

3D Characterization of the Columnar-to-Equiaxed Transition in Additively Manufactured Inconel 718

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Received: date / Accepted: date

Abstract Additive manufacturing (AM) provides enormous processing flexibility, enabling novel part geometries and optimized designs. Access to a local heat source further permits the potential for local microstructure control on the scale of individual melt pools, which can enable local control of part properties. In order to design tailored processing strategies for target microstructures, models predicting the columnar-to-equiaxed transition must be extended to the high solidification velocities and complex thermal histories present in AM. Here we combine 3D characterization with advanced modelling techniques to develop a more complete understanding of the solidification process and evolution of microstructure during electron beam melting (EBM) of Inconel 718. Full calibration of existing microstructure prediction models demonstrates the differences between AM processes and more conventional welding techniques, underlying the need for accurate determination of key parameters that can only be measured directly in 3D. The ability to combine multi-sensor data in a consistent 3D framework via data fusion algorithms is essential to fully leverage these advanced characterization approaches. Thermal modeling provides insight on microstructure development within isolated solidification events and demonstrates the role of Marangoni effects on controlling solidification behavior.

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22 **Keywords** Additive manufacturing · Tomography · Solidification · Microstructure

23 1 Introduction

24 Since the advent of additive manufacturing (AM) in the 1980s, the process has been used for the development
25 and design of rapid prototypes to inform ultimate geometries of traditionally-manufactured components.
26 Additive manufacturing is no longer a rapid prototyping tool and is now being used to develop end products,
27 with applications ranging from printed dental implants and rib cages to the manufacture of novel aerospace
28 components. The interplay between processing conditions and ultimate performance of additive parts remains
29 an area of intense study.

30 The scan strategy, or the manner in which the heat source traverses the bed, used during processing strongly
31 influences the texture and microstructure of additive parts [1–3]. Differences in the default scan strategies
32 employed by different machine manufacturers can further lead to parts printed from the same design having
33 grossly different mechanical properties. The default scan strategies available to most users typically result in
34 little control over the microstructure of a part, and commonly result in texture artifacts from changing scan
35 patterns layer-to-layer [4]. Simple raster scan strategies can result in heavily textured samples with a highly
36 columnar microstructure [5–9], which can be modified via beam scanning strategies designed to control the
37 thermal gradient and initiate the columnar-to-equiaxed transition (CET) [10–13].

38 **Due to the strong influence of microstructure on part properties, local microstructure control can similarly**
39 **enable local control of part properties, such as gradient properties across a component, or improved me-**
40 **chanical properties around critical failure sites that arise from complex geometries.** Printing AM parts with
41 such target microstructures requires *a priori* knowledge of processing-microstructure relationships. Models
42 of additive processes that focus on individual melt pools or single weld lines have shown the need to include
43 temperature-dependent physics to capture the dynamics of the melt pool [14–16]. These models are often
44 extensions of validated casting or welding models, and may not incorporate the complex fluid flow and thermal
45 histories present in AM parts. A major limitation of these models is the extensive computation time; modeling
46 a single track in a laser powder bed fusion (L-PBF) process can require tens to hundreds of thousands of
47 processing hours [17], severely limiting the extension of these models to full-scale parts. Moreover, thermal
48 models generally cannot directly predict microstructures from process parameters alone.

49 The change in thermal gradient and solid-liquid interface velocity during a solidification event can be calcu-
50 lated in high resolution using supercomputers [18], but to predict microstructure, thermal models must rely
51 on separate descriptions of the CET, namely those developed by Hunt [19] and Gäumann [20]. These models
52 provide a good basis for qualitative prediction of solidified microstructures, but incorporate the use of difficult
53 to measure properties including solidification nuclei density, as well as alloy- and interface velocity-specific
54 parameters. Additional *ex situ* characterization of additively manufactured parts on the length scale of the
55 melt pool is required to validate and improve these models. The complex grain shapes, interplay of melt
56 pool boundaries, and strong anisotropy developed in additive components makes 2D data and stereological
57 approaches ineffective at fully assessing the microstructure.

58 In this work, the microstructure of an isolated melt pool in Inconel 718 was characterized in 3D, providing
59 critical microstructural information needed for process models currently under development. The calibrated

60 process model was then used to investigate the influence of fluid flow and trace element impurities commonly
61 found in AM powders on resultant microstructures.

62 **2 Methodology**

63 2.1 Experimental Characterization

64 *2.1.1 Sample Fabrication*

65 Bulk Inconel 718 was fabricated using gas atomized Inconel 718 powder feedstock with a particle size range
66 of 40-120 μm from Praxair, Inc. in an Arcam S12 EBM. The build consisted of a block with dimensions of
67 $20 \times 20 \times 15$ mm ($l \times w \times h$). A nominal build layer thickness of 50 μm was used with a preheat temperature
68 of 1000 °C. The block was fabricated using a bidirectional raster scan strategy. The electron beam traversed
69 the part with a beam current of 20 mA at a speed of 4 m/s, with 0.10 mm spacing between adjacent lines.
70 The beam was rotated by 18 ° between build layers. On the last layer of the build, powder was raked across
71 the build surface before several isolated melt pools were created across the block surface. These spots were
72 melted using an electron beam current of 10 mA with a dwell time of 0.5 ms. Samples of the bulk material
73 from the build were analyzed for chemical composition. Major elements were characterized via inductively
74 coupled plasma optical emission spectroscopy (ICP-OES). Trace elements were analyzed via **either** glow
75 discharge mass spectroscopy (GDMS) **or LECO combustion analysis**. Results of the chemical analyses are
76 shown in [Table 1](#). **The sample material composition conforms to AMS specification 5662 for wrought Inconel**
77 **718 [21]**.

78 *2.1.2 3D Data Acquisition*

79 A sample of material containing an isolated melt pool as well as surrounding bulk material was removed
80 from the top surface of the block via wire electrical discharge machining. 3D data was collected via TriBeam
81 tomography [22–24], a serial-sectioning technique utilizing a femtosecond laser for large-scale material removal
82 inside a scanning electron microscope (SEM). Electron Backscatter Diffraction (EBSD) data was collected
83 in conjunction with secondary electron (SE) and backscatter electron (BSE) images from a volume roughly
84 $1150 \times 800 \times 500$ μm in size. EBSD data was collected with a 1.5 μm step size in a square grid with a sectioning
85 slice thicknesses of 1.3 μm . A total of 897 slices of EBSD data were collected with an acquisition time of 20
86 minutes per slice, yielding 4.02 TB of raw data. BSE images were collected once every eight slices and used
87 as a set of reference images for distortion correction and identification of the melt pool boundary.

88 *2.1.3 Multimodal Data Fusion via the Thin Plate Spline*

89 In order to leverage microstructural information present in various imaging modalities, a framework is re-
90 quired to fuse disparate imaging techniques into a coherent volume. [Figure 1](#) shows data from an EBSD scan
91 and BSE image taken from a region in the middle of the characterized volume. The melt pool boundary
92 is clearly visible in the BSE image, but is not distinguishable in the EBSD scan data. In order to locate

Table 1 Chemical composition of the Inconel 718 Block and typical composition of wrought Inconel 718 given in weight percent.

Element	Measured	Conventional*
Nickel	54.4 [†]	50-55
Chromium	17.5 [†]	17-22
Iron	18.4 [†]	balance
Niobium	4.80 [†]	4.75-5.5
Molybdenum	3.08 [†]	2.8-3.3
Titanium	0.878 [†]	0.65-1.15
Aluminum	0.428 [†]	0.2-0.8
Cobalt	0.108 [‡]	≤1
Carbon	0.0321 [§]	≤0.08
Manganese	0.0545 [‡]	≤0.35
Silicon	0.246 [‡]	≤0.35
Phosphorus	0.0080 [‡]	≤0.015
Boron	0.0013 [‡]	≤0.006
Nitrogen	0.0171 [§]	—
Sulfur	0.0018 [§]	≤0.015
Oxygen	0.0140 [§]	—

* AMS 5662 specification [21]

† ICP-OES measurement

‡ GDMS measurement

§ LECO measurement

the melt pool boundary in the EBSD data, these two imaging modalities must be registered into a single reference frame.

This process can be complicated by the source of the signal used to generate an image; secondary electrons and backscattered electrons, for example, originate from different subsurface interaction volumes in the material. More important are geometric considerations within the vacuum chamber. At the high tilt angles used for EBSD collection, minor sample misalignment can create large apparent distortions. The use of image registration approaches such as scale-invariant feature transformation (SIFT), Harris corner detection, and mutual information have been used previously to correct such distortions, and more recently machine learning techniques have also been employed [25–29]. Here we take the approach for EBSD distortion correction described by Zhang et al. that employs the thin plate spline (TPS) for transformation [30] due to its ease of implementation and straightforward physical interpretation.

TPS is a 2D formulation of the cubic spline [31]; just as a 1D cubic spline can be understood as the bending of a beam along a set of fixed control points, so too can the thin plate spline be interpreted as the local bending of a thin plate with fixed control points along the plane. Control points act as anchors with smooth interpolation between the points, wherein the extent of local bending is determined by the local density of control points. The TPS algorithm is well suited for image registration between different reference frames, even if one frame is significantly distorted in relation to the other. The classic 2D formulation for the relation of two reference frames given n control points has been extended here to 3D and is given by Equation 1:

$$(X, Y, Z) = f(x, y, z) = a_1 + a_x x + a_y y + a_z z + \sum_{i=1}^n w_i U(|P_i - (x, y, z)|) \quad (1)$$

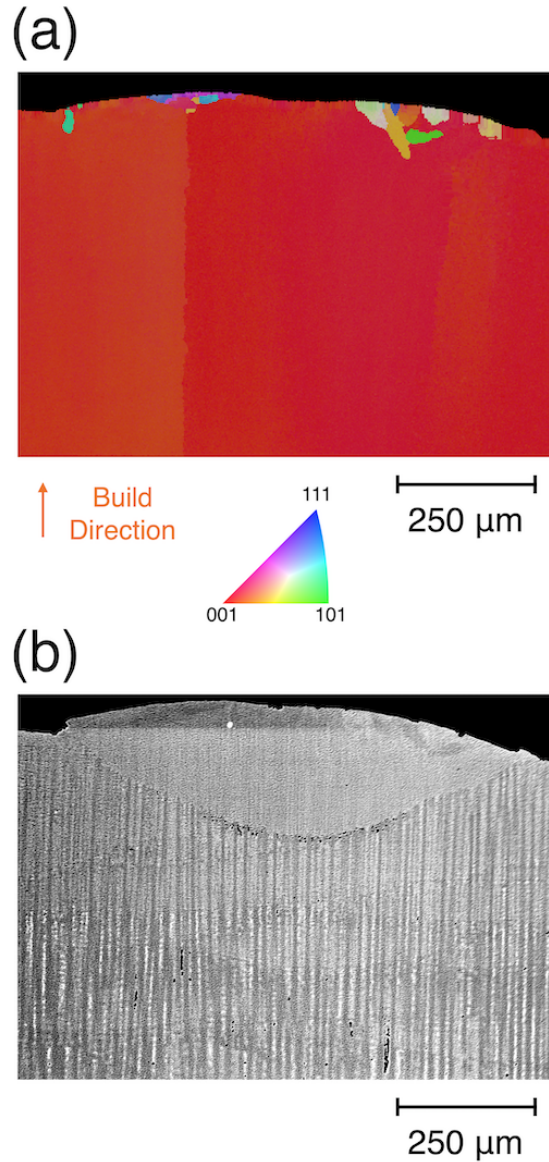


Fig. 1 EBSD map (a) and BSE image (b) from a single region of the characterized volume. The EBSD map reveals the presence of small grains that can not be identified in the BSE image, while the BSE image displays contrast along the melt pool boundary. No such contrast along the melt pool boundary can be identified in the EBSD map, where the base orientation of the substrate is maintained along the pool boundary.

112 where (X, Y, Z) is a point in the distorted frame, (x, y, z) is a point in the reference frame, $a_1 + a_x x + a_y y +$
 113 $a_z z$ represents the global affine transformation between the reference frames, and $\sum_{i=1}^n w_i U(|P_i - (x, y, z)|)$
 114 represents the local non-affine (*bending*) portion of the transformation. U is the radial basis function given
 115 by Equation 2:

$$U(r) = r^2 \log(r^2) \quad (2)$$

116 where r is the Euclidean distance between control point P_i and another point (x, y, z) in the same frame.
 117 Given the extra constraint of $U(0) = 0$, this radial basis function is a biharmonic solution to the equation for a
 118 thin plate lifted above the (x, y) plane, and therefore minimizes the overall bending of the plate [30,31].

119 The application of TPS in relating two reference frames requires knowledge of the values a_1 , a_x , a_y , and
120 a_z for the global affine transformation, and the weighting coefficients w_x , w_y , and w_z for each of the n
121 control points for the bending portion of the transformation. Given these coefficients, the location of any
122 point (X, Y, Z) in the distorted frame can be directly mapped to its corresponding location (x, y, z) in the
123 reference frame.

124 These coefficients can be solved using a set of control points identified as corresponding locations within
125 both the distorted and reference frames. For the 2D area shown in Figure 1, comprising roughly 200,000
126 EBSD points, only 20 to 30 control points are needed to establish a good relation of reference frames. Typical
127 choices for control points are features that can be distinguished in both BSE images and EBSD maps such as
128 pores, precipitates, and grain boundary triple points. Calculation of the relevant transformation parameters
129 is achieved by solving a set of linear equations, the details of which can be found elsewhere [30,31]. A total
130 of 3894 control points were used to register the BSE and EBSD data together. The improved registration of
131 the EBSD data was confirmed to match with optical profilometry data collected on the sample prior to 3D
132 characterization.

133 2.1.4 Reconstruction of a Coherent Volume

134 Using TPS as detailed in Section 2.1.3, all relevant data arrays from each voxel of EBSD data were copied into
135 the BSE reference frame. Reconstruction of the dataset was performed using the open-source DREAM.3D
136 package [32]. Data was first masked using a minimum image quality (IQ) cutoff of 2.6 standard deviations
137 less than the average measured value, providing good grain boundary contrast and following similarly to
138 prior studies of IQ as a mask [33]. Data below this cutoff was included in the mask if at least four of its
139 six nearest neighbors were within 2° of misorientation. Grains were segmented using a 2° misorientation
140 tolerance amongst nearest neighbors, which has been shown to be a good segmentation tolerance for AM
141 materials characterized in 3D [34]. Grains containing less than 8^3 voxels or having fewer than three nearest
142 neighbors were considered too small to be accurately characterized and were removed, with the remaining
143 space filled via an iterative coarsening of neighboring grains.

144 2.2 Solidification Modeling

145 The AM processing conditions used to print the melt pool sample were simulated in TRUCHAS, where 3D
146 calculations of thermal gradients and solid-liquid interface velocities are achievable at micron length scales
147 with sub-millisecond time scales that are otherwise inaccessible to modern in situ monitoring techniques
148 [35]. TRUCHAS uses a mimetic finite difference discretization technique to solve the heat equation and
149 additionally uses a finite volume discretization scheme to solve the momentum equation to incorporate fluid
150 flow. A volumetric heat source function is defined to depict the heat source, and a radiation boundary
151 condition is applied to the top surface. The details of the partial differential equations, boundary conditions,
152 heat source model, and material properties of Inconel 718 used in the calculations can be found elsewhere [18].
153 Simulations both with and without fluid flow were conducted to study the effect of surface-active elements
154 such as sulfur and oxygen, which are known to affect the temperature dependence of surface tension in
155 Inconel 718 welds [36]. In temperature regimes where surface tension decreases with increasing temperature,
156 radially outward fluid flows can develop in melt pools due to the imposed temperature gradient across the

157 melt pool (mass flux from regions of lower surface tension to regions of higher surface tension). Conversely,
158 in temperature regimes where surface tension increases with increasing temperature, radially inward fluid
159 flows can develop across the temperature gradient within a melt pool. These Marangoni flows can change
160 direction during solidification depending on the transition temperature of the surface tension temperature
161 dependence, and are highly sensitive to the sulfur content of the alloy, even in the ppm range. A higher
162 sulfur content will increase this transition temperature, enabling radially inward fluid flows earlier in the
163 solidification process. Surface tension measurements are generally difficult to perform, so available values for
164 Inconel 718 with varying sulfur contents consistent with the chemical composition of the sample were taken
165 from Lee et al. [36].

166 3 Results

167 3.1 3D Microstructure

168 The fully reconstructed volume is shown in Figure 2(a). The bulk microstructure of the sample is strongly
169 textured, with large columnar grains that are well-aligned with the build direction of the block. These
170 columnar grains with $\langle 001 \rangle$ -type orientations form via epitaxial growth from subsurface layers, which
171 are remelted multiple times as additional layers of material are deposited. The top surface of the block
172 shows periodic surface roughness that forms line artifacts on the surface of the build, which arise from the
173 bidirectional raster scan strategy used to fabricate the blocks. After reaching steady state build conditions,
174 the single spot melt was deposited onto a fresh layer of powder, resulting in the roughly circular melt pool
175 that interrupts the linear artifacts seen across the rest of the top surface.

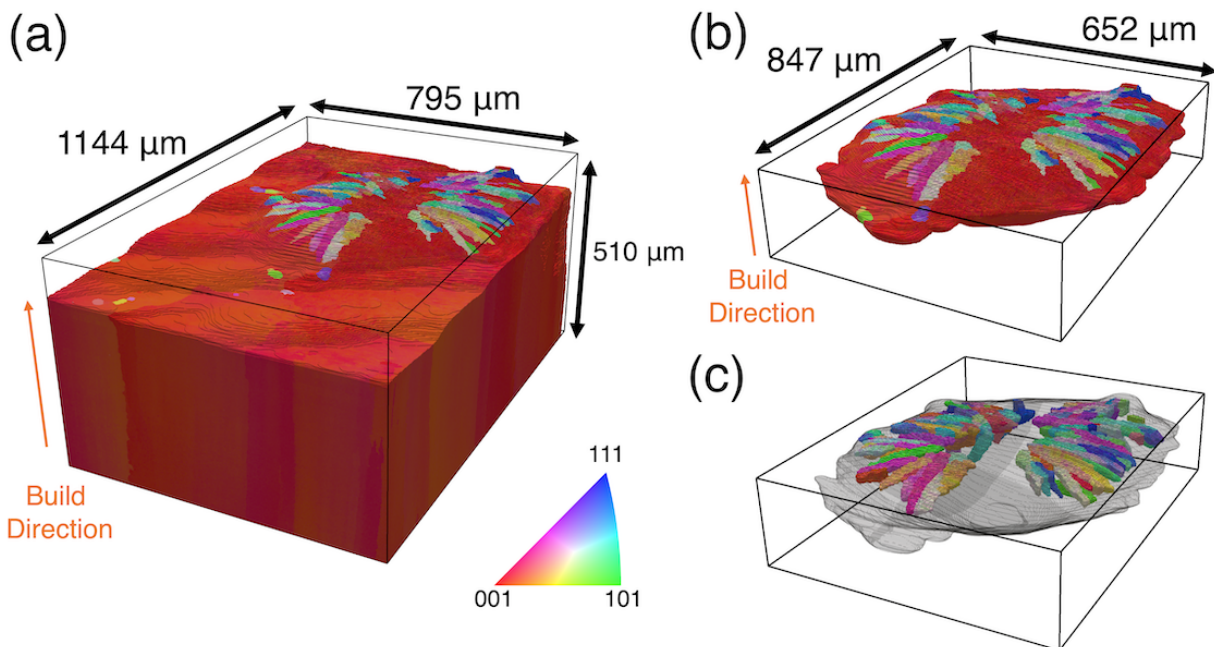


Fig. 2 3D EBSD data of Inconel 718 from TriBeam tomography. Fully reconstructed volume of isolated melt pool and surrounding bulk material on top surface of EBM build (a). Melt pool volume segmented from the bulk using BSE images (b). Nucleated grains that are fully contained within the melt pool volume form radially around the center of the melt pool near the top surface(c). All EBSD is shown in inverse pole figure (IPF) coloring, with the build direction taken as the reference direction.

176 The isolated melt pool was segmented from the bulk using BSE images collected during serial sectioning,
 177 which provide strong contrast at the melt pool boundary, as shown in [Figure 1](#). Below the isolated melt pool,
 178 arrays of dendrites from the bulk grains are visible in images of the laser machined surface, but these features
 179 are not visible within the melt pool, most likely due to the differing thermal gradients generated by the spot
 180 melt. The use of the TPS algorithm to align the BSE and EBSD references frames enables segmentation of
 181 the melt pool volume from the EBSD data, which is shown in [Figure 2\(b\)](#).

182 The melt pool has a roughly circular boundary on the build surface, with a small depression in the center,
 183 indicative of shrinkage occurring at the end of solidification as the melt pool contracts. Although a large
 184 portion of the melt pool contains resolidified portions of the bulk grains, nucleated grains with differing
 185 orientations are spread radially around the center of the melt pool. As the isolated spot melt will solidify
 186 radially from the melt pool boundary inwards, the maximum thermal gradient direction will point toward
 187 the center of the melt pool. Any grains that were partially remelted, including the large bulk columnar grains
 188 and any stray nucleated grains, will resolidify along their $\langle 001 \rangle$ -type directions toward the center of the
 189 melt pool, as this is the standard growth direction for cubic materials [37]. The changing thermal gradient
 190 direction is evident in the two grains depicted in [Figure 3](#). Both a large bulk grain, with crystallographic
 191 orientation near $[001]$ with respect to the build direction (red IPF coloring) and a stray nucleated grain,
 192 with orientation near $[111]$ with respect to the build direction (blue IPF coloring) lie across the melt pool
 193 boundary. These two grains maintain their base crystallographic orientation but grow perpendicularly along
 194 their respective $\langle 001 \rangle$ -type directions toward the center of the spot melt.

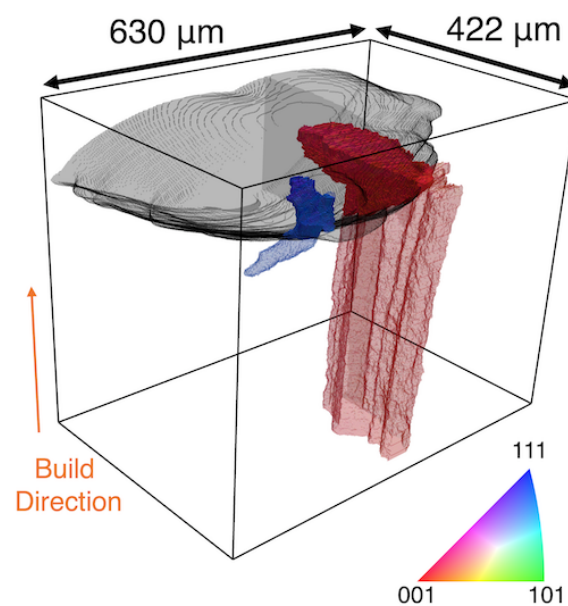


Fig. 3 Remelted grains lying across the spot melt pool boundary. The changing thermal gradient direction imposed by the spot melt results in perpendicular growth of these two grains from their initial growth direction. The portion of the grains lying outside the spot melt pool are semi transparent, while the portion of the grains within the melt pool are opaque. The melt pool boundary is shown as a semi-transparent gray surface. IPF coloring is shown using the build direction as the reference direction.

195 Segmentation of the spot melt pool boundary enables a direct measurement of the fraction of nucleated
 196 grains that form during the single solidification event. Only grains fully contained within the melt pool

197 boundary were considered for determination of a nucleated grain fraction, as any grains crossing the melt
 198 pool boundary were formed prior to the formation of the spot melt. The nucleated grains contained within
 199 the melt pool are shown in Figure 2(c), and account for 11.4% of the melt pool volume. These approximately
 200 columnar grains have no discernible texture with respect to the build direction as shown by their inverse
 201 pole figure (IPF) coloring. The nucleated grains also lie only on the top surface of the melt pool, and are
 202 not found in the center of melt pool, which is comprised of epitaxially-grown columnar grains.

203 3.2 Simulations

204 Calculated thermal gradients (G) and solid-liquid interface velocities (R) during solidification from three
 205 TRUCHAS simulations are shown in Figure 4. The three simulations show qualitatively similar behavior,
 206 with lower interface velocities and higher thermal gradients at the beginning of solidification (lower right
 207 portion of Figure 4), and higher interface velocities and lower thermal gradients at the end of solidification
 208 (upper left portion of Figure 4). All three simulations generally fall within the same range of G and R , with
 209 calculated gradients in the range of 10^4 to 10^6 K/m and interface velocities in the range of 10^{-3} to 1 m/s.
 210 Although incorporation of the fluid flow in the simulation does not affect the overall trend of G and R during
 211 solidification, there are differences at both the early and late stages of solidification. Generally, incorporation
 212 of fluid flow decreases the initial interface velocity at the beginning of solidification and increases the final
 213 interface velocity at the end of solidification. This effect is greater in the simulation that incorporates fluid
 214 flow for a high sulfur content.

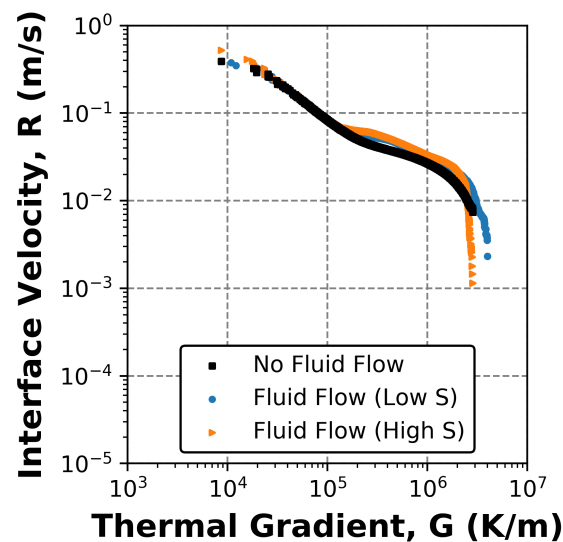


Fig. 4 Calculated thermal gradients (G) and solid-liquid interface velocities (R) from TRUCHAS simulations. The three simulated cases show qualitatively similar behavior throughout solidification, but the incorporation of fluid flow in the simulation creates a wider range of interface velocities. Solidification begins at the edges of the melt pool in the lower right portion of the figure. As solidification proceeds, G will decrease and R will increase, resulting in late stages of solidification at the upper left portion of the figure.

215 The differing G and R at early and late stages of solidification manifest in an altered melt pool shape and local
 216 solidification time, as shown in Figure 5. Local solidification time is measured as the time a volume element
 217 (voxel) in the simulation spends between the equilibrium liquidus and solidus temperatures, equivalent to
 218 the time the voxel spends in the mushy zone. 3D renderings of the melt pool volumes demonstrate the
 219 impact of fluid flow on the melt pool shape. The simulation that only incorporates heat transfer is fully
 220 radially symmetric, whereas the low sulfur simulation is shallower and wider, particularly at the top of the
 221 melt pool, which spreads out significantly at the edges. The high sulfur simulation is narrower and deeper
 222 than the low sulfur case, with a higher average local solidification time. The heat transfer simulation has
 223 the narrowest range of local solidification time. Although incorporation of fluid flow does not significantly
 224 change the average solidification time, the range of solidification times was nearly doubled as compared to
 225 the simulation without fluid flow.

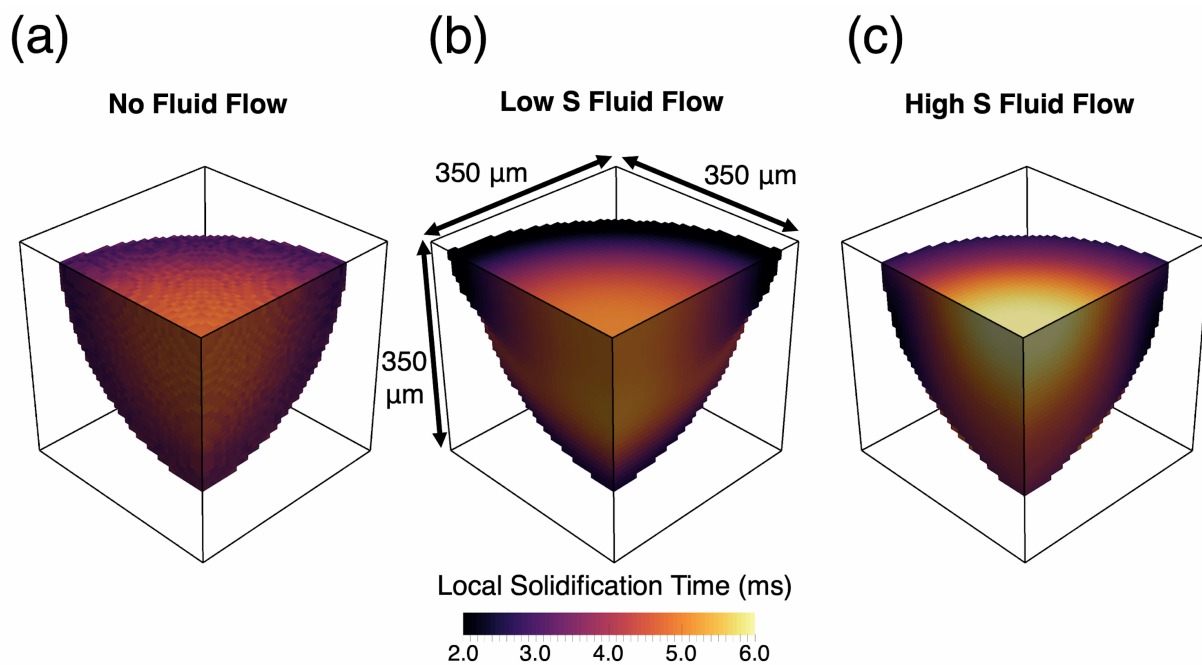


Fig. 5 Melt pool shape and local solidification time. 3D volume representations of the solidified portions of the melt pool for the simulation with heat transfer only (a), fluid flow with low sulfur content (b) and fluid flow with high sulfur content (c). The heat transfer simulation is fully symmetric, whereas the fluid flow simulations decrease local solidification time at the pool edges and increase local solidification time at the pool center.

226 To better understand the impact of fluid flow, several snapshots of the simulations are shown in Figure 6.
 227 These are a series of cross-sections showing the temperature profile and direction of fluid flow within the
 228 melt pool. Fluid flow velocities are displayed as arrows, whose direction and size indicate the direction
 229 and magnitude of flow within the mushy zone for a given time step. Without fluid flow, the arrows are
 230 fully symmetric and point along the maximum thermal gradient direction toward the pool center. With
 231 fluid flow, however, the temperature-dependence of surface tension in the molten alloy creates gradients in
 232 surface tension which establish fluid vortices within the melt pool. In the low sulfur simulation, a radially
 233 outward fluid flow is established in the early stages of solidification by 4 ms due to the negative dependence
 234 of surface tension with temperature in the super-heated liquid. As solidification progresses, radially inward
 235 flow dominates because the liquid temperature drops and surface tension begins to decrease with decreasing

236 temperature. This transition from radially outward to radially inward flow will occur at a higher temperature
 237 in the high sulfur simulation, which provides additional time for radially inward flows to develop. The
 238 lower surface tension at a given temperature for the high sulfur case also enables higher magnitude flows
 239 to establish, which are shown by the larger magnitude arrows in this simulation. The last snapshot at
 240 10 ms also demonstrates differences in total solidification time for the various simulations, with the heat
 241 transfer simulation having the largest remaining melt pool volume and the high sulfur simulation having the
 242 least.

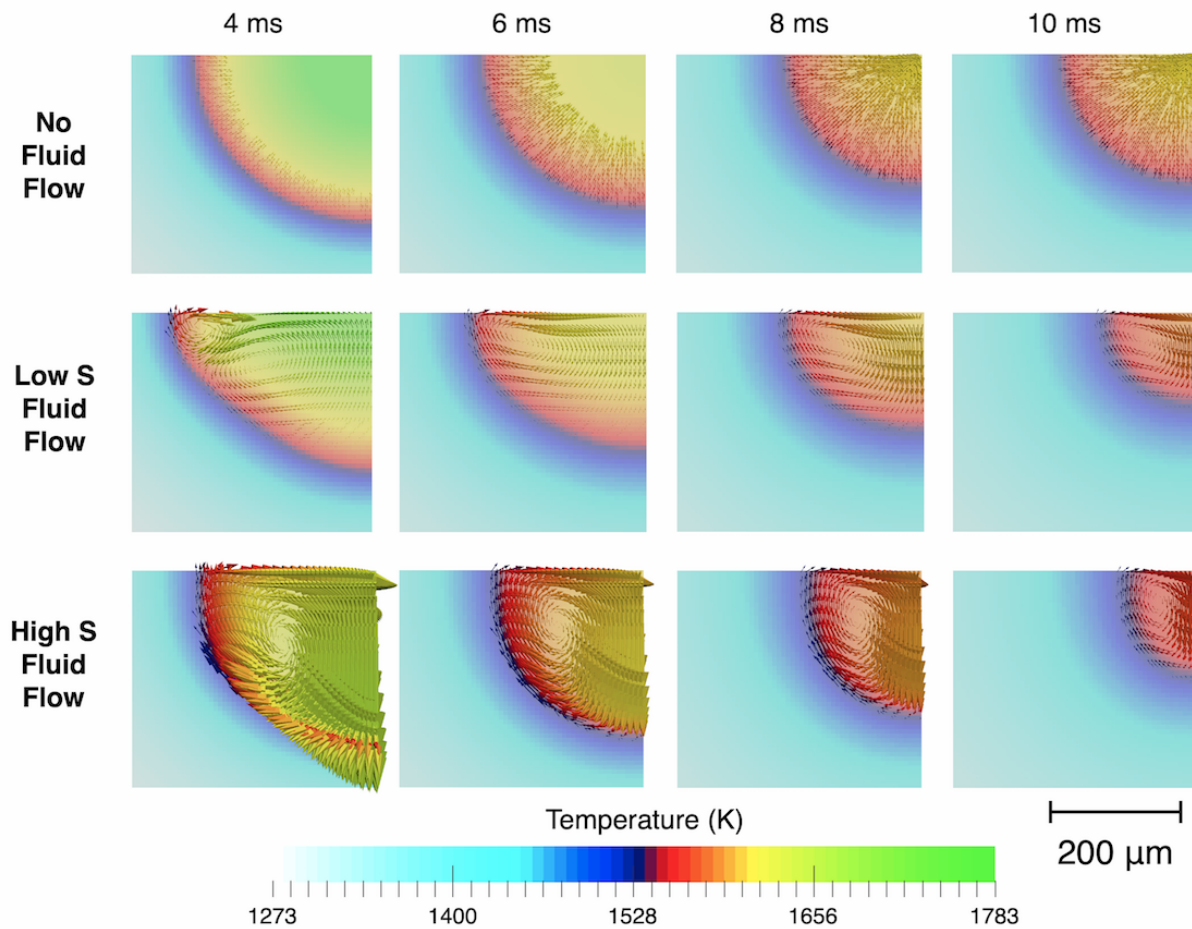


Fig. 6 2D snapshots from different time steps of TRUCHAS simulations performed for Inconel 718. Fluid flow directions are shown using arrows with size directly proportional to the magnitude of the velocity. When fluid flow is incorporated into the simulations, radially inward flow dominates for the most of the solidification event. Material below the solidus temperature is depicted in colors ranging from white (preheat temperature) to blue (solidus temperature), the mushy zone is depicted in colors ranging from red to green (liquidus temperature), and material above the liquidus temperature is shown in solid green.

243 3.3 Calibrated Microstructure Prediction Model

244 As TRUCHAS does not incorporate microstructure prediction directly, an additional model is required to
 245 predict microstructure given simulated thermal data. Solidification will begin epitaxially from the base metal
 246 with a columnar morphology. Depending on thermal conditions experienced as solidification progresses, grains
 247 may nucleate in front of the advancing interface to initiate the CET. Here we use a model derived from Hunt's

248 criterion [19], which describes the CET as occurring when nucleated grains begin to block the advancing
 249 columnar front. The transition to fully equiaxed growth is achieved when the columnar front is completely
 250 blocked by nucleated grains. Hunt’s criterion can be expressed in its general form via the following equation:

251

$$G = \frac{1}{n+1} \sqrt[3]{\frac{-4\pi N_0}{3 \ln [1-\phi]}} \cdot \left(1 - \frac{\Delta T_n^{n+1}}{(a \cdot R)^{(n+1)/n}}\right) \cdot (a \cdot R)^{1/n} \quad (3)$$

252 Where G is the thermal gradient, N_0 is the nuclei density, ϕ is the equiaxed grain fraction, ΔT_n is the
 253 critical undercooling to activate nuclei, R is the solid-liquid interface velocity, and parameters a and n are
 254 alloy-dependent material parameters. Gäumann et al. [20, 38] modified Hunt’s criterion to the high thermal
 255 gradients present in typical welding processes, which simplifies the relationship by removing the dependence
 256 on nuclei activation, given by:

$$G = \frac{1}{n+1} \sqrt[3]{\frac{-4\pi N_0}{3 \ln [1-\phi]}} \cdot (a \cdot R)^{1/n} \quad (4)$$

257 Gäumann et al. investigated autogenous laser welds on CMSX-4 for the epitaxial-laser metal forming (E-
 258 LMF) process, which is similar to the directed energy deposition (DED) techniques utilizing blown powder
 259 in modern AM processes. A key parameter of this model is the nuclei density, N_0 , which is generally not
 260 possible to directly measure given a single 2D cross-section. Gäumann et al. were able to estimate N_0 in
 261 CMSX-4 by correlating the measured number of nucleated grains in several cross-sections of steady-state
 262 autogenous welds as a function of $\frac{G^n}{R}$ for various welding conditions, ultimately determining a nuclei density
 263 of $2.0 \times 10^{15} \text{ m}^{-3}$ [20]. However, given the full 3D characterization performed on the isolated melt pool in
 264 Inconel 718, a direct measurement of nucleated grain density is possible. A total of 259 grains exist within
 265 the 3D volume, 206 of which can be said to nucleate in the melt pool as they are fully contained within its
 266 boundaries (Figure 2(c)). Using the melt pool volume of 38.4 nL, we have a measured value of 5.4×10^{12}
 267 m^{-3} nucleated grains. Just as with the measurements taken from multiple cross-sections, this represents a
 268 lower bound of nuclei density that could be resolved with the given imaging technique of EBSD in both
 269 cases.

270 The material constants a and n are dependent on the undercooling at the dendrite tip, which fits the following
 271 form:

$$\Delta T_{tip} = (a \cdot R)^{1/n} \quad (5)$$

272 This form of the relationship is generally true for most solidification conditions, the major exception being
 273 near planar front growth conditions at low growth velocity, similar to those used for single-crystal casting [19].
 274 These constants are alloy-specific and only applicable over a limited range of solidification velocities, so it
 275 is necessary to calculate the undercooling at the dendrite tip over a wide range of velocities in order to
 276 ensure an optimal fit. Despite significant differences in solidification behavior and alloy composition between
 277 CMSX-4 and commonly-studied nickel-superalloys for additive manufacturing, alloy constants for CMSX-4
 278 are typically used when applying Gäumann’s model. To determine these material parameters more accurately
 279 for Inconel 718, we follow the approach of Gäumann et al. using the Ivantsov-Marginal Stability (IMS) model
 280 developed by Langer for a paraboloidal dendrite tip growing at marginal stability [38–40].

281 Relevant material constants, including liquidus slopes and partition coefficients for Inconel 718 were taken
 282 from a Scheil analysis performed by Boettinger [41], who helped develop the routines for multi-component
 283 Scheil analysis with the CALPHAD approach [42]. The results of the undercooling calculation over the

284 relevant velocity range are shown as a function of velocity in Figure 7, which also includes the original
 285 data for CMSX-4 as calculated by Gäumann for the E-LMF process [43]. There are key differences between
 286 these two alloys and processes that this analysis highlights, namely there are a wider range of relevant
 287 solidification velocities for the EBM process as compared to the E-LMF process, and in general the material
 288 constants calculated for CMSX-4 do not accurately capture the undercooling at the dendrite tip in Inconel
 289 718, particularly at higher interface velocities. Inconel 718 shows less undercooling for all interface velocities,
 290 indicating it is a less strongly segregating alloy than CMSX-4. Fits for material constants for E-LMF of
 291 CMSX-4 were $a = 1.25 \times 10^6 (\frac{K^n}{m \cdot s})$ and $n = 3.4$ over the relevant velocity regime. Fits for material constants
 292 for EBM of Inconel 718 are $a = 1.23 \times 10^5 (\frac{K^n}{m \cdot s})$ and $n = 3.13$.

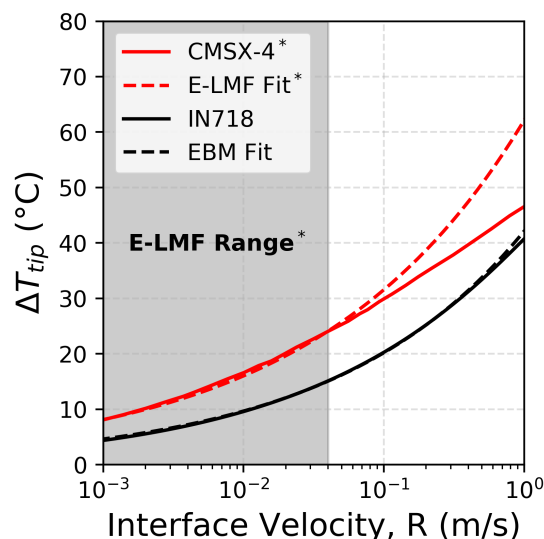


Fig. 7 Dendrite tip undercooling as a function of interface velocity calculated via the IMS model for CMSX-4 and Inconel 718. Data for CMSX-4 and fits for the E-LMF process from [43].

293 Given G and R at every voxel in the TRUCHAS simulations, Equation 4 can be rearranged to solve for ϕ ,
 294 which represents the likelihood to nucleate grains at that point. The total expected nucleated grain fraction
 295 for the entire melt pool, Φ , can then be determined as the volume weighted average from the simulation
 296 following Raghavan et al. [18]:

$$\Phi = \frac{\sum V_i \phi_i}{\sum V_i} \quad (6)$$

297 Where V_i is the volume of the voxel in the simulation. The predicted nucleated grain fractions for each of
 298 the three simulations are shown in Table 2 for different combinations of the nuclei density and material
 299 constants developed by Gäumann et al. for E-LMF of CMSX-4 and those determined in this work for
 300 EBM of Inconel 718. Constants from Gäumann et al. do not give good agreement with the experimentally
 301 observed nucleated grain fraction of 11.4%. Use of the fully calibrated model, however, using the directly
 302 determined nuclei density and calculated material constants for Inconel 718, achieves the best agreement
 303 with experimental observations in the high sulfur fluid flow simulation, with a difference in nucleated grain

Table 2 Results of Microstructure Prediction Model

Nuclei Density (m^{-3})	a ($\frac{K^n}{m \cdot s}$)	n	Predicted Nucleated Grain Fraction (Φ)		
			Heat Transfer Only	Fluid Flow Low S	Fluid Flow High S
2.0×10^{15}	1.25×10^6	3.4	61.6 %	71.8 %	81.8 %
2.0×10^{15}	1.23×10^5	3.13	45.8 %	57.4 %	70.9 %
5.4×10^{12}	1.25×10^6	3.4	5.6 %	10.4 %	19.9 %
5.4×10^{12}	1.23×10^5	3.13	2.6 %	5.1 %	10.8 %

Values from Gäumann et al. [20]

Values from this work

fraction of only 0.6%. The sulfur content used for surface tension values in this simulation was 20 ppm, which is very close to the measured sulfur content of 18 ppm from the AM build.

4 Discussion

Additive processing of the block up to a height of 15 mm ensures the EBM process has reached steady-state build conditions, ensuring the isolated spot melt is created on an additively manufactured substrate under additive processing conditions. This can be a major drawback in single-track melting experiments, which may use conventionally wrought or cast substrates for welding studies but critically fail to capture the effects of powder agglomeration and the complex thermal histories present in AM processing. Powder-powder interactions and wetting effects due to surface roughness, for example, are not easily captured without the use of AM substrates.

Full 3D characterization of the melt pool enables a more thorough analysis of the solidification process than can be achieved through conventional 2D metallography. This analysis relied on multi-modal data to both identify nucleated grains and to isolate the melt pool boundary. The use of multi-modal data collection, both in 2D and 3D, requires robust registration algorithms to fully leverage advanced characterization techniques. The thin plate spline algorithm described in Section 2.1.3 was useful in achieving this registration, but requires significant user input and tuning to acquire a good fit. Progress in machine learning and forward modeling approaches could create more robust, more automated algorithms that take into account the geometry of the detectors within the microscope as well as the source of the signal (secondary electrons, backscattered electrons, etc.) to achieve distortion-free registration of large data volumes.

The vast parameter space offered by AM machines precludes exhaustive experimental studies to determine empirical relationships. The adoption of AM components in critical applications necessitates the use of thermal modeling tools as a key element of the so-called “digital twin” framework to predict part properties without the need for destructive characterization [44]. However, a significant gap still remains in computationally affordable models that can capture all of the relevant physics occurring in the melt pool over length scales relevant to entire AM parts. The close agreement of G and R in all three TRUCHAS simulations shown in Figure 4 suggests that simplified models that only consider heat transfer should qualitatively capture the thermal history behavior, creating a potential pathway for simulation of full-scale parts. However, small changes in the simulated thermal history data, particularly at the beginning and end of solidification, can create large changes in the predicted nucleated grain fraction.

333 The presence of impurities in AM powder is an important consideration in controlling material properties,
334 both for surface-active elements like sulfur and oxygen that can affect melt pool shape [45], and how impurities
335 may lead to the formation of deleterious precipitates such as nitrides, which can serve as nucleation sites for
336 fatigue cracks in Inconel 718 [46]. Figure 6 shows that strong radially inward fluid flows are established early
337 in the solidification process, which can explain the radial distribution of nucleated grains. The $\langle 001 \rangle$ -type
338 growth directions of the nucleated grains, well-aligned with the major axis of the grain, indicate solidification
339 growth toward the center of the melt pool. Any activated solidification nuclei in front of the advancing solid-
340 liquid interface are brought up from the bottom to the top of the melt pool. The growing nuclei are caught
341 in the advancing interface and begin to grow toward the pool center, which has been observed previously
342 in the trapping of alumina particles in larger spot melts of Inconel 718 [36, 47]. The coupling of advanced
343 characterization with modeling provides a more complete understanding of microstructure evolution during
344 additive manufacturing.

345 Table 2 shows the sensitivity of the microstructure model to both different constants and simulation data.
346 The original formulation of the model over predicts the nucleated grain fraction due to critical differences
347 in material properties and processing conditions. The microstructure prediction model is most accurate
348 when material- and processing-specific parameters are included with fluid flow. Significant differences in
349 alloy constants between CMSX-4 and Inconel 718 highlight the importance of accurately capturing chemical
350 composition when attempting to predict microstructure. The faster solidification velocities predicted in the
351 EBM process also demonstrate the need to recalculate the material constants for the relevant processing
352 regime. This framework can be easily extended to other well-studied alloy systems through the use of multi-
353 component phase diagrams.

354 The nuclei density, which is typically used as a calibration value for models, has a more significant impact
355 on the model's prediction. The much lower measured nuclei density observed in the AM sample serves to
356 suppress the CET by minimizing the available sites for grain nucleation. Previous studies in AM have taken
357 advantage of the microstructural sensitivity to nuclei density by incorporating inoculants on the prealloyed
358 powder [48], but these approaches may not be applicable to all alloy systems and processing conditions. The
359 large discrepancy between experimentally determined nuclei in this work and that of Gäumann et al. may
360 not stem simply from material properties; the role of heat sources (laser versus electron beam) in controlling
361 super-heating and energy density in the melt, as well as differences in substrate material (single crystal
362 castings versus AM block) are likely important factors. As only one melt pool was characterized in this
363 work, it is not possible to clearly approximate variability from spot to spot in nucleation density measure-
364 ments, which is inherently a stochastic process. Nucleation kinetics may also be different in laser powder-bed
365 processes, in which gas flow and vaporization of the metal can create denuded zones as those powder beds
366 are not typically sintered. However, the uniformity of the microstructure in the rest of the build indicates
367 that similar behavior would be expected regardless of the location of the isolated melt pool.

368 The use of 3D characterization enables a full calibration of the microstructure prediction model that can
369 not only be used to analyze simulation data, but can also be used to generate an updated processing-
370 microstructure map for this AM process. Using Equation 3 and Hunt's original criterion for qualifying
371 growth modes, the CET can be calculated for the full range of G and R for EBM of Inconel 718. Processing
372 maps for the original formulation of the model as well as the updated model for AM processing are shown
373 in Figure 8. The changing material properties and nuclei densities serve to shift the CET to higher interface
374 velocities and lower thermal gradients for the EBM process than for E-LMF. The suppression of the CET

375 in EBM is likely responsible for the heavily textured, columnar microstructures that are typically observed
 376 in AM processes, with any nucleated grains forming near the end of solidification likely being remelted upon
 377 subsequent deposition. The processing map calibrated in this work can be extended for microstructure pre-
 378 diction of simulated bulk melting strategies. Continued development of this approach could further enable
 379 microstructure prediction of entire parts via simulation.

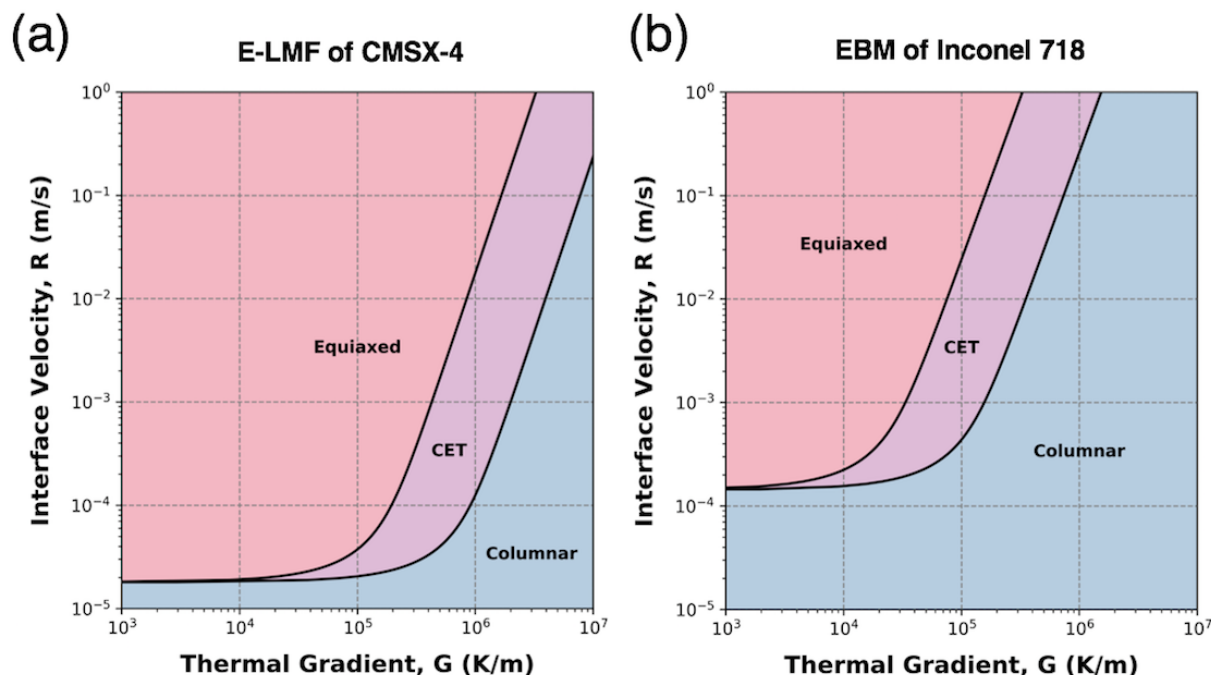


Fig. 8 Microstructure processing maps for epitaxial laser metal forming (E-LMF) of CMSX-4 (a) and electron beam melting (EBM) of Inconel 718 (b). The location of the CET was calculated using Hunt's criterion in [Equation 3](#).

380 5 Conclusion

381 A full 3D characterization of an isolated melt pool in AM Inconel 718 has been presented. Experimental
 382 characterization and solidification simulations were used to calibrate previous models of the CET devel-
 383 oped for a laser-based welding process using a directly measured nuclei density of $5.4 \times 10^{12} \text{ m}^{-3}$. A new
 384 microstructure processing map for EBM of Inconel 718 has been developed using this approach, which demon-
 385 strates the suppression of the CET in EBM of Inconel 718 as compared to the original model. Advanced
 386 characterization techniques are critical for advancing and validating modern modeling approaches, which in
 387 turn can help explain the complex microstructures observed in additively manufactured components. This
 388 approach also provides a future pathway for achieving location-specific properties through control of scan
 389 parameters.

390 **6 Acknowledgements**

391 This research was sponsored by the US Department of Energy, Office of Energy Efficiency and Renewable
392 Energy, Advanced Manufacturing Office, under contract DE-AC05-00OR22725 with UT-Battelle, LLC and
393 performed in partiality at the Oak Ridge National Laboratory's Manufacturing Demonstration Facility, an
394 Office of Energy Efficiency and Renewable Energy user facility. This research was also supported by the
395 Department of Energy RAMP-UP program under award number 4000156470.

396 **7 Conflicts of Interest**

397 On behalf of all authors, the corresponding author states that there is no conflict of interest.

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