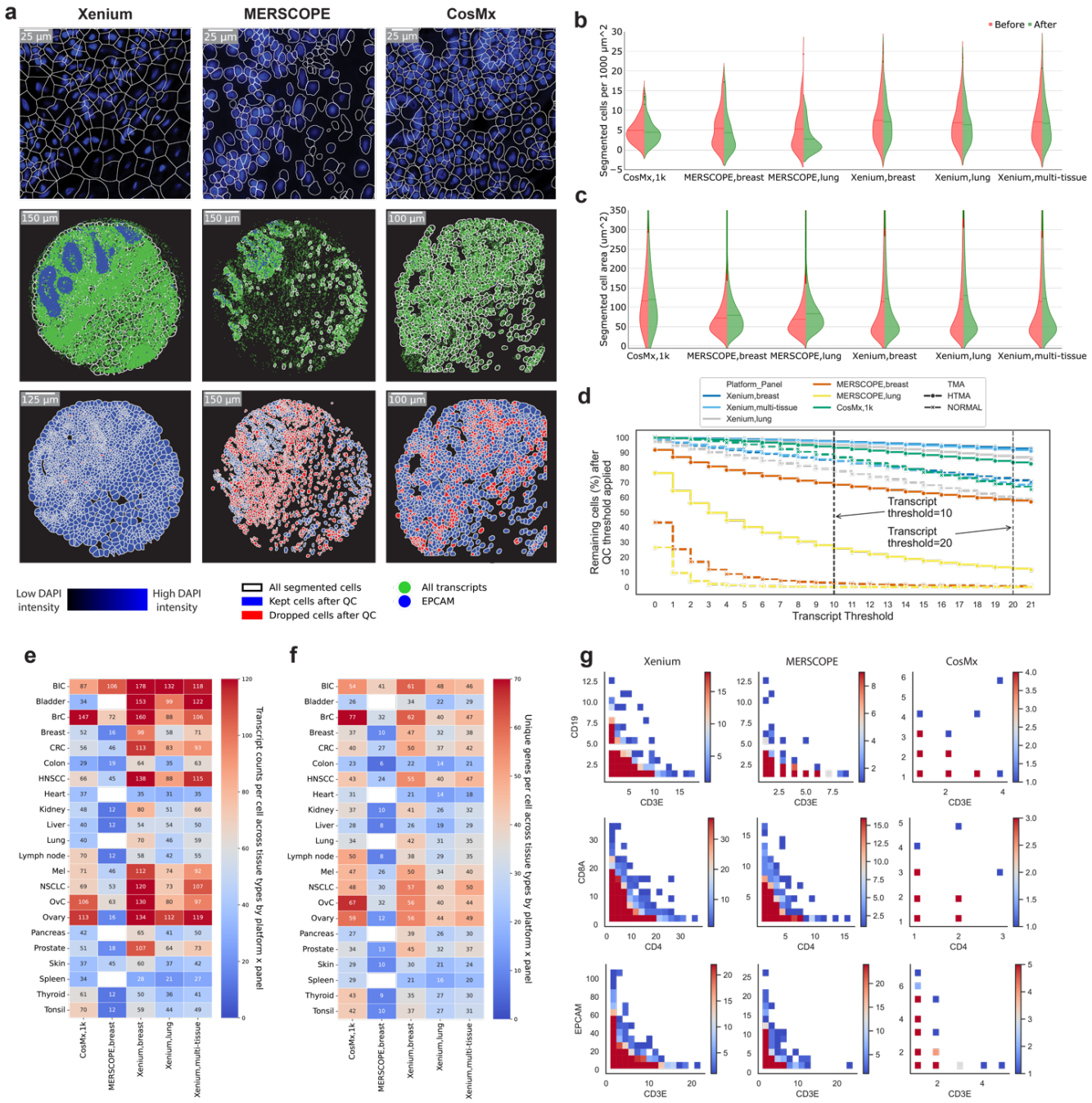

Figure 4: Comparison of cell segmentation results from each iST platform. (a) Top row: DAPI image overlaid with cell segmentation boundaries (subset). Middle row: all the transcripts in green dots, white lines for the cell boundaries, and *EPCAM* in blue dots. Bottom row: segmented cell boundaries before and after filtration. **(b)** Violin plot of segmented cells per unit area before (left half) and after filtration (right half) grouped by panel with tumor and normal TMA data combined. **(c)** Same as (b) but showing cell areas before and after filtration. **(d)** Line plot showing remaining cells in percentage after filtering with various thresholds (transcripts per cell). Dotted lines indicate selected thresholds: 10 transcripts or above for Xenium and MERSCOPE and 20 for CosMx. **(e)** Heatmap of transcripts per cell after filtration. All available genes are considered here for each

panel. MERSCOPE lung panel (5 µm) excluded from this heatmap. **(f)** Same as (e) but showing unique genes per cell. **(g)** Co-expression density map for three pairs of disjoint genes (rows) from all three platforms (columns). All cells across all tissues which include at least one detected transcript of either of the indicated genes are plotted together, with color indicating the number of cells at the indicated expression levels of each gene.

Clustering analyses reveal differences in cell type recovery across platforms

In a typical iST workflow, a key step is reducing the dimensionality of the data by identifying cell types, their unique states, and their expression patterns for further analysis leveraging spatial information[28]. To compare across platforms, we clustered the data from the filtered cells from all the cores for each TMA with a focus on breast tissues. The initial clustering of TMAs from datasets (except MERSCOPE normal tissue) showed expected batch effects caused by patients and tissue types with broadly similar cluster arrangements around morphological tissue features (**Supplementary Fig. 4a-d**). We removed batch effects (**see Methods**) and then performed targeted clustering and cell type annotation for breast samples from the CosMx and Xenium breast datasets; lung samples from the CosMx and Xenium lung datasets; and breast cancer from the CosMx, MERSCOPE breast, and Xenium breast datasets.

In breast samples, we were able to identify nine cell types, including all known major cell types, (adipocytes, alveolar cells, B cells, basal cells, fibroblast cells, hormone-sensing cells, myeloid, T cells, vascular & lymphatic cells) from the Xenium data, using previously established markers (**Fig. 5a, Supplementary Fig. 5**) [29,30,31]. In the CosMx data, we were only able to identify six cell types, including several major cell types, but failed to recognize cell subtypes (B cells, basal cells, fibroblast, hormone-sensing cells, immune cells, and vascular & lymphatic cells) (**Fig. 5a, Supplementary Fig. 5**). A high gene-to-gene correlation was found between all overlapping cell types between Xenium and CosMx (**Fig. 5a**). Similarly, in the lung samples, we were able to

386 identify nine cell types (alveolar epithelial type 1 cell, alveolar epithelial type 2 cell, endothelial
387 capillary cells, endothelial cells, fibroblasts, immune cells, macrophages, mast cells, and stroma
388 cells) in the Xenium lung panel, successfully covering all known major cell types (**Fig. 5b,**
389 **Supplementary Fig. 5**) [32,33]. Four of the six major clusters were identified and annotated in the
390 lung samples from the CosMx data (endothelial cells, epithelial cells, immune cells, and
391 macrophages), while the other two clusters remained difficult to annotate due to the non-traditional
392 enriched gene markers (**Fig. 5b, Supplementary Fig. 5**). Correlation heatmaps show a strong
393 correlation between the two macrophage clusters identified in Xenium and CosMx (**Fig. 5b**). The
394 epithelial cell cluster from CosMx correlates strongly with alveolar epithelial type 1 cell from
395 Xenium and the endothelial cell cluster from CosMx correlates with endothelial capillary cell
396 cluster from Xenium (**Fig. 5b**).

397 Finally, in breast cancer, after batch effect removal (**Supplementary Fig. 5d-f**), Xenium
398 resulted in nine cell types (alveolar cells, B cells, basal cells, fibroblast, hormone-sensing cells,
399 immune cells, myeloid, T cells, and vascular & lymphatic cells) (**Fig. 5c, Supplementary Fig. 5**)
400 [34,35,36]. On the other hand, CosMx resulted in eight cell types (alveolar cells, basal cells, epithelial
401 cells, fibroblast cells, hormone-sensing cells, immune cells, myeloid, and vascular & lymphatic
402 cells). MERSCOPE resulted in six cell types, including alveolar cells, fibroblast cells, hormone-
403 sensing cells, myeloid cells, T cells, and vascular & lymphatic cells. The cell type annotation of
404 Xenium and CosMx is comparable in terms of both transcriptomic profile and subtype depth, with
405 CosMx only unable to annotate immune cell subtypes (B cell and T cell). Gene expression of the
406 same cell type from both platforms correlated well (**Fig. 5c, Supplementary 5**). The cell type
407 annotation of CosMx, however, was especially difficult compared to Xenium because of its
408 atypical gene markers shown for each cluster in the heatmaps (**Supplementary Fig. 5**) and low

expression of transcripts from canonical markers (**Supplementary Fig. 5g-h**). MERSCOPE, on the other hand, identified most, but not all, the cell types recognized by Xenium and CosMx, including alveolar cells, fibroblast cells, hormone-sensing cells, myeloid, T cells, and vascular & lymphatic cells. MERSCOPE and Xenium showed a high correlation for almost all matching clusters. The correlation map shows a clearer one-to-one mapping between MERSCOPE and Xenium clusters than Xenium and CosMx clusters.

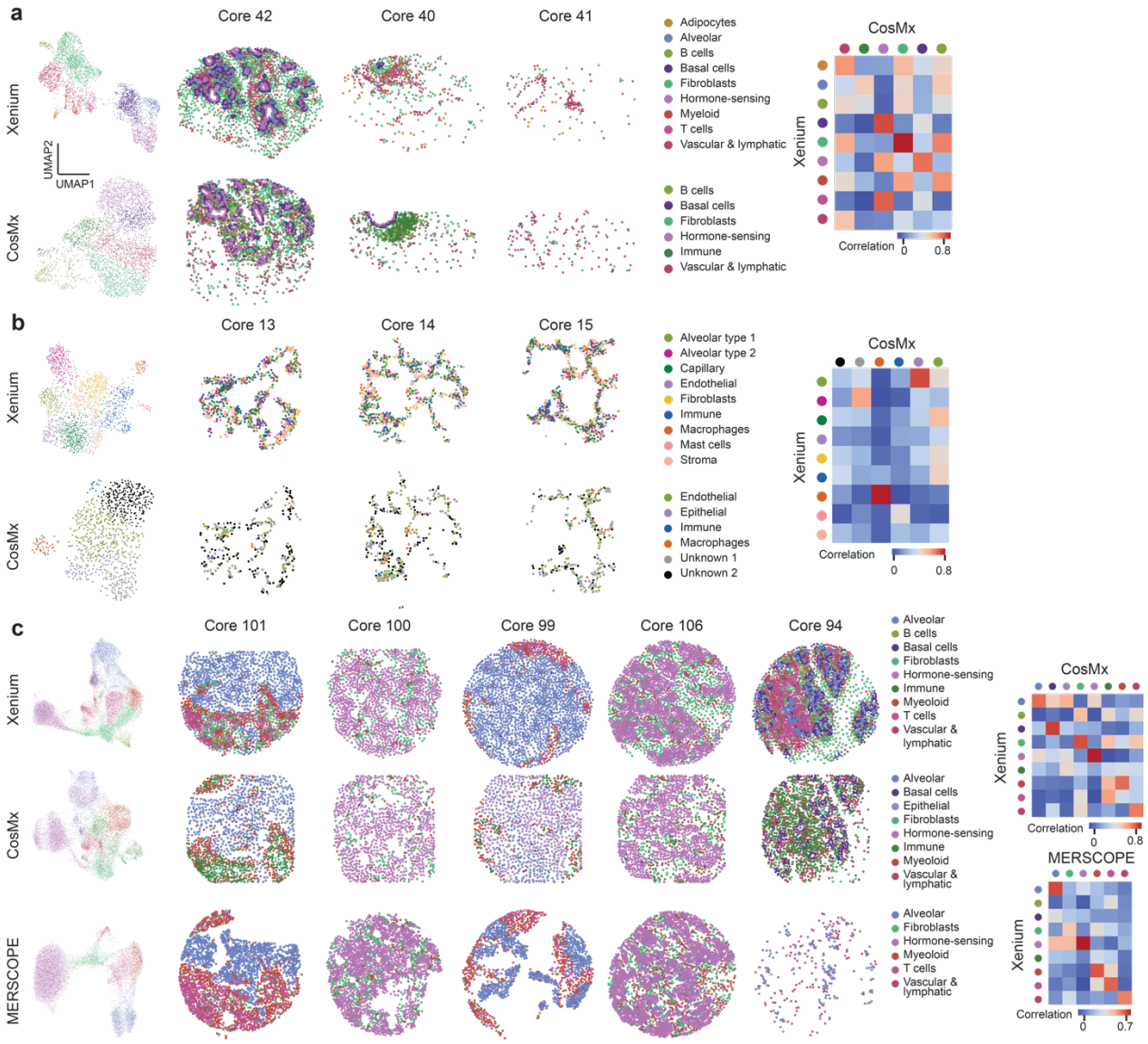

Figure 5: Cell type recovery performance across technology. (a) Clustering results of breast samples in normal TMA from Xenium breast (bottom left) and CosMx multi-tissue 1k (top). Correlation plot showing the correlation between cell types identified (bottom right). **(b)** Clustering results of lung samples in normal TMA from Xenium lung (bottom left) and CosMx multi-tissue 1k (top). Correlation plot showing the correlation between cell types identified (bottom right). **(c)** Clustering results of breast cancer samples in tumor TMA from Xenium breast (bottom left), MERFISH (bottom right) and CosMx multi-tissue 1k (top). Correlation plot showing the correlation between cell types identified in CosMx and Xenium (left), MERFISH and Xenium (right).

427 **DISCUSSION**

428 In this study, we compared data obtained with three commercially available iST platforms
429 with archival FFPE tissues to assess overall technical performance and help guide experimental
430 design with human samples that represent an important use case of these platforms. We focused
431 our analyses on technical performance as a function of tissue type, including 7 different tumor
432 types and 16 normal tissue types. Overall, we found that each iST platform presented various
433 tradeoffs in terms of implementation, panel design and panel options, and resulting total transcript
434 quantification and downstream analyses, including cell segmentation, cell quality, and biological
435 interpretation. All these factors must be considered when designing iST experiments.

436 There are significant workflow differences between the different platforms which factor
437 into the choice of method. Cutting samples onto MERSCOPE coverslip is more difficult than on
438 standard microscope slides. The total hands-on time for running a slide on Xenium is 2-3 days
439 compared to 5-7 days for MERSCOPE and 2 days on CosMx. We found that MERSCOPE and
440 CosMx are well set up for batch processing in the wet lab, either due to built-in pause points or the
441 instrument's ability to run multiple samples. Xenium is limited for batch processing by a need for
442 a separate thermocycler for each slide pair processed in parallel. After staining, selecting regions
443 of interest (ROIs) presented a surprising challenge for some systems: the Xenium platform could
444 readily image the entire slide as a single ROI which easily covered entire TMAs, but the
445 MERSCOPE ran into a 1cm^2 imaging area limit which meant cores in the addressable region were
446 left unimaged, while the CosMx workflow required a demanding manual selection of ROIs for
447 each core. These factors are likely to change as each company updates its protocol, but currently,
448 Xenium offers the shortest and least hands-on workflow.

449 From a technical perspective, we analyzed each resulting dataset with a combination of
450 manufacturer recommended processes for each platform and computational tools that can be
451 implemented by the user downstream. These pipelines each result in count matrices and detected
452 transcripts that can be analyzed using a whole suite of emerging tools. For our purposes, when
453 analyzed at a core level to abrogate the effects of individual cell-segmentation performance, we
454 found that the total number of transcripts varied substantially across iST platform, with Xenium
455 yielding the highest number of transcripts captured followed by CosMx. Indeed, this trend held
456 when normalized for the number of cores imaged and on a per cell basis per area. When this
457 analysis was also restricted to shared genes, we also found that Xenium consistently had higher
458 expression levels across each tissue type, with no clear differences between performance on either
459 tumor or normal tissue.

460 Using a pseudo-bulk approach, again at the core level, we assessed overall correlation,
461 reproducibility, and sensitivity of each platform. We found high correlation between replicates of
462 the same patient, suggesting that there is high reproducibility across technical replicates on each
463 platform. This is important to consider since cost or input material availability can be prohibitive
464 to implementing experimental designs that leverage technical replicates—though additional tissue
465 may still be valuable for powering cell-cell interaction analysis. We additionally found high
466 correlation on a gene-by-gene basis between MERSCOPE and Xenium platforms. Xenium and
467 MERSCOPE also showed consistently high specificity across tissue types. CosMx displayed a
468 characteristic upward curve when compared to MERSCOPE or Xenium on a gene-by-gene basis,
469 indicating more frequent calls in the lower expression regime. This, coupled with the lower
470 specificity across several tissues for CosMx and the high false discovery rate, suggest that CosMx
471 is prone to errors in calling lowly expressed genes. Finally, Xenium had the highest sensitivity

472 across tissues. CosMx and MERSCOPE both detected fewer transcripts than Xenium.
473 MERSCOPE outperformed CosMx in the higher quality (as judged by relative performance across
474 all platforms) tumor TMA but underperformed it in lower quality normal tissue TMA. In general,
475 our analyses also suggest similar performance within a given platform across a vast array of tissue
476 types assayed here. We note that given the small number of replicates from each tissue, particularly
477 in the normal tissue, we stop short of making blanket statements about relative performance across
478 a particular tissue type. The data suggests, instead, that Xenium and MERSCOPE provide more
479 reliable true-positive signals of lowly expressed genes and that Xenium's overall performance is
480 less dependent on sample input quality than the other two platforms. MERSCOPE, especially,
481 appears to be particularly sensitive to sample input, highlighting the importance of prescreening
482 RNA integrity according to manufacturer instructions.

483 When we compared each dataset to existing RNA-seq datasets, we found comparable
484 correlation of pseudo-bulk data to RNA-seq data from GTEx or the TCGA across each panel and
485 platform. However, the presence of a characteristic upswing for CosMx, even when comparing to
486 orthogonal data, further shows that there is a higher false positive rate for lower expression level
487 genes in CosMx data. This upswing could be explained by the absence of probing genes in a
488 particular tissue in a larger panel. However, the Xenium multi tissue panel also includes genes not
489 expressed in breast and lung but does not show a similar upswing. Thus, a more likely
490 interpretation is that the CosMx is prone to a high FDR at the low expression regime. This could
491 also suggest that the CosMx transcript counts and detected gene numbers may be slightly inflated
492 by false discoveries.

493 From a tissue-specific expression perspective, Xenium showed a distinct expression
494 pattern of key tissue-markers, whereas CosMx and MERSCOPE did not. Additionally,

495 MERSCOPE and CosMx consistently showed expression of known tissue markers in unexpected
496 tissue types. This could be partly explained by an overall low performance on this particular normal
497 tissue TMA for MERSCOPE due to RNA quality. This performance difference could be
498 problematic for studies that are designed to compare tissue-specific factors. For studies whose
499 main biological variable of interest are within the same tissue, factors like sensitivity, specificity,
500 and panel availability may be a more important guide for iST experimental design.

501 A significant advantage of spatial transcriptomics data is the ability to map expression in
502 single cells. We compared each platform on a cell-level basis by assessing cell identification and
503 cell clustering. Overall, it appears that the out of the box segmentation from Xenium performs
504 poorly in terms of drawing cell boundaries specific to a single cell, while MERSCOPE and Xenium
505 much more closely match cell boundaries. This did not appear to differ on a tissue-by-tissue basis,
506 thus, is likely inherent to the overall approach used by each platform. After applying an expression
507 level filter, Xenium overall retained the highest number of cells across various filtering
508 stringencies. Despite Xenium's cell boundaries not clearly matching nuclei, both it and
509 MERSCOPE were able to effectively separate cells from different lineage markers, as judged by
510 finding minimal coexpression of disjoint markers, while CosMx showed more double positive
511 cells (out of, it should be noted, fewer cells expressing the target genes overall).

512 To determine whether clearer identification of lineage markers resulted in improved ability
513 to identify cell types, we performed clustering analyses specifically in the breast tissue and breast
514 cancer samples. We note that we used the full panel, not only the shared genes, when performing
515 these clustering analyses. Xenium allowed for identification of all major cell lineages in the breast
516 when compared to several reference breast atlases. Both the global and tissue clustering results
517 show that CosMx is also able to recognize the major cell types, but cannot identify cell subtypes.

518 Additionally, since the cluster-enriched genes do not correspond to well-known markers, probably
519 due to the low expression caused by low sensitivity and specificity, cell type annotation was
520 particularly difficult. Lastly, despite lower transcript counts and fewer cells, MERFISH still
521 successfully identified cell groups, capturing the patterns seen in other platforms. These
522 differences in cell typing, can also be attributed to the differential performance of cell segmentation
523 pipelines [37,38 39,40]. Since all platforms provide the underlying DAPI stain and morphology images
524 (in the case of CosMx and MERSCOPE) it is likely that segmentation performance could be
525 improved on a sample-by-sample or tissue-type-by tissue-type basis. Future work should seek to
526 assess cell segmentation tools and their performance across data from each platform to help inform
527 the choice of analytical method where needed.

528 Plex is an important factor in ST experiments which we have not explicitly considered. The
529 kinds of questions that may be answered by a 1,000-plex panel are clearly different than those
530 answered by a 300-plex panel, offering more opportunities to explore intra- and intercellular
531 signaling interactions. Thus, we note that for the right question, the higher false positive rates and
532 lower sensitivities of CosMx relative to Xenium could be tolerated for a broader coverage of the
533 biology. On the other hand, the fully configurable nature of Xenium and MERSCOPE panels could
534 be better suited for branches of biology not well sampled by the 1,000 plex CosMx panel. We
535 recommend subsampling existing atlas data to determine whether the gene set which can be studied
536 will be sufficient to cluster the cell types of interest and identify the necessary biological programs.
537 We note that each of the manufacturers has publicly stated plans to grow their product offerings
538 to increasing panel sizes.

539 There are several limitations of our study. While we attempted to match time post slicing,
540 the unintentional acquisition of MERSCOPE tissues at thinner thicknesses meant that the rerun

541 MERSCOPE data had a longer time on slide than other panels. However, the fact that the increase
542 in counts in the rerun matched the increase in imaging volume, and the fact that Xenium runs
543 showed stable expression levels over time suggests that this contribution was minimal.
544 Additionally, our panel design for MERSCOPE required removal of genes so the panel was
545 compatible with all tissues, lowering the plexity slightly. This could have compromised
546 MERSCOPE's ability to identify cell types relative to Xenium.

547 Most importantly, we only attempted to compare the performance of iST platforms under
548 typical use cases for clinical samples obtained from archival biobanks. Our results don't
549 necessarily extend to non-human samples, frozen samples, and even FFPE samples which have
550 been extensively validated for high RNA integrity. Indeed, there have been reports that
551 MERSCOPE, in previous studies of the mouse brain, shows comparable or even superior results
552 to those reported by 10X Xenium[41]. Given the large change in data quality between the normal
553 and tumor TMA, we cannot exclude the possibility that in the highest quality samples MERSCOPE
554 would provide higher transcript numbers, with the associated downstream benefits relative to
555 Xenium and CosMx. However, the current guidance of $DV_{200} > 0.6$ restricts studies to the upper
556 regime sample quality and limits archival investigations.

557 Despite these limitations, our overall interpretation of these results is that amplification of
558 RNA signal is especially important for recovery of transcript counts by iST in low-quality samples
559 where RNA may be highly degraded and fewer landing sites are available for probes. Platforms
560 (such as Xenium) which rely on small numbers of landing sites and are subsequently heavily
561 amplified are robust to RNA degradation and are thus more broadly compatible with a broad range
562 of samples. On the other hand, when sample quality is high (as in some of our tumor samples) the

563 gap between amplified and unamplified platforms' performance closes and most platforms can
564 yield useful data for subsequent downstream spatial analysis.

565 **Methods**

566 **Sample choice and TMA construction**

567 Two TMAs were constructed using FFPE clinical discards at Brigham and Women's
568 Hospital Pathology Core and were acquired with a waiver of consent for non-sequencing based
569 readouts under IRB 2014 P 001721. The samples included:

570 1. A tumor TMA of 170 cores, 0.6 mm in diameter, including a variety of cancer samples
571 and healthy lymphoid tissue as a positive staining control. The TMA samples were
572 selected from samples previously characterized by ImmunoProfile and were selected
573 to encompass both high and low levels of the biomarkers in the ImmunoProfile panel
574 [*CD8*, *PD-1*, *PD-L1*, *Foxp3*, tumor marker (*Cytokeratin*, *Sox10*, or *PAX8*)].
575 Annotations were performed by KF and SR based on H&E and immunofluorescence
576 staining. Cores included both tumor and healthy control annotation, though for the
577 purpose of this study, all were combined under their tumor label. Tumors were also
578 chosen to be a mixture of *PD-L1* high and *PD-L1* low, a parameter to be analyzed at a
579 future date. This TMA had previously been studied by both H&E, and several highly
580 multiplexed immunostaining approaches, and was known to be of high morphological
581 integrity.
582 2. A normal TMA of 45 cores 1.2 mm in diameter representing a broad range of normal
583 tissues. Samples were sourced from the same patient in either duplicate or triplicate.

584 This TMA was chosen for the breadth of tissue lineages included and the relatively
585 large core size.
586 All samples were fully de-identified before assembly into TMAs. The breakdown of the number
587 of samples per tissue and the number of cores per tissue is included in **Supplementary Table 1-**
588 **2**.
589 **Preparation of sequential sections**
590 Sequential sections were prepared according to manufacturer instructions ("Tissue
591 Preparation Guide Demonstrated Protocol CG000578" for Xenium, "91600112 MERSCOPE User
592 Guide Formalin-Fixed Paraffin-Embedded Tissue Sample Preparation RevB" for Vizgen, and
593 "MAN-10159-01CosMx SMI Manual Slide Preparation Manual" for CosMx) at the Brigham and
594 Women's Hospital Pathology Core. Prior to collecting samples, ~50 µm of each TMA were faced
595 off to reach deeper into the sample where RNA integrity was likely higher. 5 µm sequential
596 sections were then collected, floated in a 37˚C water bath, and adhered to Xenium slides (10X, PN
597 1000460), Vizgen FFPE coverslips (Vizgen, PN 10500102), or standard Superfrost+ slides for
598 CosMx (Leica BOND PLUS slides, Leica Biosystems S21.2113.A). TMAs were sliced as close to
599 the center of the active area as possible for each platform. Samples were baked at 42˚C for 3 hours
600 for Xenium, 55 ˚C for 15 minutes for MERSCOPE, and 60˚C for 16 hours for CosMx. Sections
601 were stored according to manufacturer instructions prior to processing, with 10X Xenium stored
602 in a desicator at room temperature, Vizgen MERSCOPE coverslips stored at -20˚C, and Nanostring
603 CosMx slides stored at 4˚C. Samples for 10X Xenium and Vizgen MERSCOPE were brought to
604 the Spatial Technology Platform at the Broad Institute for processing, while samples for
605 Nanostring CosMx were processed at the Wei lab at Brigham and Women's Hospital.
606

607 **Vizgen MERSCOPE probe selection**

608 Pre-designed probe panels from Vizgen were not available at the time of the experiment.
609 Therefore, we ordered custom gene panels to match the pre-released gene panels from 10X for the
610 human breast and human lung panels. Gene lists were uploaded to the Vizgen panel design portal
611 and were checked against all profiled tissues, removing genes that were overexpressed in any
612 individual tissue based on Vizgen's design guidelines (FPKM > 900), and ensuring that the total
613 panel FPKM did not exceed the allowed limit in any individual sample type. Panels were
614 manufactured at the 300 gene scale as custom panels BP0892 and BP0893. The final gene lists, for
615 all three iST modalities are available in **Supplementary Table 3.**

616

617 **Vizgen MERSCOPE data acquisition**

618 MERSCOPE samples were imaged according to manufacturer protocol "9160001
619 MERSCOPE Instrument User Guide RevF". Samples were processed in two batches, the first of
620 four samples, two of each TMA and with each library prepped in parallel; and a follow up sample
621 of each TMA re-run with the breast panel. Samples were first hybridized with anchoring probes
622 overnight before being embedded in a polyacrylamide gel. Samples were incubated for two hours
623 with a digestion solution at 37˚C and then overnight at 47˚C overnight in a detergent clearing
624 solution and proteinase K to remove native proteins while the anchoring probes kept nucleic acids
625 bound to the gel. After clearing, samples were additionally photobleached using Vizgen's
626 MERSCOPE Photobleacher for three hours at room temperature in the clearing solution. Samples
627 were hybridized with encoding probes and a cell boundary stain (PN 10400118) and then imaged
628 with imaging kits (PN 10400005). Samples were stored at 37˚C in clearing solution after
629 hybridization and before final imaging. After an initial examination of the data, a second batch of

both TMAs was run a second time with the human breast panel, increasing the set imaging capture thickness from 5 µm to 10 µm to capture more tissue from cores that had lifted during the gel embedding process. Data was processed on premises through the standard Vizgen workflow to generate cell by gene and transcript by location matrices. We segmented the data with a built-in Cellpose method on the most accurate looking cell boundary stain.

10X Xenium data acquisition

10X Xenium samples were processed in three batches according to manufacturer protocols "Probe Hybridization, Ligation & Amplification, User Guide CG0000582" and "Decoding & Imaging, User Guide CG000584". Samples were stained utilizing 10X's predesigned Human Breast (10X, PN 1000463), Human Multi-Tissue and Cancer (10X, PN 1000626), and Human Lung panels (10X, PN 1000601), as they became available from the manufacturer. Slides for both TMAs were processed in pairs according to which probe library they were receiving. Slides were stained with a Xenium imaging kit according to manufacturer instructions (10X, PN 1000460). Briefly, padlock probes were incubated overnight before rolling circle amplification and native protein autofluorescence was reduced with a chemical autofluorescence quencher. Slides were processed on a 10 Xenium Analyzer, with ROIs selected to cover the entire TMA region. Data was processed on premises through the standard 10X workflow to generate cell by gene and transcript by location matrices.

Nanostring CosMx

Nanostring CosMx samples were prepared with one 1000 plex panel. Samples were hybridized with probes and stained with cell markers. Samples were loaded onto the CosMx SMI

653 at the same time for imaging, during which branched fluorescent probes were hybridized onto the
654 samples to amplify the signal above the background.

655 Nanostring CosMx samples were prepared with Human Universal Cell Characterization
656 1000 Plex Panel (part number 122000157) according to manufacturer protocol "MAN-10159-01
657 CosMx SMI Manual Slide Preparation Manual". Firstly, slides were baked at 60℃ overnight for
658 better tissue adherence. After baking, slides were treated sequentially with deparaffinization, target
659 retrieval (15 min at 100°C), permeabilization (3µg/mL proteinase K, 15 min at 40°C), fiducials
660 application, post-fixation, NHS-acetate application and then hybridized with denatured probes
661 from universal panel and default add-on panel. After *in situ* hybridization (18 hours at 37°C), slides
662 were washed and incubated with DAPI (15 min at RT) and marker stain mix (with *PanCK, CD45,*
663 *CD68* and cell segmentation marker *CD298/B2M*). Slides were washed and loaded onto the
664 CosMx SMI for UV bleaching, imaging, cycling and scanning. Raw images were decoded by
665 default pipeline on Atomx SIP (cloud-based service). Machine: CosMx_0020. Serial Number:
666 INS2301H0020

667 **Data preprocessing**

668 After data acquisition, the resulting outputs were uploaded to a Google bucket associated
669 with a terra.bio Workspace for distribution and follow on analysis.

670 To facilitate standardized data formatting and subsequent analytical processes, we built a
671 data ingestion pipeline with the following objectives: a) to grab cell-level and transcript-level
672 data from diverse platforms and normalize the data structure; b) to tag each cell and transcript
673 with essential metadata including tissue type, tumor status, *PD-L1* status, among others
674 (**Supplementary Fig. 6**); and c) to transform the data into various formats tailored to the
675 requirements of particularized analyses. Specifically, to tag the data, core centers in the TMA

676 were manually identified using DAPI images (Xenium) or cell metadata that contains global
677 coordinates (MERSCOPE and CosMx) using QGIS(version:3.16.10-Hannover). Cells or
678 transcripts within a specified radius were then labeled with core metadata via spatial joining
679 (implemented by GeoPandas, version:0.13.0). In instances where cores are in close proximity or
680 when a uniform radius cannot be applied effectively, we manually generated the core boundary
681 masks.
682
683 **Reproducibility**
684 To evaluate panel to panel reproducibility we summed the expression level of shared
685 genes between indicated panels (breast vs. multi-tissue and breast vs. lung panels from Xenium
686 and breast vs. lung panels from MERCOPE) over an individual core and plotted all cores present
687 in each panel, before calculating a Pearson's correlation. The format of the data used is shown in
688 **Supplementary Table 10.** To evaluate core to core reproducibility, the individual gene counts of
689 core 1 were plotted against those of core 2 and a Pearson's r correlation was calculated.

690 **On target rates and false-discovery measurements**

691 To compare across panels and platforms, we subset all datasets to include only cores
692 assayed in all runs. The fraction of on-target barcodes was calculated as a percentage of all
693 transcripts corresponding to genes relative to the total number of calls (including negative
694 control probes and unused barcodes or blank barcodes). These measurements were performed on
695 individual cores and averaged across all cores of the same tissue type.

696 Because the difference in relative numbers of controls and target barcodes across
697 different platforms, we adopted the false discovery rate (FDR) calculation to evaluate the
698 specificity in a more normalized way (**Fig. 2f-g**). We calculated the FDR of platform *p* panel *m*
699 data in tissue *t* using the following equation and cell level data (**see example in Supplementary**
700 **Table 11**):

701 $$FDR(negative\ control\ probes)_{p,m}^{t} = mean\left(\frac{\sum_j neg_{jn}}{\sum_i g_{in} + \sum_j neg_{jn}} \times \frac{I}{J} \times \%\right), \qquad n = \{1, \dots, N\}$$

702 Where *N* is the total number of cores that belong to tissue type *t*, *I* is the total number of unique
703 genes, *J* is the total number of negative control probes, g_{in} is the gene expression of gene *i* in
704 core *n*, neg_{jn} is the total calls negative control probe *j* in core.

705 Since MERSCOPE does not include negative control probes, FDR was recalculated by
706 substituting negative control with blank barcodes (**Fig. 2f**) using the following equation:

707 $$FDR(blank\ barcodes)_{p,m}^{t} = mean\left(\frac{\sum_l blank_{ln}}{\sum_i g_{in} + \sum_l blank_{ln}} \times \frac{I}{L} \times \%\right), \qquad n = \{1, \dots, N\}$$

708 Where *N* is the total number of cores that belong to tissue type *t*, *I* is the total number of unique
709 genes, *L* is the total number of unused barcodes or blank barcodes, g_{in} is the gene expression of
710 gene *i* in core *n*, $blank_{ln}$ is the total calls of unused barcode or blank barcode *l* in core *n,*
711 specifically, we used BLANK for Xenium data, Blank for MERSCOPE data, and SystemControl

712 for CosMx data. We only used the data from matched cores, so *N* is same for different platform
713 *p*.
714
715 **Sensitivity comparison**
716 Sensitivity was measured by the percentage of the total number of unique genes detected
717 above noise level, where the noise was estimated as two standard deviation above average
718 expression of the negative control probes.
719
720 **Orthogonal RNA-Seq concordance analysis**
721 RNA TCGA cancer sample gene data summarizes 7,932 samples from 17 different cancer
722 types, and it provides FPKM for each gene documented. We used all samples which were
723 annotated as BRCA (Breast cancer), BLCA (Bladder cancer), COAD and READ (colorectal
724 cancer), HNSC (head and neck squamous cell carcinoma), LUAD and LUSC (non-small cell lung
725 cancer), SKCM (melanoma), and OV (ovarian cancer). For GTEx, we selected the tissue types
726 matching the annotation in our normal tissue TMA. For each panel, the genes probed by iST were
727 averaged across all patients with the matching tissue label from the RNA-seq database.
728 To get pseudo-bulked iST values, the expression level of each gene in each core was normalized
729 to the sum of all genes in that core and scaled by 100,000. We then averaged these scaled pseudo-
730 bulk expression values across cores and plotted them against the averaged FPKMs from reference
731 RNA-seq data sets.
732
733 **Tissue marker enrichment analysis**

734 To determine the assay's ability to specifically identify known lineage markers, we focused
735 on the normal tissue TMA profiled with multi-tissue panel of Xenium, breast panel of MERSCOPE,
736 and 1K panel of CosMx. We selected genes with known canonical expression patterns using based
737 on transcriptomics data from GTEx. If a gene had 20-fold higher expression in a specific tissue
738 than every other tissue combined, this gene was considered to be a tissue marker and was used for
739 assessing specificity for each platform. Counts for each gene were normalized to the total counts
740 within the core, and then the Z-score of this gene across tissue types was plotted in a heatmap **Fig.**
741 **3e**. We calculated average expression of a gene across cores of the same tissue type and normalized
742 to the total averaged expression of all genes. Z-scores were calculated with the mean and standard
743 deviation across all averaged genes.
744
745 **Evaluation of cell segmentation performance**
746 In the absence of ground truth data, we conducted a comparative analysis of cell counts,
747 cell areas, coexpression across various platforms and panels, utilizing the segmentation results
748 supplied by each respective company. To facilitate comparison, cell counts were normalized to a
749 consistent area of 1000 μm^2. Both cell count and cell area were then delineated at two distinct
750 levels of detail: a consolidated assessment encompassing all tissue types (see **Fig. 4b-c**), as well
751 as a segregated evaluation by individual tissue types (refer to **Supplementary Table 6-7**). To
752 evaluate the biological performance of the segmentation, we plotted coexpression plots of gene
753 pairs that are mutually exclusive including *CD3e* vs. *CD19*, *CD4* vs. *CD8*, and *CD3e* vs.
754 *EPCAM*. We pooled all the filtered cells from matched cores and all available panels of each
755 platform, dropped cells which do not express either gene, plotted the expression of one gene

against the other, and converted the scatter plot to a 2D histogram showing cell numbers in each co-expression bin (**Fig. 4g**).

Cells per area quantification

Segmented cells were aggregated by TMA cores. For Xenium and MERSCOPE data, the estimation of tissue area was performed by calculating the area of a discernible circle, utilizing respective radius of 0.3 µm and 0.6 µm for tumor and normal TMA samples. Conversely, for the CosMx dataset, the tissue area estimation was approached differently due to its square-like data presentation, a result of the FOV selection process. Here, the tissue area was deduced by multiplying the number of FOVs covered by each core with the area of a single FOV.

Clustering

For cell filtering, cells with less than 10 transcript counts in MERFISH and Xenium datasets were removed, and cells with less than 20 transcript counts in CosMx datasets were removed. We followed standard processes to then cluster and annotate cell types across each dataset using Scanpy[42]. Briefly, data was normalized and scaled, dimensionality reduction was performed and cell clusters were identified[43, 44]. To identify the cell type for each cluster, we used a t-test to find the markers for each Leiden cluster and annotated them according to previous literature[29-36]. These are some of the example markers used for cell type annotation: in breast samples, PIGR and KIT for alveolar cells, for B cells, KRT5, DST, and MYLK for basal cells, LUM, MMP2 and CXCL12 for fibroblast, etc. Heatmaps of the top 3 markers for each cluster are drawn for each dataset from all three panels (refer to **Supplementary Figure 5a-c**). For datasets that showed batch effect with patients, Harmony was used to remove this variance[45]. Correlation

heatmaps were generated over overlapping genes that exist in both datasets, and the Pearson correlation coefficient was calculated.

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Author contributions

Conceptualization: A.Y., S.F., tissue-microarray construction: K.F., K.P., T.B., S.R., pathological annotation: K.P., S.R., gene selection: A.Y., S.F., Xenium and MERSCOPE data acquisition: J.N., CosMx data acquisition: C.G., M.T.,K.W., analysis: H.W., R.H., B.G.,S.F., figure generation: H.W., R.H., B.G.,S.F., writing original draft: H.W., R.H., J.N., B.G., S.F., draft reviewing and editing: H.W., R.H., B.G., S.F., supervision: B.G., S.F., funding acquisition: S.F. K.W.

Data and Code Availability

Cell level data and gene level data will be made available at the time of final publication. All code used in this manuscript for data processing and analysis will be made available on github prior to final publication.

Declaration of interests

All authors declare that they have no conflicts of interest.

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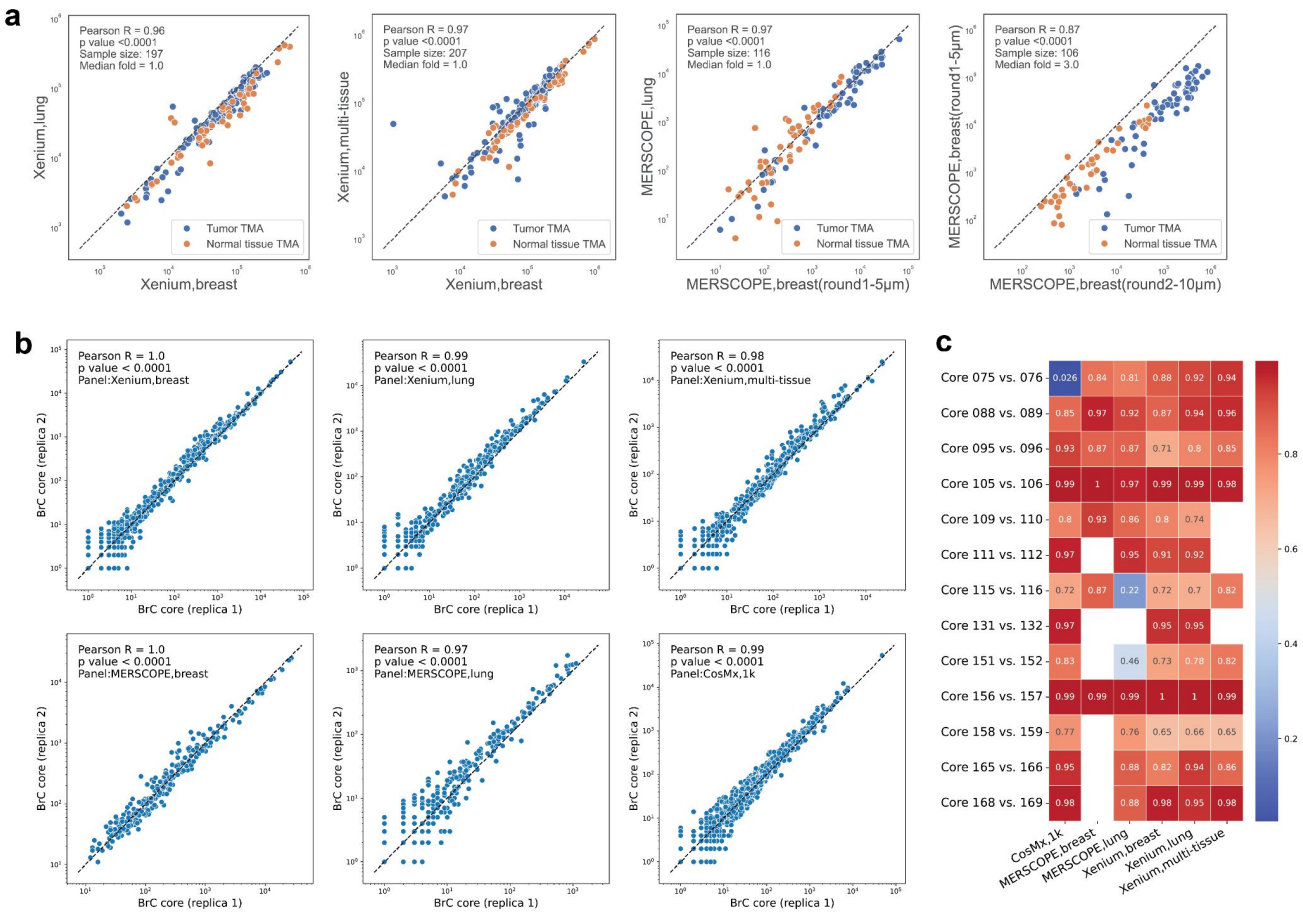
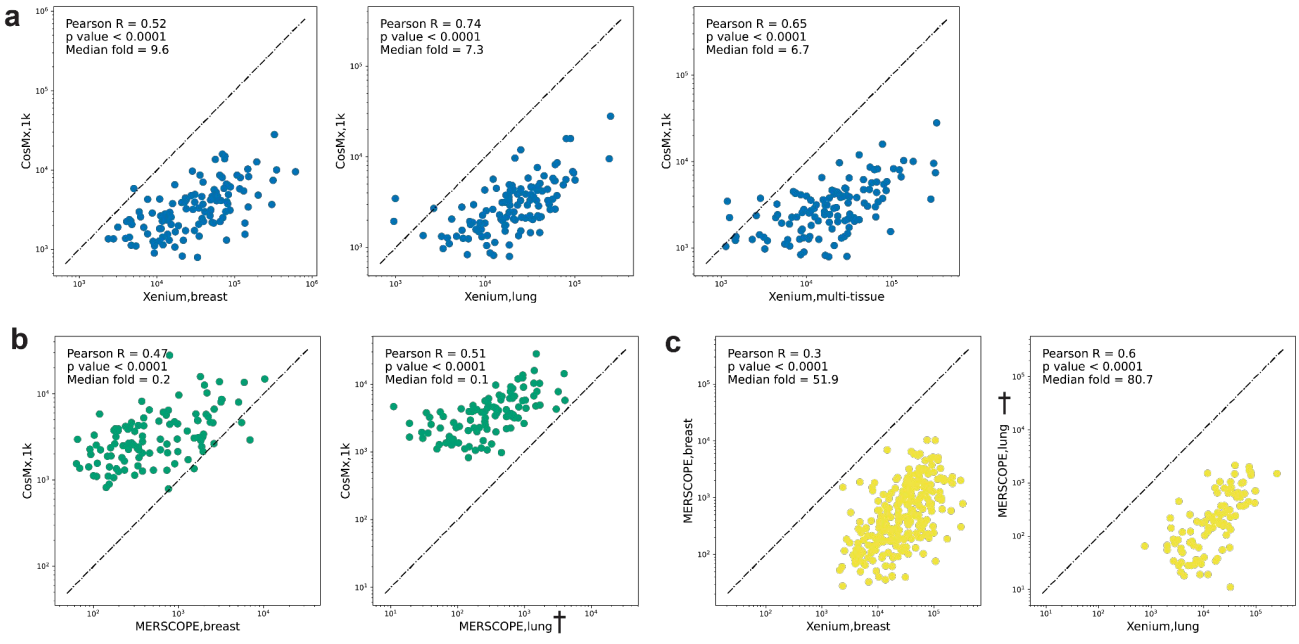
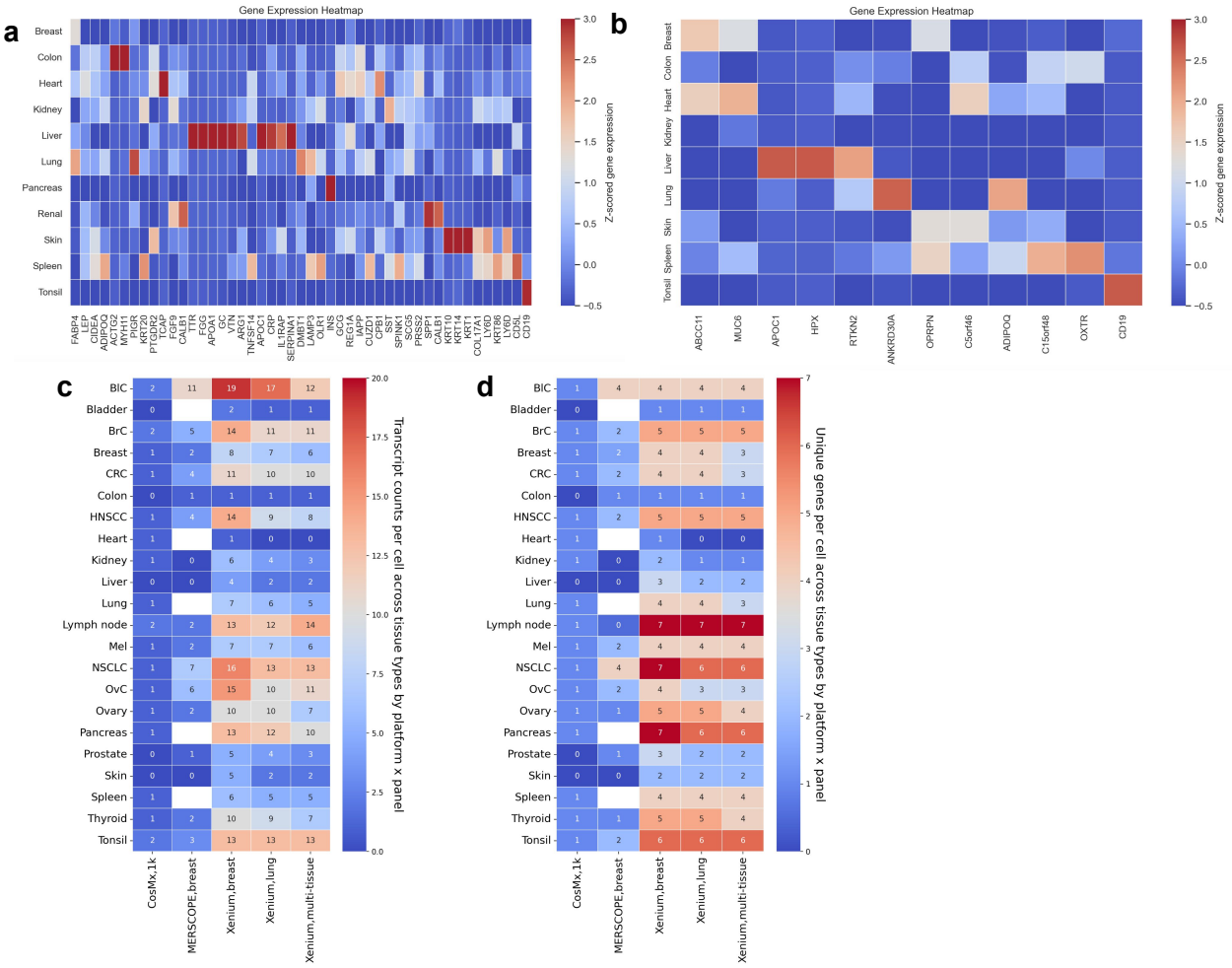
Supplementary Figures and Supplementary Tables: [link]



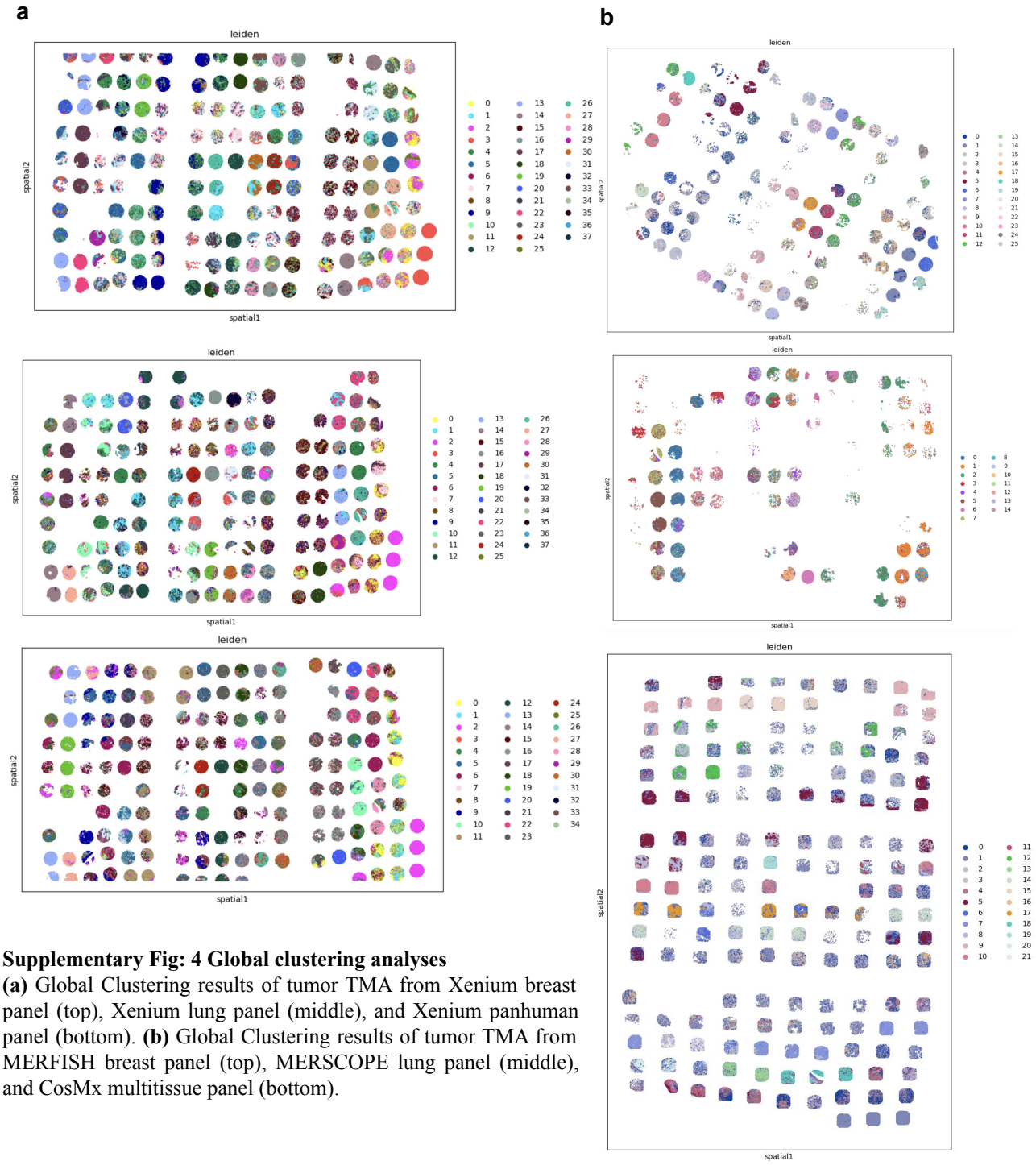
Supplementary Figure 1: Reproducibility across different panels and cores from same patient. **(a)** Scatter plots of cumulative gene expression levels (natural log transformed) of shared genes between two panels within each platforms, captured from matched tissue cores. Column 1: Xenium breast vs. Xenium lung; Column 2: Xenium breast vs. Xenium multi-tissue; Column 3: MERSCOPE breast round 1(5 µm) vs. MERSCOPE breast round 2(10 µm). Each data point corresponds to a TMA core. **(b)** Scatter plots of gene expression levels (natural log transformed) of every shared gene between two cores of the same tissue type from the same patient. In this example, cores are from breast cancer tissue. Each data point corresponds to a gene. **(c)** Heatmap of correlation coefficient expressed as Pearson's r values, indicating good core-to-core or sample-to-sample reproducibility. Core pairs are selected from same tissue/tumor type from the same patients.



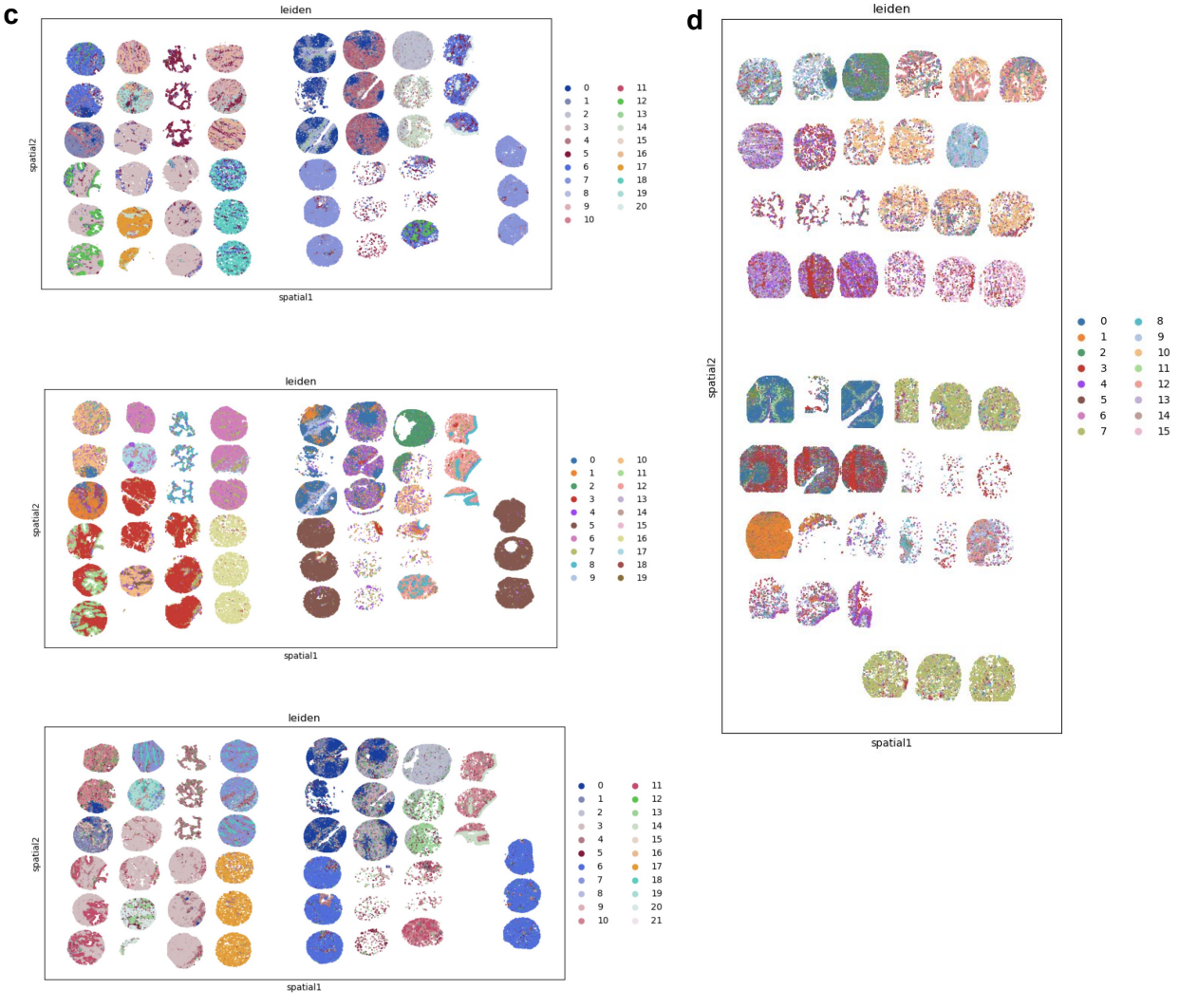
Supplementary Figure 2: Gene by gene plots of iST results by panel and by tissue microarray. **(a)** Scatter plots of summed gene expression levels (natural log transformed) of every shared gene between Xenium (breast/lung) and CosMx (1k) data, captured from matched normal tissue TMA cores. Each data point corresponds to a gene. **(b)** Same as (a) but between MERSCOPE (breast/lung) and CosMx(1k). **(c)** Same as (a) but between Xenium(breast/lung) and MERSCOPE(breast/lung). **(d)** Same as (a) but between Xenium(multi-tissue) and CosMx(1k). † denotes the MERSCOPE lung panel acquired with a 5 µm imaging thickness.



Supplementary Figure 3: Tissue marker analyses and cell level measurements.
(a) Heatmap of Z-scored gene expression showing CosMx's ability to specifically identify known lineage markers. We focused on the normal tissue TMA profiled with multi-tissue panel and selected genes with canonical expression patterns for this analysis. **(b)** Same as (a) but for MERSCOPE (breast panel). **(c)** Heatmap of transcripts per cell after filtration. Only shared genes (40) are considered here for each panel. **(d)** Same as (c) but showing unique transcripts from the same gene set.

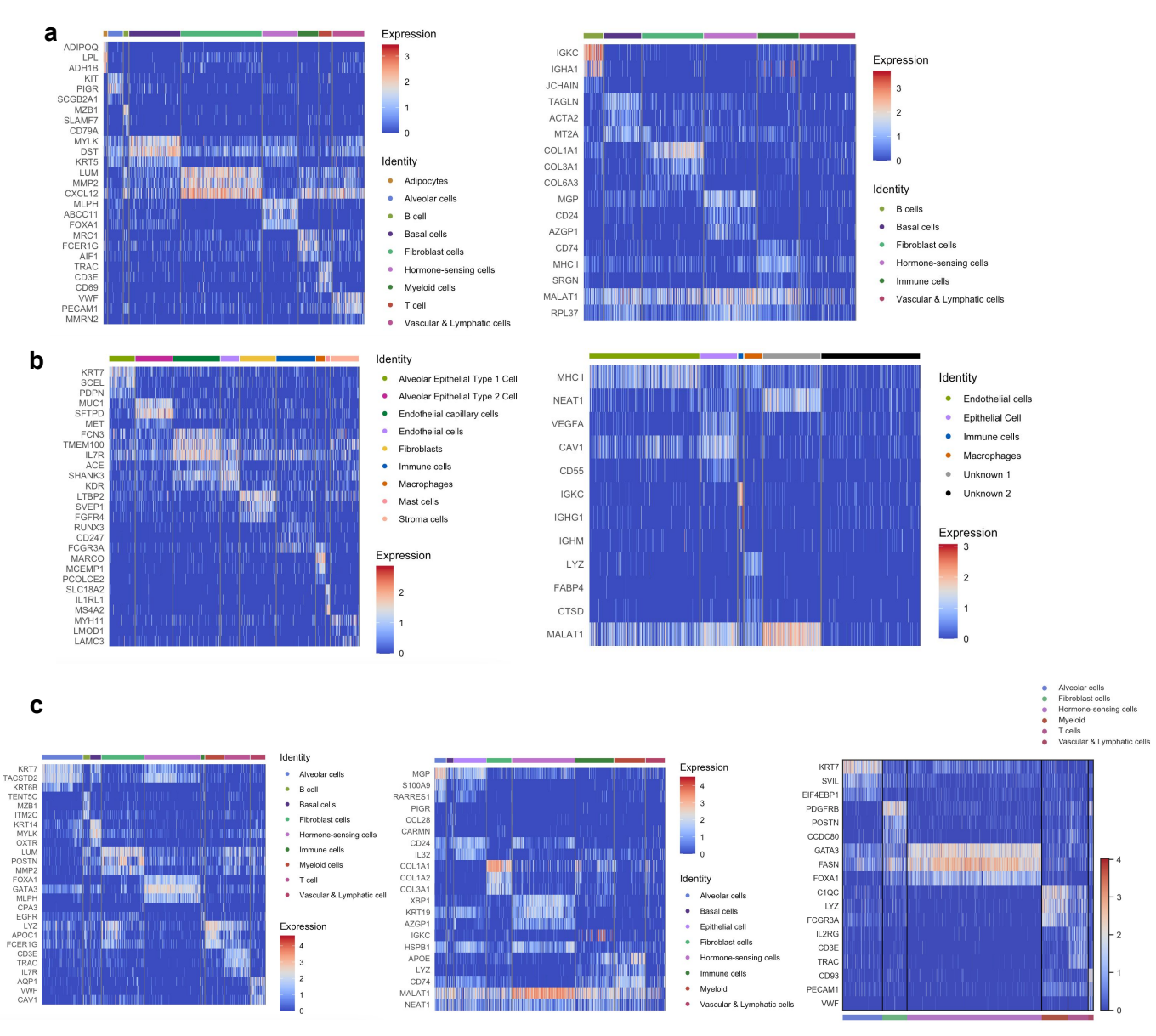


Supplementary Fig: 4 Global clustering analyses
(a) Global Clustering results of tumor TMA from Xenium breast panel (top), Xenium lung panel (middle), and Xenium panhuman panel (bottom). **(b)** Global Clustering results of tumor TMA from MERFISH breast panel (top), MERSCOPE lung panel (middle), and CosMx multitissue panel (bottom).



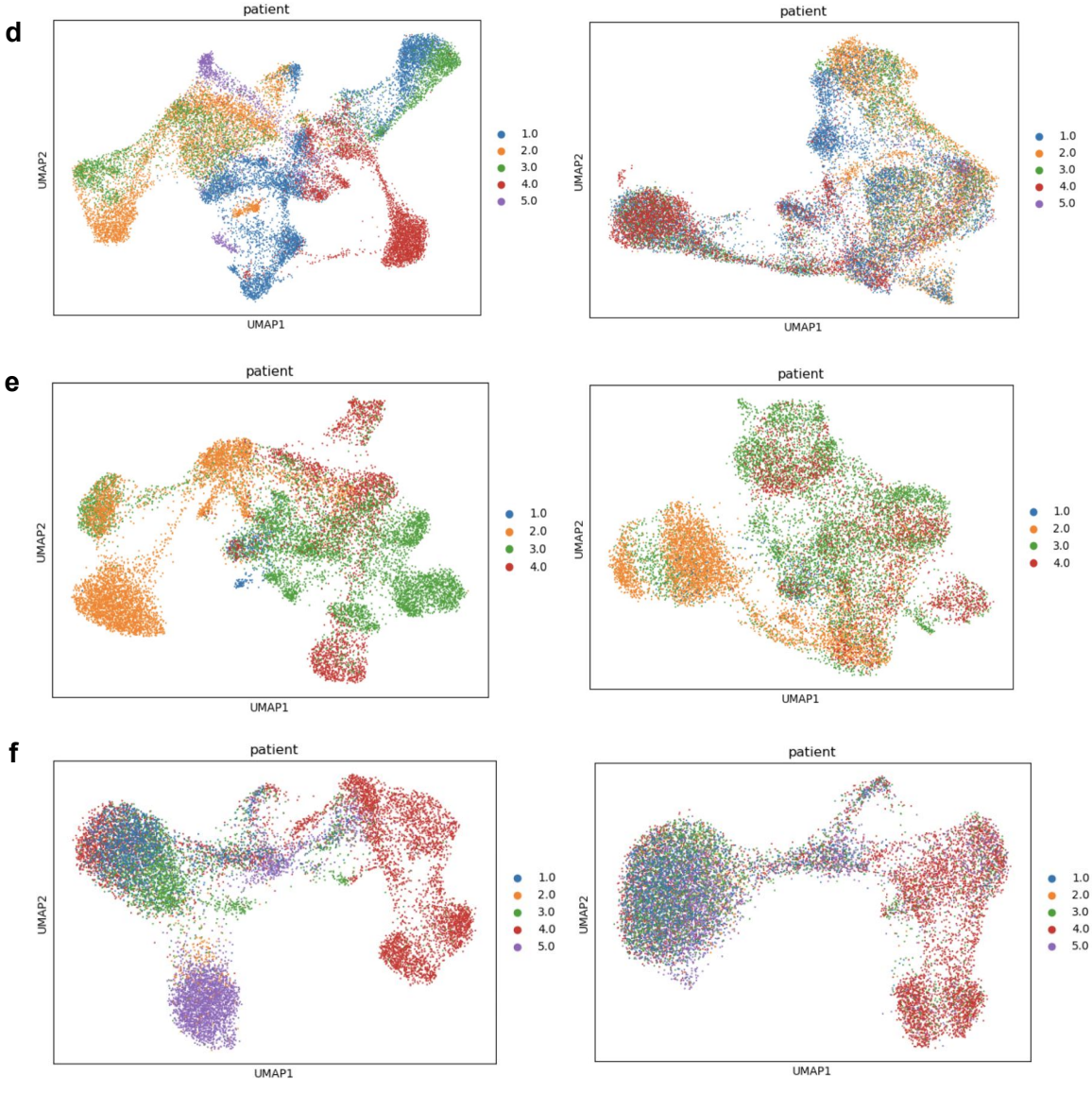
Supplementary Fig: 4 Global clustering analyses

(c) Global Clustering results of normal TMA from Xenium breast panel (top), Xenium lung panel (middle), and Xenium panhuman panel (bottom). **(d)** Global Clustering results of normal TMA from MERSCOPE breast panel (top), MERSCOPE lung panel (middle), and CosMx multitissue panel (bottom).

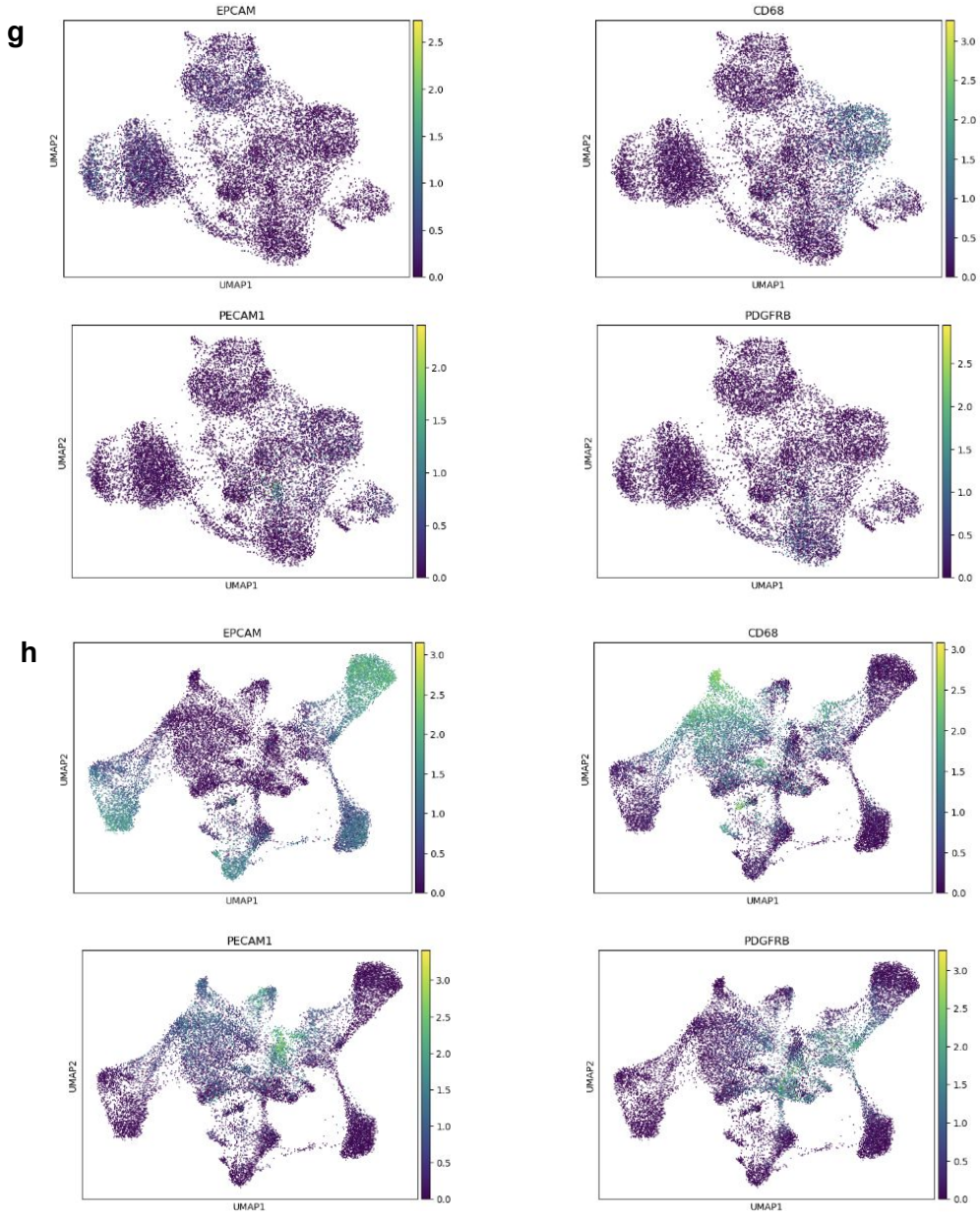


Supplementary Fig: 5. Cell type recovery and UMAPs

(a) Heatmap showing the top gene markers for cell types annotated in breast samples of normal TMA from Xenium breast (left) and Cosmx multitissue (right). **(b)** Heatmap showing the top gene markers for cell types annotated in lung samples of normal TMA from Xenium lung (left) and Cosmx multitissue (right). **(c)** Heatmap showing the top gene markers for cell types annotated in breast cancer samples of tumor TMA from Xenium breast (left), Cosmx multitissue (middle), NERSCOPE breast (right).

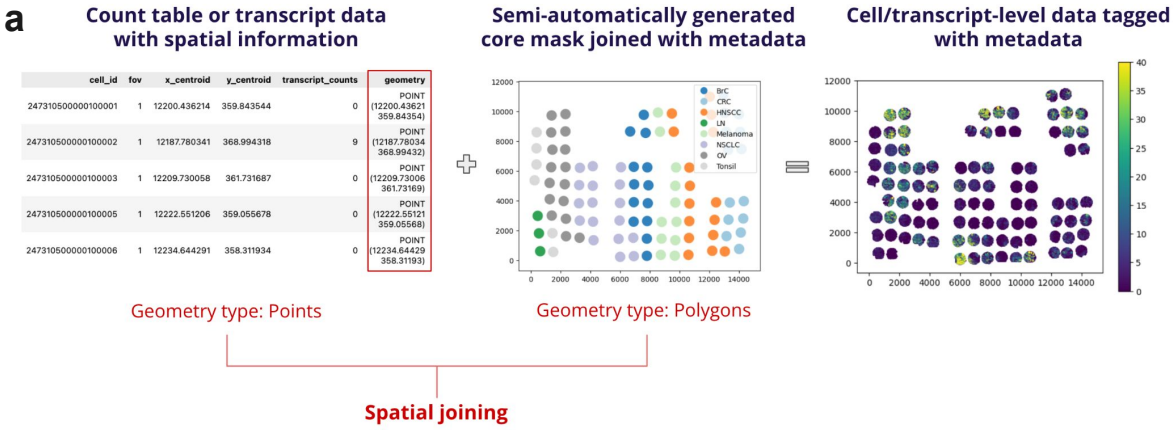


Supplementary Fig: 5. Cell type recovery and UMAPs
(d) UMAP of breast cancer samples of tumor TMA from Xenium breast panel pre (left) and post (right) batch effect removal. **(e)** UMAP of breast cancer samples of tumor TMA from Cosmx multitissue panel pre (left) and post (right) batch effect removal. **(f)** UMAP of breast cancer samples of tumor TMA from MERFISH breast panel pre (left) and post (right) batch effect removal



Supplementary Fig: 5. Cell type recovery and UMAPs

(g) UMAP plot of well-known gene markers for BrC, in breast cancer samples of tumor TMA from CosMx multitissue panel. **(h)** UMAP plot of well-known gene markers for BrC, in breast cancer samples of tumor TMA from Xenium multitissue panel.



Supplementary Figure 6: Workflow for tagging imaging spatial transcriptomics data
(a) To facilitate standardized data formatting and subsequent analytical processes, we built this data ingestion pipeline with the following objectives: 1) to grab cell-level and transcript-level data from diverse platforms and normalize the data structure; 2) to tag each cell and transcript with essential metadata including tissue type, tumor status, PD-L1 status, among others; and 3) to transform the data into various formats tailored to the requirements of particularized analyses. Specifically, to tag the data, core centers in the TMA were pinpointed using DAPI images (Xenium) or cell metadata that contains global coordinates (MERSCOPE and CosMx) using QGIS(version:3.16.10-Hannover). Cells or transcripts within a specified radius were then labeled with core metadata via spatial joining (implemented by GeoPandas, version:0.13.0). In instances where the cores are in close proximity or when a uniform radius cannot be applied effectively, we manually generated the core boundary masks.