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1 Title: Mapping microplastic movement: A phase diagram to predict microplastics modes of transport

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9 **Key words:** microplastics transport, the transport stage, phase diagram, bedload transport, suspension

10 **Highlights**

- 11 • The transport stage U_* / W_s can predict microplastics trajectory characteristics
- 12 • Microplastics modes of transport can be predicted by the transport stage
- 13 • Microplastics density and nominal diameter governed their particle trajectories
- 14 • Particles susceptibility to suspension increase as they deviated from perfect spheres
- 15 • A phase diagram was developed to predict microplastics modes of transport

16 **Abstract**

17 Microplastics pose numerous threats to aquatic environments, yet general understanding of the
18 mechanisms governing their transport remains limited. Drawing upon research on natural sediment
19 provides a valuable resource to address this knowledge gap. One key dimensionless number used to
20 describe sediment transport is the transport stage, referring to the ratio between the fluids shear velocity
21 and the particle settling velocity. However, differences in physical properties (e.g., shape, density) raise
22 concerns regarding the applicability of existing sediment transport theories to microplastics. To address
23 this challenge, we employed a physical modelling approach to examine the trajectories of 24 negatively
24 buoyant microplastic particles varying in size, shape and density. Utilizing a 3D particle tracking setup,
25 we captured the movement of the particles in turbulent open channel flow. A total of 720 trajectories
26 where recorded and analysed. The results revealed a strong correlation between the transport stage and
27 the mean forward velocity of the particles, as well as their mean position in the water column. Notably,
28 particle shape emerged as a critical factor influencing particle transport dynamics. Fibres showed a
29 tendency to be transported closer to the water surface while experiencing slower mean forward velocities
30 compared to spheres. The microplastic particles exhibited rolling/sliding, saltation and suspension as
31 transport modes, comparable to natural sediment. The results show a strong correlation between the
32 transport stage and the percentage of time in which microplastics experienced a certain mode of
33 transport. Based on the laboratory results, a new phase diagram for microplastics is introduced,
34 analogous to an existing diagram for sediments.

35 **1. Introduction**

36 Microplastics are abundant in aquatic environments, posing a pervasive environmental concern (Browne
37 et al., 2011; Koelmans et al., 2019; Rhodes, 2018; Sundt et al., 2015). In response, various initiatives,
38 spanning legislative, scientific, and social realms, target reduced microplastic emissions and the removal
39 of environmental microplastics (Barcelo and Pico, 2020; Nikiema et al., 2020). The success and
40 advancement of these initiatives are impeded by our limited ability to assess and monitor their
41 performance and outcomes (Whitehead et al., 2021). A comprehensive understanding of microplastic
42 transport pathways, such as the vertical distribution in the water column, is crucial for accurately

43 estimating quantities, advancing risk characterization by comparing established effect thresholds with
44 these estimated quantities, and evaluating the efficacy of removal initiatives. Especially the mechanisms
45 governing microplastic transport in rivers, which represent an important route for microplastics to the
46 oceans (Klein et al., 2015; Lebreton et al., 2017; Lechner et al., 2014; Rech et al., 2014), remain not
47 fully understood (Waldschläger et al., 2022).

48 Flow characteristics can influence the transport of microplastic particles in rivers in a manner
49 comparable to other natural riverine components (e.g., sediment, organic matter and air bubbles)
50 (Cowger et al., 2021; Lofty et al., 2023; Waldschläger and Schüttrumpf, 2019a). Recently, the literature
51 on microplastics has been enriched by efforts examining the applicability of the fundamental principles
52 governing the flow-sediment interactions and the resulting modes of transport to fill this knowledge gap.
53 Examples include the settling and rising velocity of microplastics based on equations known for
54 sediment (Van Melkebeke et al., 2020; Waldschläger and Schüttrumpf, 2019a), the estimation of the
55 vertical distribution of microplastics in the water column using the Rouse model (Born et al., 2023;
56 Cowger et al., 2021; Eggenhuisen et al., 2020), the incipient motion of microplastics based on the
57 Shields number (Waldschläger and Schüttrumpf, 2019b), and the saltation behaviour of spherical
58 microplastics compared to sediments (Lofty et al., 2023).

59 Microplastics were found to be transported in suspension and as bed load, analogous to natural sediment
60 (Born et al., 2023). However, the broad variation in density and particle geometry challenges the direct
61 adoption of equations and models developed for sediment transport. For instance, the settling velocity
62 and the critical shear velocity dictating the incipient motion of microplastics varied largely from the
63 theoretical values based on sediment transport equations (Waldschläger and Schüttrumpf, 2019b,
64 2019a). Our understanding of the modes of transport experienced by microplastic particles (i.e.,
65 suspension or bed load) has benefited from recent work in the field. For instance, the work of Lofty et
66 al. (2023) showed that the probability of saltation and rolling was governed by the Rouse number at the
67 particle scale for perfect spheres with size and density ranges comparable to microplastics. Here, we
68 further investigate the modes of transport of microplastic particles with different shapes, including
69 fibres, fragments, pellets and spheres, under different turbulent flow conditions. Guided by the well-
70 established practice in natural sediment (Abbott and Francis, 1977; Francis, 1973; Nino et al., 2003), we
71 focus on the transport stage, referring to the ratio between the flow shear velocity (U_*) and the particle
72 settling velocity (W_s), as a key parameter in describing the trajectory and transport modes exhibited by
73 microplastics.

74 Our primary objectives are to establish and understand particle trajectories, encompassing the mean
75 position in the water column (Z_p) and transport rate of plastic particles (U_p) with the flow. Based on
76 further analysis of the particle trajectories we identify the different modes of transport encountered by
77 microplastics, aiming to contribute essential insights for developing effective mitigation measures and
78 predicting transport rates in river environments. Informed by our laboratory experiments, we provide
79 the first phase diagram to predict microplastics modes of transport based on the transport stage.

80 **2. Material and methods**

81 **2.1. Material matrix**

82 A total of 24 types of microplastics were examined in the present study (Figure 1). The selection of
83 microplastics was based on the types of polymers and shapes predominantly found in riverine systems
84 (Duis and Coors, 2016; Kumar et al., 2021a; Mai et al., 2020). The particles cover a density range
85 between 1.04 and 1.49 g cm⁻³, and the upper limit of the nominal particle diameters was approximately
86 5 mm, which is the commonly used upper size limit for microplastics (NOAA, 2008). The lower limit

87 was approximately 0.5 mm as it is the smallest size detectable by the cameras adopted for the
 88 experimental set-up. Further, the selected microplastics included a variety of shapes including spheres,
 89 semi-spheres (balls), fibres, fragments, cylinders, and lentils. The microplastic particles were coated
 90 with a thin layer of water-based black ink, serving dual purposes. Firstly, this coating minimized the
 91 influence of surface roughness and variations in affinity to air bubbles and water among different
 92 polymers, factors deemed beyond the study's scope. Secondly, it enhanced the visibility of the particles
 93 for the tracking system, ensuring accurate and effective monitoring. To account for the diversity and
 94 complexity of the particle shapes, dimensionless shape descriptors proposed by Van Melkebeke et al.
 95 (2020) were used. The shape factors used in the present study are summarized in Table 1.

96 **Table 1: Summary of the descriptive shape factors adopted for the present study.**

Shape factors					
Corey shape factor (<i>CSF</i>)	Sphericity (ϕ)	Elongation (e)	Flatness (F)	Aspect ratio (φ)	Nominal diameter (d_n)
$\frac{S}{\sqrt{LI}}$	$\frac{A_{sph}}{A_p}$	$\frac{I}{L}$	$\frac{S}{I}$	$\frac{I+S}{2L}$	$\sqrt[3]{L \times I \times S}$
Input parameters					
L (mm): orthogonal long axis		d_p (mm): the diameter of an equivalent sphere ($\sqrt[3]{\frac{6}{\pi} v_p}$)			
I (mm): intermediate axis		where v_p (mm ³): the measured volume of the particle			
S (mm): short axis					
A_{sph} (mm ²): the surface area of the equivalent sphere $4\pi \left(\frac{d_p}{2}\right)^2$					
A_p (mm ²): the surface area of the particle, which is calculated as $2\pi r h + 2\pi r^2$ for perfect cylinders and as					
$\left(4\pi \left[\frac{\left(\frac{L}{2}\right)^2 \left(\frac{L}{2}\right)^2 + \left(\frac{L}{2}\right)^2 \left(\frac{I}{2}\right)^2 + \left(\frac{L}{2}\right)^2 \left(\frac{S}{2}\right)^2}{3}\right]^{1/2}\right)$ for the remaining particles					

97
 98 The classification of the particles included two steps. First, the three principal dimensions L , I , and S
 99 were determined for each particle primarily using Image J (see Table 1). A caliper was used to determine
 100 the third dimension whenever the particle geometry did not allow for adjusting the orientation of the
 101 particles in the images to determine the third dimension. In both cases, these three dimensions were
 102 determined based on the average of 10 measurements per microplastic type, following the work of
 103 Kerpen et al. (2020). The percentage standard deviation was reported for the three principal dimensions
 104 ($STD\% = 100 \cdot \frac{STD}{\bar{X}}$, where \bar{X} is the mean of the measurements of the dimension of interest). The three
 105 principal dimensions were used to calculate the aspect ratio (φ), Corey shape factor (*CSF*), flatness (F),
 106 and elongation (e). Further, the settling velocities of the particles were calculated following the equation
 107 developed by Waldschläger & Schüttrumpf (2019a). This method in determining the settling velocity
 108 was based on the availability of information about the particle shape and its proven reliability compared
 109 to other methods (Van Melkebeke et al., 2020) for the range of particles used in the present study.
 110 Therefore, the nominal particle diameter was determined (d_n) using the equation in Table 1, which was
 111 the input parameter for the settling velocity calculations. Additionally, the particle density and size were
 112 characterized using the dimensionless particle diameter, D^* , defined as

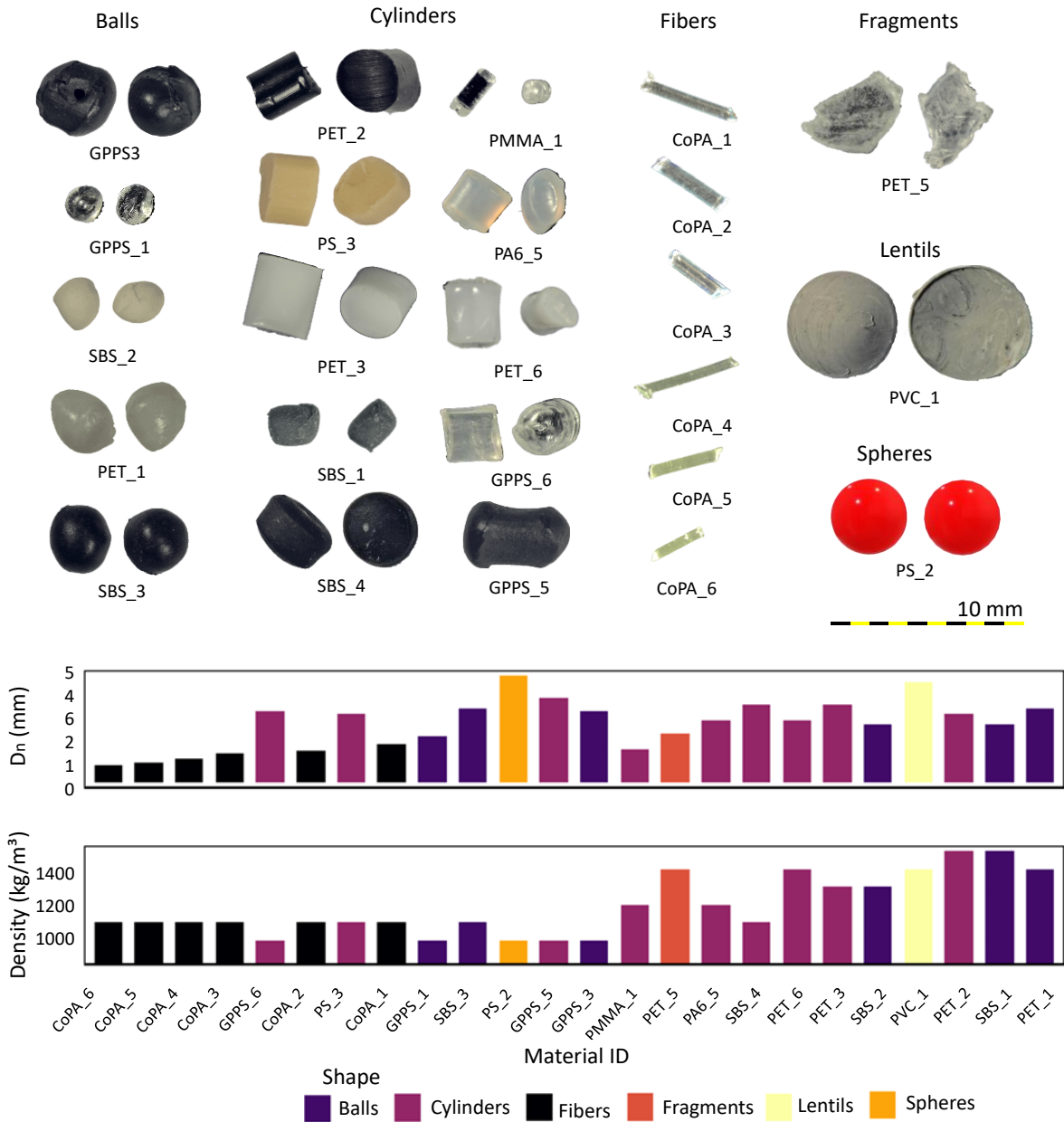
$$113 \quad D^* = \left(\frac{Sg}{\nu}\right)^{\frac{1}{3}} d_n$$

114 , where ν is the kinematic viscosity of the fluid (m²/s) and S is the ratio of excess particle density to
 115 water density (-), defined as

116

$$S = \frac{\rho_{particle} - \rho_{water}}{\rho_{water}}$$

117 This parameter is used both in sediment and in microplastic analyses (Camenen, 2007; Dietrich, 1982;
 118 Waldschläger and Schüttrumpf, 2019a; Zhiyao et al., 2008).



119

120 Figure 1: an overview of the tested microplastic particles properties (further information on the
 121 corresponding shape factors can be found in supplementary materials).

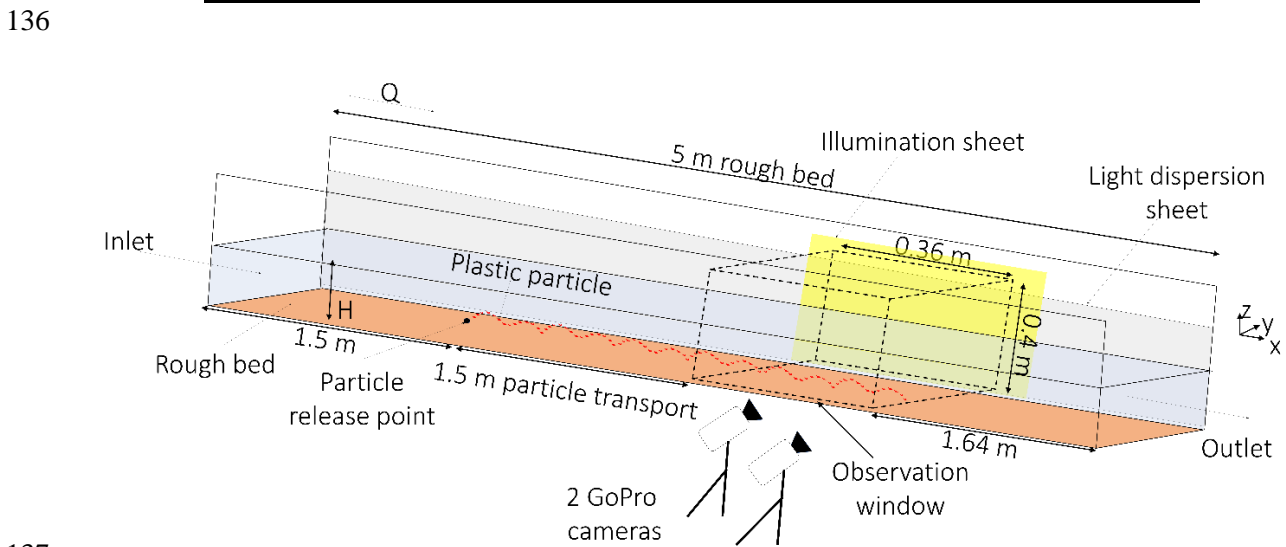
122 **2.2. Experimental setup**

123 A 5 m long recirculating flume with a cross-section of 450 mm by 300 mm at the Kraijenhoff van de
 124 Leur Laboratory at Wageningen University was used for the experiments. The flume allows for a
 125 maximum discharge of 40 l s⁻¹ with an adjustable slope (Figure 2) and the water depth can be controlled
 126 through a vertical gate downstream of the flume. The experiments were conducted using a fixed flume
 127 bed, where a layer of fine sand (with a diameter of 1.85 mm) was glued to the bed to introduce a

128 roughness sufficient to establish fully developed turbulence conditions. The transport of each
 129 microplastic group was assessed under three flow conditions (Table 2). The selected flows represented
 130 subcritical turbulent flow conditions. The flow conditions were not scaled to a specific river, rather they
 131 were selected based on flows commonly occurring in natural rivers. The flow velocity profiles in two
 132 dimensions (parallel to the flow (u), and orthogonal to the flume bed (w)) were obtained at the centreline
 133 of the effective section using a UB-Lab 2C velocity vector profiler (ADVP). Instantaneous velocity
 134 measurements were used to obtain the bed shear velocity.

135 Table 2: Overview of flow conditions within the experimental setup.

Flow condition	Discharge	Water depth	Mean velocity	Reynolds number	Froude number	Shear velocity	Bed slope
ID	Q	H	U	Re	F	U_*	S
(-)	(m^3/s)	(cm)	(m/s)	(-)	(-)	(m/s)	(-)
F1	40.0	17.4	0.83	14442	0.635	0.103	0.15%
F2	25.0	23.0	0.47	10810	0.313	0.051	0.15%
F3	15.0	24.3	0.31	7533	0.201	0.018	0.15%



137
 138 Figure 2: Layout of the experimental setup (distances not to scale).

139 **2.3. Loading regime**

140 The microplastics were introduced 1.5 m from the flume inlet, specifically at the centreline of the flume
 141 bed, given the density range of the tested microplastics ($>1 \text{ g/cm}^3$). To minimise the interference with
 142 the flow, a 3 cm wide and 30 cm long stainless-steel clamp was used to place the particle on the flume
 143 bed. This positioning aimed to initiate particle motion from their terminal position relative to settling
 144 velocities. The particles were transported freely for 1.5 m before reaching the observation window,
 145 where their transport trajectory was recorded. This approach ensured that the particles attained
 146 equilibrium before tracking their transport and minimized the influence of the flume inlet and outlet,
 147 located 3 m and 1.64 m away from the observation window, respectively. Additionally, prior to injection
 148 into the flume, the particles underwent water soaking to prevent air bubbles from attaching to their
 149 surfaces.

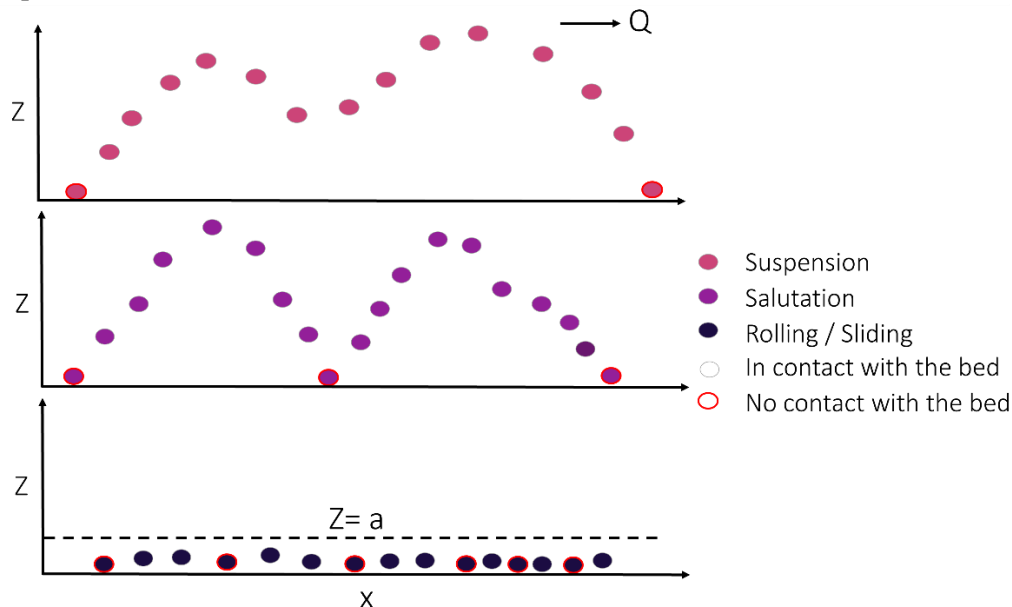
150 **2.4. Particle tracking setup and analysis**

151 The motion and transport of the microplastic particles were recorded using a particle tracking
152 photogrammetry setup (PTV). The setup was composed of two GoPro Hero 11 cameras, which allowed
153 for collecting videos with a frame rate of 50 fps and 5.3 K resolution. The cameras were located facing
154 one side of the flume wall, covering an observation window of 0.36 m parallel to the flow direction
155 (5312 pixels) and about 0.3 m perpendicular to the flow direction (2933 pixels). To improve the contrast
156 between the tracked particles and the background, the roughened flume bed was sprayed with a thin
157 layer of white paint. Further, a light source was placed facing the cameras on the other side of the flume
158 where a dispersive white sheet was used to evenly distribute the light. The use of two synchronized
159 cameras allowed for generating the 3D trajectory of the particles, by employing the concepts of epipolar
160 distance and stereoscopy (Willneff, 2003). Although both cameras were controlled using a remote
161 control to start recording at the same starting point, further postprocessing was needed to ensure that
162 frames obtained from both cameras were in synchronization. This was achieved through postprocessing
163 based on a distinctive sound at the beginning of the video recording. The calibration for the cameras
164 was performed using a 3D calibration grid placed in the observation window at a known distance relative
165 to the flume coordinate system.

166 The trajectory of the particles was obtained using stereoscopic reconstruction following the work of
167 Douxchamps et al. (2005). The collected videos were treated using a MATLAB code developed in-
168 house, where first the video frames were obtained, and then transformed from RGB to grayscale.
169 Further, foreground detection was performed to separate the particles from the background and
170 determine their centroid in each frame relative to the camera 2D coordinate system. For some frames,
171 noise elimination was achieved by cropping the frame to the segment of interest where the particle is
172 moving. Then, translation for the camera 2D coordinates system to real-world 3D coordinates was
173 performed with the aid of the camera translation vector and rotation matrix obtained from the
174 calibrations. The calibration and retrieval of the 3D trajectories was performed following the work of
175 Spinewine et al. (2003). The detection of the 3D trajectories did not account for refraction. However,
176 the camera angles were kept very low relative to the flume glass walls, to limit the effect of refraction
177 (Kwon and Casebolt, 2006). The system accuracy was determined based on its capacity to detect
178 multiple predefined reference points of known coordinates at different locations within the observation
179 window. The developed setup allowed for the reconstruction of the reference points coordinates with an
180 accuracy of ± 5 mm, which is sufficient for the present study objectives.

181 A total of 720 individual runs were conducted, including 24 microplastic particles under 3 different flow
182 conditions, with 10 repetitions each. The selection of this number of test repetitions aligns with
183 established practices in literature (Lofty et al., 2023; Waldschläger and Schüttrumpf, 2019b). The
184 experimental assessment involved instantaneous measurements systematically organized based on flow
185 and material variables, where each measurement of velocity and position represented a statistically
186 independent event. To evaluate test reproducibility, the relative error was determined for both mean
187 particle position and mean forward velocity for each flow-particle combination. In the context of
188 classical sediment studies, the analysis of particle transport trajectories traditionally focuses on
189 suspended sediments (Francis, 1973; Niño and García, 1998). In the present study we adopt a similar
190 approach in defining the mean forward velocity and position of the particle. The mean forward velocity
191 (U_p) is the average particle velocity component parallel to the primary flow direction (u), calculated as
192 the average of all recorded instantaneous velocities. Similarly, the mean position in the water column
193 (Z_p) is the average particle position within the water column relative to the flume bed, measured as the
194 average of the recorded instantaneous particle positions. This approach allows for predicting
195 microplastics transport and occurrence relative to the water column regardless of their modes of
196 transport, with an acceptable accuracy of about $\pm 25\%$. This is in line with the range of variation in
197 particle velocity between the different modes of transport as shown by Frances (1973) for sediments.

198 The study focuses on three transport modes: rolling/sliding, saltation, and suspension, mirroring key
 199 modes identified in sedimentology (Abbott and Francis, 1977; Francis, 1973). The individual modes
 200 were determined based on analysing the full particle trajectory following predefined criteria (Figure 3).
 201 If all measurement points between two points of contact with the bed were below the longest particle
 202 dimension (a), the particle was classified as rolling/sliding. Trajectories without local minima but with
 203 one or more local maxima were categorized as saltation, and in cases where both local maxima and
 204 minima occurred, the particles were considered to be in suspension. Then, the full trajectory was
 205 segmented into intervals corresponding to each transport mode. These segments were translated into a
 206 percentage of time relative to the total duration it took for the particle to pass through the observation
 207 window. To streamline this process, a MATLAB code was developed for accurate and efficient analysis.
 208 While this approach effectively addressed spherical and semi-spherical particles, additional visual
 209 inspection became imperative for other particle shapes. This need arose because multiple additional
 210 local maxima and minima were encountered in trajectories due to the rotation of particles and changes
 211 in the dimension facing toward the cameras. Thus, visual inspection was necessary to filter out these
 212 observations as they are irrelevant to the modes of transport. Moreover, this step proved crucial for
 213 rectifying errors in estimating particle locations due to inaccuracies caused by the physical limitations
 214 of the setup.



215
 216 Figure 3: Conceptual diagram illustrating the criteria for determining the particle modes of transport.

217 Following the video analysis process, the impact of particle characteristics on the particle trajectory was
 218 examined through principal component analysis (PCA) and a multi-variable Anova test. The PCA test
 219 was utilized to determine the overall structure and patterns in the data, and to determine the variables
 220 describing most of the variances in the data. Then, the Anova test provided information about the
 221 statistical significance of each variable. Combining PCA and the Anova test results allowed for a
 222 comprehensive understanding of the underlying structure and the key variables governing the variations
 223 in the dataset. The tests were performed using R studio and the detailed results can be found in the
 224 Supplementary Material. The particle shape was evaluated using the five descriptive shape factors
 225 introduced earlier, while D_* was used to examine the combined effect of size and density.

226 3. Results and discussion

227 The findings of the present study are outlined in two subsections. In the particle trajectory section, results
 228 regarding the mean forward velocity and mean particle position are presented, focussing mainly on the

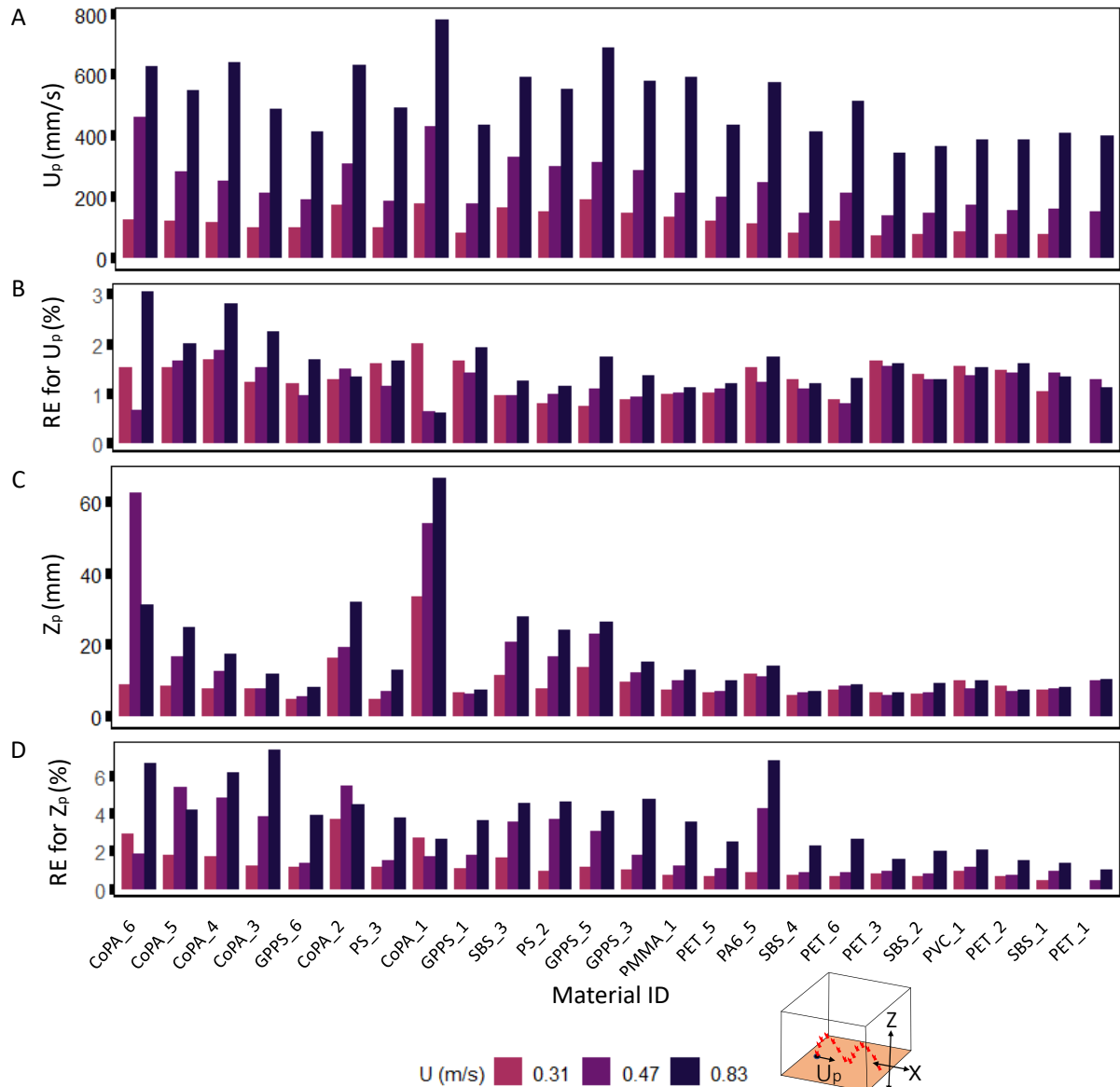
229 test reproducibility, the impact of the transport stage and the effect of the particle characteristics. In the
230 next section, the impact of the particle characteristics and the transport stage on the modes of transport
231 are presented.

232 **3.1. Particle trajectory**

233 **3.1.1. Test reproducibility and reliability**

234 Test reproducibility was assessed through the calculation of the relative error, considering all
235 instantaneous measurements for each flow-particle combination. This comprehensive analysis provided
236 a robust evaluation of the reliability of the experimental results across various conditions. In Figure 4,
237 the resulting relative errors are graphically depicted in an ascending order based on the dimensionless
238 particle diameter (D_*). The relative error concerning mean particle position exhibited a range from 0.5%
239 to 7.4%. There was an observable trend of decreasing relative error with increasing particle density,
240 suggesting a potential restriction in the randomness of the process for denser particles that tend to remain
241 closer to the bed. Conversely, the relative error increased as the flow increased, which could be attributed
242 to increased scatter introduced by higher turbulence. Lower relative errors were apparent in the mean
243 forward velocity, ranging between 0.61% and 3.05%. Overall, an increase in particle density was
244 associated with an increase in relative error for the mean forward velocity, indicating a higher level of
245 randomness introduced by the friction forces impeding the particle transport due to increased particle-
246 bed interactions.

247 Further, fragmented PET particles (PET_5) had one of the highest relative errors for the position (up to
248 6.5%), which could be attributed to the variabilities in the fragment shapes as they are the most
249 heterogeneous particles in the present study. Indeed, the three principal dimensions determined for
250 fragmented PET had the highest percentage standard deviation, ranging between 40 and 80%. This
251 observation supports the assumption that shape and size are crucial factors in determining microplastics
252 occurrence and transport in the water column.



253

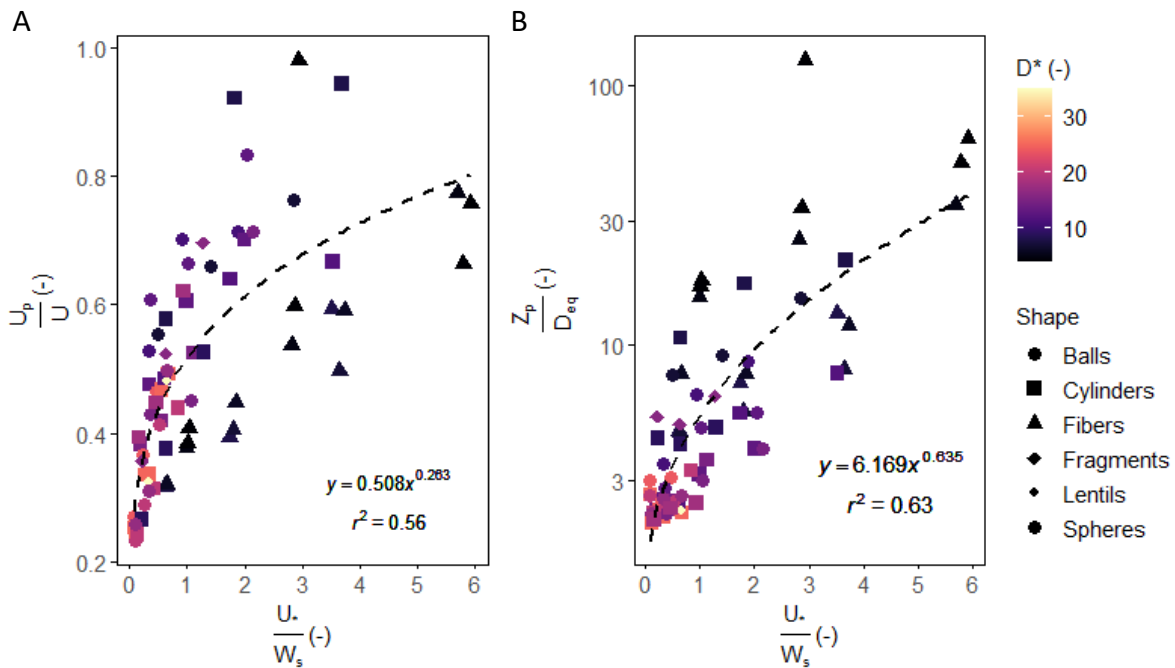
254 Figure 4: Mean results of the experiments grouped by material type and ordered by D_* in an ascending
 255 order. A) The mean forward velocity. B) The relative error of the mean forward velocity, C) The mean
 256 particle position in the water column (Z_p), D) The relative error for Z_p . The specific characteristics of
 257 the particle are presented in Figure 1.

258 3.1.2. The impact of turbulence - Trajectory correlation with the transport stage

259 In previous studies, focusing on both sediments and microplastics, the normalized particle trajectory
 260 characteristics were found to be dependent on the transport stage (U_*/W_s), representing the ratio between
 261 bed shear and the particle settling velocities (Abbott and Francis, 1977; Francis, 1973; Lofty et al., 2023;
 262 Nino et al., 2003; Niño and García, 1998). In the present study, despite one anomaly discarded for the
 263 smallest fibre (CoPA_6), the particle mean velocity normalized to the flow velocity (U) and position
 264 normalized to the equivalent particle diameter (D_{eq}), were strongly correlated with the transport stage,
 265 which was found to be a statistically significant factor (p value < 0.05) based on the Anova test. Higher
 266 stage ratios correspond to scenarios with increased relative turbulent forces, influencing the trajectory
 267 characteristics. Figure 5 illustrates the strong correlation between the normalized particle trajectory
 268 characteristics and the transport stage, fitting well to a power function. These results confirm the
 269 suitability of the power function proposed by Lofty et al. (2023) for the saltation trajectory

270 characteristics of spheres, to the mean forward velocity and particle position introduced in the present
 271 study, albeit with lower correlation values. The lower correlation could be attributed to the fact that the
 272 mean forward velocity and position here represent a heterogeneous mix of particle transport regimes,
 273 combining saltation, suspension and rolling. For the present study, the particle position was normalized
 274 to D_{eq} , whereas in previous work on spheres the diameter of the particle was used for normalization
 275 (Abbott and Francis, 1977; Lofty et al., 2023). Such an approximation of the particle length scale could
 276 reduce the correlation for the mean normalized particle position (Z_p / D_{eq}). The forces governing particle
 277 transport in the flow are strongly correlated with the surface area (Waldschläger and Schüttrumpf,
 278 2019b). As the particles deviated from perfect spheres, the fluctuations in the surface area of a rotating
 279 particle perpendicular to the flow increased. As a result, the variations in the forces balance increased
 280 leading to a lower correlation. Further, the drag coefficient and settling velocity of the particles were
 281 determined based on equations developed for settling column experiments. The deviation from spherical
 282 particles in the present study produces complex relations between the flow condition and the drag
 283 coefficient which can largely affect the transport and settling processes of microplastics (Holjević et al.,
 284 2023). Further investigation of the drag coefficient and settling velocity in turbulent flow streams can
 285 contribute to better determination of particle behaviour and transport.

286 The results indicated a positive correlation between the particle location (Z_p) relative to the water depth
 287 (H) and the normalized mean forward velocity (U_p/U). Under the same flow conditions, particles present
 288 closer to the water surface experienced higher velocities. These findings align with the work of Francis
 289 & Abbott (1977), where an increase in water depth resulted in higher forward velocities of saltating
 290 particles. The position of the particle relative to the water column can lead to the particle being at
 291 different heights within the logarithmic velocity profile which explains the positive correlation between
 292 the particle forward velocity and particle position ($R^2 = 0.65$). In terms of particle position, the water
 293 depth was found insignificant in the present study, which deviated from the observations in the work of
 294 Francis & Abbott (1977). The water depth in the present study allowed the particles to reach maximum
 295 height without rebounding from the surface, which could explain the discrepancy.



296
 297 Figure 5: A) The mean forward velocity of the particles relative to the transport stage and B) the mean
 298 particle position relative to the transport stage. It is important to note that, for Z_p , an anomaly was

299 observed in the mean position of the smallest PA fibre (CoPA_6), necessitating its exclusion from the
300 fit.

301 **3.1.3. The impact of particle characteristics on particle trajectory**

302 Employing PCA statistical tests indicated that CSF, elongation, sphericity, and aspect ratio play pivotal
303 roles in the normalized particle velocity and position. The PCA test shows that these four shape factors
304 can be interpreted collectively to explain up to 55% of the variance. The second principal component of
305 the PCA is primarily affected by the transport stage and D^* . Utilizing a significance threshold of $p <$
306 0.05 , the Anova test highlighted that elongation is the significant contributor for the normalized mean
307 position. In terms of normalized mean forward velocity, significant contributors included elongation and
308 aspect ratio. This variation in the results between PCA and the Anova implies a redundancy or overlap
309 between the information conveyed by the different shape factors. This overlap could be explained by
310 the fact that the shape factors are strongly correlated among each other as they are all derived from the
311 particle side lengths. For both the normalized mean position and forward velocity, D^* and the transport
312 stage are significant contributors. The results are illustrated in Figure S4 and Tables S1 & S2 within the
313 supplementary materials.

314 Despite their statistical significance, the shape factors maintained relatively low regression values
315 individually (r^2 ranged between 0.005 and 0.35), compared to the transport stage. However, the impact
316 of particle properties can be observed qualitatively in Figure S2, showing a scatter of the normalized
317 mean forward velocity and mean position against the transport stage, where the impact of the particle
318 properties is visualised. The particle normalized position and mean forward velocity decreased as D^*
319 decreased, similar to the observations for sediments (Francis, 1973). Relying only on D^* proves
320 insufficient in explaining the overall trend. In addition to gravitational forces, two crucial forces,
321 buoyancy and drag, can act on a particle moving in water. These forces are intricately linked to the
322 particle's surface area, which, in turn, is influenced by its geometry (Waldschläger and Schüttrumpf,
323 2019b). Notably, fibres exhibit a higher susceptibility to suspension in the water column compared to
324 fragments and spherical particles, due to their increased buoyancy and reduced settling velocity (Kumar
325 et al., 2021b). In our study, fibres reached the highest normalized mean position in the water column
326 (Fig 4). This observation aligns with an inverse correlation between the normalized mean particle
327 position and sphericity and elongation. The lift force, influenced by the particle's surface area, tends to
328 push the particle higher in the water column as it deviates from a perfect sphere.

329 In terms of the normalized mean forward velocity, fibres had lower velocities compared to spheres
330 (Figure 5.A). This can be attributed to two key factors. Spherical particles are more prone to entrainment
331 from the bed compared to fibres, where the particle entrainment potential is expected to increase as
332 sphericity approaches one (Gomes and Mesquita, 2013; Waldschläger and Schüttrumpf, 2019b).
333 Spherical particles experience less friction once in contact with the bed, leading to reduced kinetic
334 energy loss during rolling or saltating. Moreover, the migration of non-spherical spheres is highly
335 influenced by their orientation and rotation regime (Tohme et al., 2021). Fibres tended to exhibit an
336 oscillating velocity, moving up and down, which could explain the large relative error for the mean
337 forward velocity of fibres (Figure 4.B). Thereby, fibres needed more time to travel through the
338 observation window, which reduced their average mean forward velocity.

339 **3.2. Modes of transport - The phase diagram**

340 In this study, all particles exhibited mobility, except for the PVC pellets with a shape similar to lentils
341 (PVC_1), which remained stationary under the lowest flow condition. Unsurprisingly, the particle
342 diameter (D^*) emerged as a determinantal factor for the three distinct transport modes exhibited by the

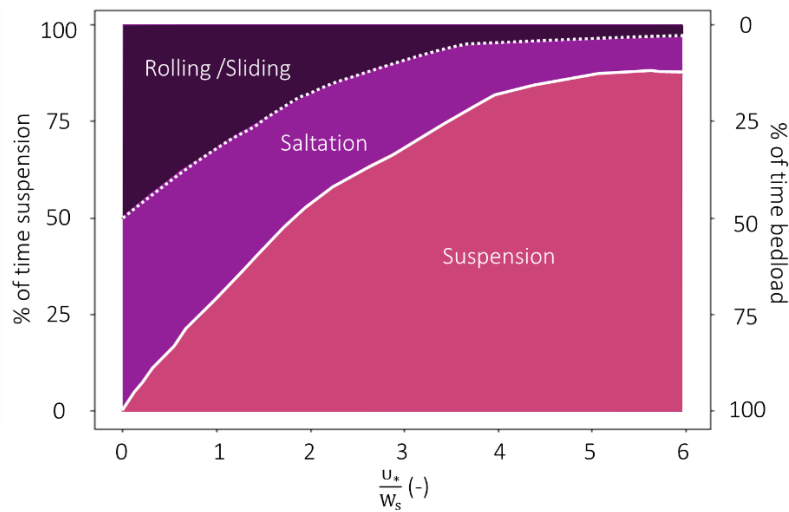
343 particles based on both Anova and PCA tests (see Tables S1 & S2 and Figures S3 & S4). Higher D^*
344 values correlated with bedload transport, whereas decreasing D^* values were associated with an
345 increased duration of particle suspension. Further, the particle shape had a pronounced effect on the
346 particle transport mode. Spherical particles exhibited susceptibility for rolling and saltation, while fibres
347 demonstrated a proclivity for suspension. The PCA test showed that the particle shape factors CSF,
348 sphericity, elongation, and aspect ratio were the primary contributors. The Anova test further confirmed
349 the significance of the particle shape for the three modes of transport. Shape parameters, specifically
350 elongation, manifested statistically significant influence on particle suspension behaviour. For bedload
351 transport modes, encompassing saltation and rolling/sliding regimes, the particle shape factors CSF and
352 elongation were found to be the statistically significant contributors. These findings highlighted the
353 intricate interplay between particle geometry, surface area, and the governing forces influencing particle
354 transport, hence aligns with previous observations in both sediment (Deal et al., 2023) and microplastic
355 transport research (Waldschläger and Schüttrumpf, 2019b). For the saltation mode, the effect of the
356 particle shape can play an additional role in the characteristics of the collision with the bed and the
357 associated energy losses induced by the impact and the rebound dynamics (Ali SZ and Dey, 2019; Baran
358 et al., 2018; Pätz et al., 2020). Spherical particles have a constant projected area in contact with the bed
359 at any collision point, which reduces heterogeneities in the collision and the associated energy losses.
360 The contact area for other particles tends to vary over time, increasing the randomness of the collisions.
361 Further investigation of the impact of the particle shape on the collision characteristics could prove
362 influential in improving the predictability of microplastics saltation behaviour.

363 The modes of transport exhibited by the particles appeared to be correlated with the transport stage (see
364 Figure S5 in supplementary materials). Due to the irregularly spaced nature of the collected data the fit
365 was determined based on a locally weighted regression algorithm (LOESS) (Cleveland, 1979; Cleveland
366 and Devlin, 1988). The analysis was performed following the method described in de Ruijsscher et al.
367 (2018). It should be noted however, that the Anova test suggested that the transport stage is not a
368 significant factor governing particle saltation, possibly due to the already discussed randomness of
369 collisions for non-uniform particles (Table S2). While the normalization to the bed roughness has
370 significantly improved the correlation for spherical particles in the previous work (Lofty et al., 2023),
371 this impact was negligible in our investigation. This discrepancy can be attributed to the influence of
372 particle shape, which profoundly alters the hiding exposure effect—a fundamental aspect addressed by
373 the modified stage. For instance, fibres were found to be more prone to be trapped in the bed material
374 compared to spherical particles (Waldschläger and Schüttrumpf, 2019a).

375 Previous sediment studies suggested that bed roughness becomes inconsequential for particle suspension
376 when the ratio of particle diameter (d_p) to bed material diameter (d_b) exceeds 0.5 (Nino et al., 2003).
377 This observation elucidates the insignificance of bed roughness in particle suspension in our study, given
378 that all examined particles had a d_p/d_b ratio greater than 0.5. Further examination of a wider range of
379 bed material could contribute to unpacking the impact of the bed material on microplastics modes of
380 transport.

381 Overall, the result of the present study allows for the generation of a phase diagram to predict the modes
382 of transport experienced by a microplastic particle as a function of the transport stage (Figure 6). The
383 obtained phase diagram is comparable to the transport diagram developed for sediment by Abbott &
384 Francis (1977). In the present study, microplastics were found to be in motion at lower stage values
385 compared to natural sediment, which could be explained by their lower critical shear as evident in the
386 work of Waldschläger & Schüttrumpf (2019b). Further examination to improve the fit for the suspension
387 phase can enhance the performance of the phase diagram as a prediction tool for the modes of transport
388 of microplastic particles. It should be noted, however, that the presented phase diagram does not capture

389 the full range of possible particle shapes at each stage value, due to the limited number of microplastic
 390 particles tested. For instance, at stage values above 3, fibres were the dominant particle shape, which
 391 could lead to a bias in predicting the modes of transport. Testing a wider range of shapes at each stage
 392 value could improve the phase diagram performance.



393
 394 Figure 6: Phase diagram for the transport of microplastic particles, where the bedload covers saltation
 395 and rolling/siding

396 4. Conclusions

397 Flume experiments conducted in this study have yielded insights into the influence of particle shape,
 398 size, and density on the trajectory characteristics of microplastics across varying flow conditions.
 399 Utilizing a three-dimensional tracking system, we comprehensively analysed the trajectory of 24 types
 400 of microplastic particles with diverse characteristics. Our results revealed that the transport stage
 401 (U_*/W_s) can be used to effectively describe and predict the normalized mean forward velocity (U_p/U)
 402 and the normalized mean position in the water column relative to the bed (Z_p/D_{eq}), aligning with
 403 established practices in sediment studies. A correlation between the percentage of time a specific
 404 transport mode was encountered and the transport stage was found, enabling the development of a phase
 405 diagram for microplastics. Intuitively, the statistical analysis confirmed the dependence on the nominal
 406 particle diameter (D^*), describing density and nominal diameter, for the trajectory characteristics and
 407 modes of transport. Further, several particle shape factors emerged as primary determinant factors,
 408 indicating their pivotal role in governing particle behaviour.

409 In the present study, as particles deviate from a spherical shape, their susceptibility to suspension
 410 increased, accompanied by a decrease in their transport velocity). In terms of the mean position in the
 411 water column, fibres tended to be transported closer to the water surface compared to other particle
 412 shapes. However, the particle shape factors on their own displayed an overall weak relation with the
 413 particle trajectory and transport mode. Once incorporated in the settling velocity calculations (W_s), and
 414 hereby also in the transport stage, they support a better understanding of the particle trajectories. These
 415 findings hold profound implications. Research suggests that fragments (particles of irregular shapes)
 416 represent the second most abundant microplastic shape in water and sediments (Burns and Boxall, 2018).
 417 Therefore, finding methods to describe their irregular shapes and to understand the shapes' impact on
 418 the transport dynamics of these microplastics becomes imperative. The particle shape plays a crucial
 419 role in determining the main coefficient dictating the forces governing particle transport in water (e.g.,
 420 drag and friction coefficients). Further fundamental investigation of the impact of the particle shape on
 421 these forces could improve the predictability of their transport in riverine systems. Additionally, the

422 diversity in particle shapes increases the complexity of the particle collision – a phenomenon inherent
423 with particle saltation. Despite accounting for the particle shape in determining the transport stage in the
424 present study, the particle saltation proved to be the least predictable. A deeper investigation of the
425 collision characteristics for particles of different shapes could significantly improve the predictability of
426 saltation behaviour for microplastics.

427 To enhance the robustness of our findings and refine the developed phase diagram, future research may
428 explore a broader spectrum of bed materials and particle characteristics. Despite their pivotal
429 significance, the comprehensive application of experimental investigations conducted at the particle
430 scale, such as the present study, requires coupling with some descriptive models accounting for the full
431 mixture of particle properties in the environment. Such coupling would undoubtedly contribute to a
432 more comprehensive understanding of microplastics' complex behaviour in turbulent flows. Further, it
433 can lead to a more robust mathematical integration of particle characteristics effects on transport models
434 in the environmental domain.

435 In summary, this study underscores the parallels in behaviour between microplastics and sediments,
436 emphasizing the role of particle characteristics (i.e., shape and D^* which covers the size and density) in
437 capturing potential differences. Our findings have significant implications for prediction models,
438 providing valuable insights into transport rates and potential accumulation zones of microplastics in
439 river systems. Utilizing the transport stage offers a simplified way to incorporate turbulence effects into
440 transport models. The study results can be applied to predict the average transport rate and position of
441 microplastics in rivers, supporting the development of targeted mitigation measures. Projecting the
442 present findings regarding the effect of the particles shape on their distribution in the water column
443 could support a better interpretation of sampling campaigns. In rivers, where turbulence is the dominant
444 process governing plastic particle transport, fibres are more likely to be present at higher levels in the
445 water column compared to spherical particles present closer to the bed. Hence, surface sampling is more
446 likely to capture fibres while spheres are expected to be captured in sediment samples. Utilizing this
447 knowledge when extrapolating microplastic particles abundance along the water column could support
448 a better prediction of microplastics' abundance from single-point sampling measurements.

449 **CRedit authorship contribution statement**

450 Hadeel Al-zawaidah: Conceptualization, Methodology, Formal analysis, Investigation, Visualization,
451 Writing – original draft, Writing – review & editing.

452 Merel Kooi: Supervision, and Writing – review & editing.

453 Ton Hoitink: Supervision, Funding acquisition, Formal analysis, and Writing – review & editing.

454 Bart Vermeulen: Conceptualization, Methodology, and Supervision.

455 Kryss Waldschläger: Conceptualization, Methodology, Supervision, Writing – review & editing.

456 **Declaration of Competing Interest**

457 The authors declare that they have no known competing financial interests or personal relationships that
458 could have appeared to influence the work reported in this paper.

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473 **Data availability**

474 Data will be made available on request.

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601

602 Supporting information to:

603 **Mapping microplastic movement: A phase diagram to predict microplastics modes**
604 **of transport**

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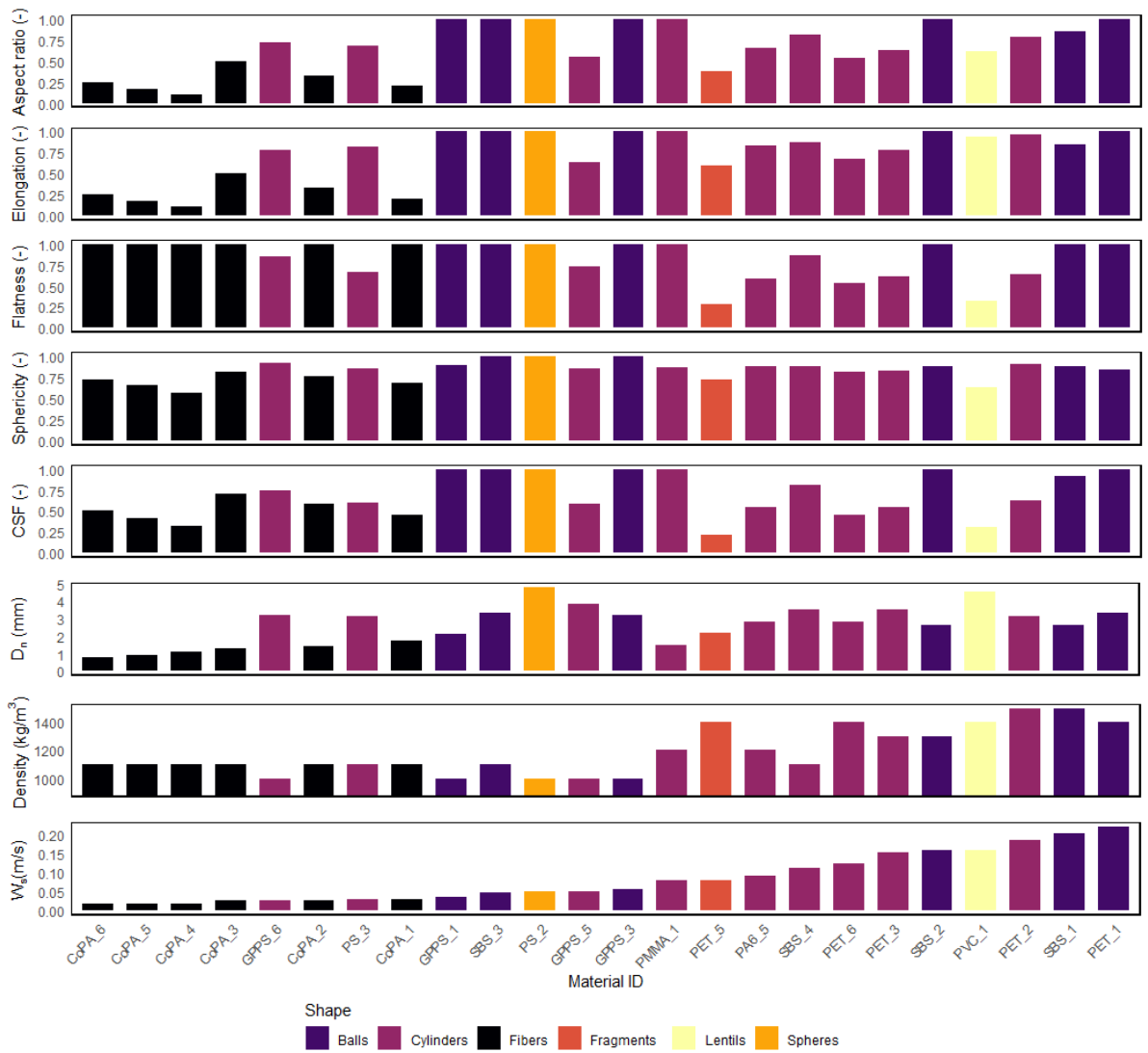
614 S2) Visual inspection of the effect of the particle shape 21

615 S3) Statistical analysis of the effect of the particle shape 22

616 S4: Derivation of the phase diagram 23

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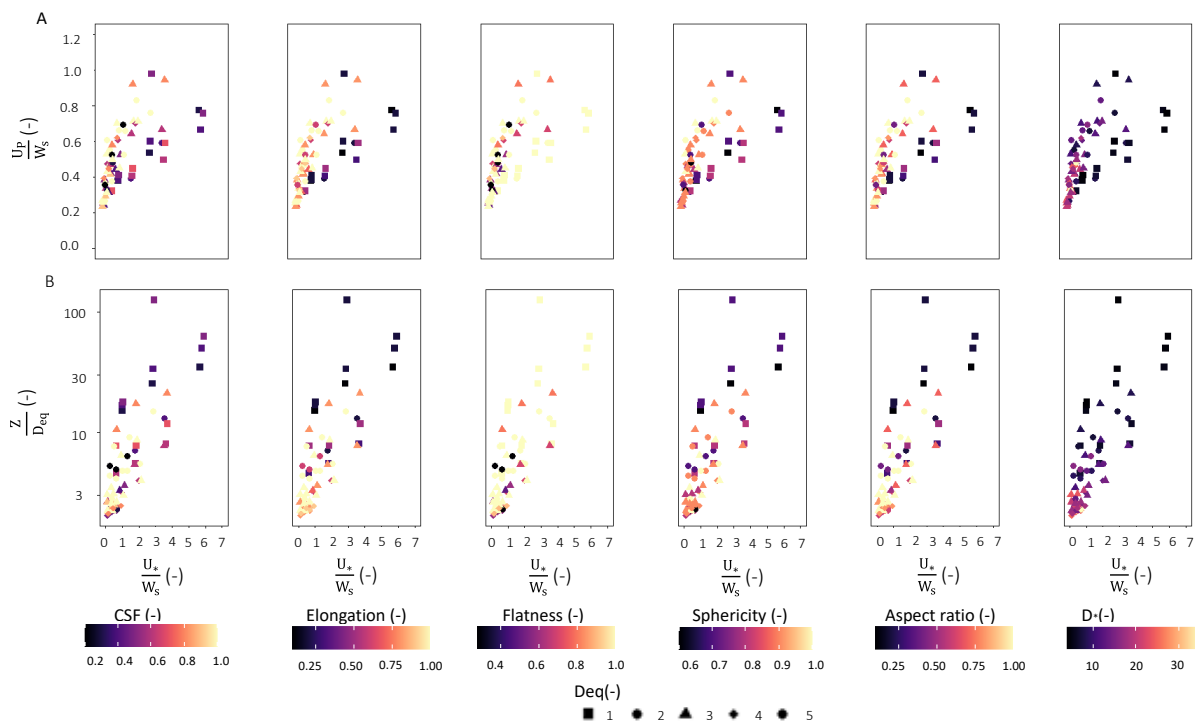
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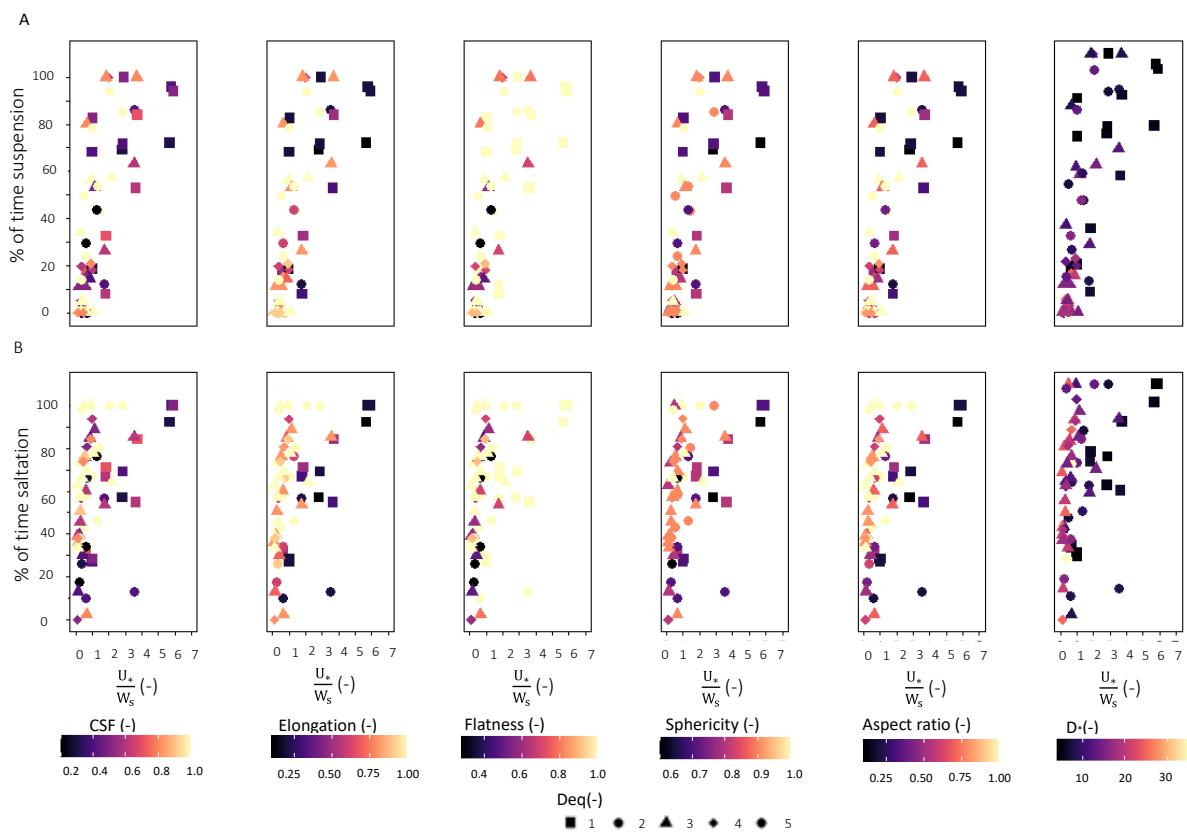
620 **Figure S1:** Layout of the particle properties.

621 **S2) Visual inspection of the effect of the particle shape**



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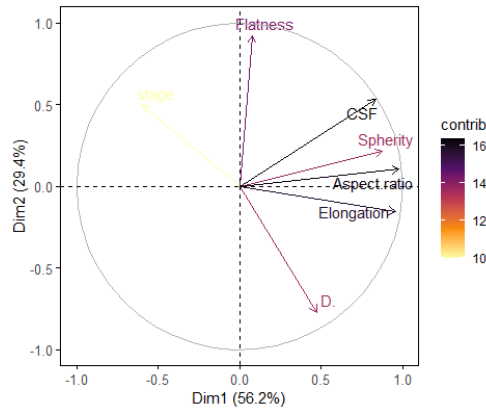
623 **Figure S2:** Layout of the particle trajectory characteristics faceted by microplastics characteristics.



624

625 **Figure S3:** Layout of the particles modes of transport faceted by microplastics characteristics.

626 **S3) Statistical analysis of the effect of the particle shape**



627
628 **Figure S4:** Graphical representation for the PCA results in the two primary principal components.

629 **Table S1 :** PCA loading results for the predictor variables.

Parameter	PC1	PC2	PC3
CSF	0.42083961	0.37114203	-0.08036899
Sphericity	0.44300254	0.15163019	0.23729534
Elongation	0.48419153	-0.10847351	0.24345468
Flatness	0.03893025	0.64223866	-0.39129138
Aspect ratio	0.49432135	0.07275268	0.13119666
D*	0.23813821	-0.53861589	0.05266317
$\frac{U_*}{W_S}$	-0.29936994	0.34586826	0.83956337

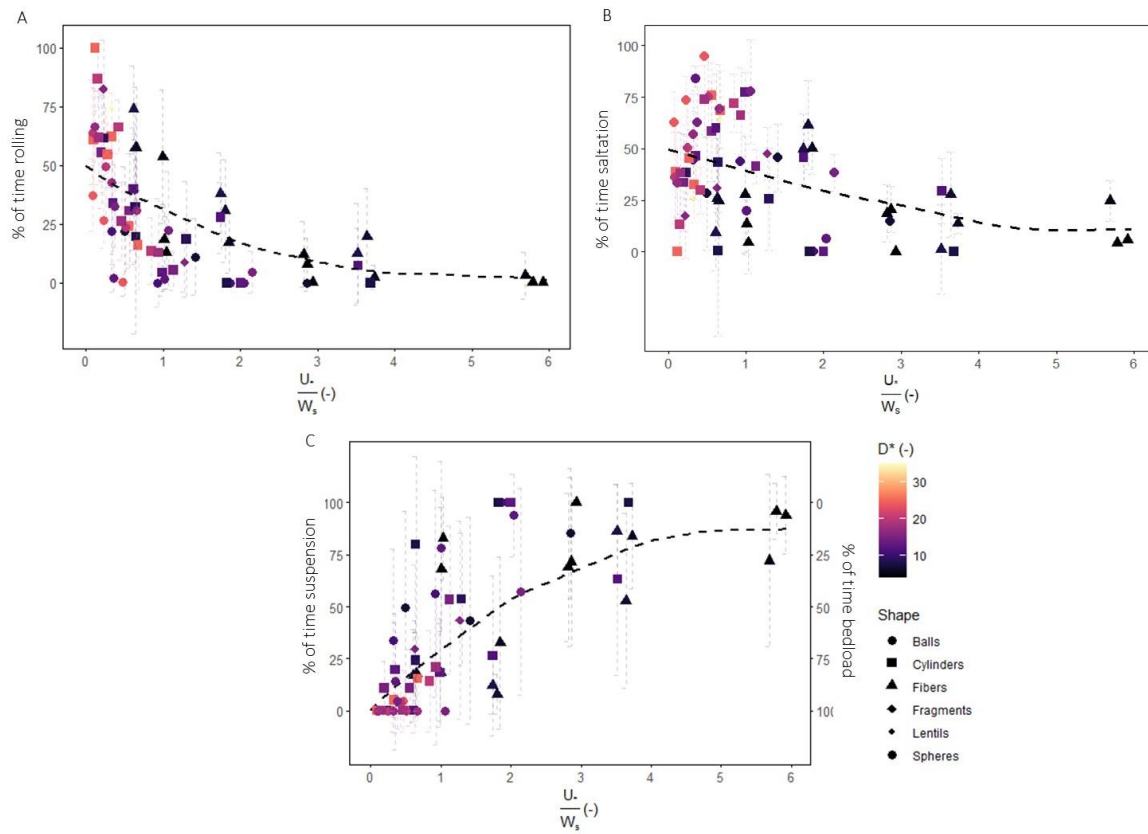
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632

Table S2 : Summary of the Anova test results.

Parameter	$\frac{Z}{D_{eq}}$	$\frac{U_P}{U}$	P value		
			% of time in suspension	% of time in saltation	% of time in rolling/sliding
CSF	0.120909	0.607662	0.3883	0.00687	0.035184
Sphericity	0.073360	0.092176	0.4815	0.54678	0.857247
Elongation	0.001217	0.000346	9.55e-09	0.00185	0.000497
Flatness	0.411414	0.129317	0.0777	0.62975	0.132576
Aspect ratio	0.798507	0.048424	0.1643	0.82737	0.209002
D*	0.009648	4.23e-07	1.10e-07	0.00193	0.002448
$\frac{U_*}{W_S}$	0.000849	8.65e-11	2.05e-08	0.16333	3.13e-07

633

634 **S4: Derivation of the phase diagram**



635

636 **Figure S5:** The percentage of time a particle exhibited rolling against the stage, A, the percentage of
 637 time a particle exhibited saltation against the stage, B, and the different modes of transport of the
 638 particles relative to the stage, C.